

Improvement of Inertial Profiler Measurements of Urban and Low-Speed Roadways

by

Steven M. Karamihas

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Doctoral Committee:

Professor Huei Peng, Chair
Professor Greg Hulbert
David J. LeBlanc, Associate Research Scientist
Professor Jerome P. Lynch
Professor Noel C. Perkins

Steven M. Karamihas

stevenk@umich.edu

ORCID iD: 0000-0002-7480-3952

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This dissertation is dedicated to my wife Cheryl and my daughter Emily.

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Table of Contents

Dedications	ii
Acknowledgements	iii
List of Figures.....	viii
List of Tables.....	xii
List of Appendices.....	xiv
List of Abbreviations.....	xv
List of Notations.....	xvi
Kinematics.....	xviii
Kalman filtering notation	xix
Abstract.....	xx
Chapter 1 Introduction.....	1
1.1 Motivation	1
1.2 Problem Description.....	3
1.2.1 Background.....	3
1.2.2 Measurement Principle.....	4
1.2.3 Measurement Errors	7
1.3 Literature Review	10
1.3.1 Error Suppression	10
1.3.2 Sensor Augmentation	11
1.3.3 Estimation Using Vehicle Response	12
1.3.4 Non-Inertial Systems	13
1.3.5 Assessment	14
1.4 Problem Definition	14
1.5 Dissertation Organization.....	15
Chapter 2 Technical Background	17
2.1 Profile Measurement Requirements	17
2.1.1 International Roughness Index (IRI).....	17
2.1.2 The IRI Scale.....	18
2.1.3 Roughness Profiles	20
2.1.4 Waveband of Interest.....	22
2.1.5 Objective Trace Comparison.....	28

2.2 Signal Flow.....	31
2.2.1 Signal Interaction.....	31
2.2.2 High-Pass Filtering.....	34
2.3 System Kinematics and Dynamics.....	36
2.3.1 Three Dimensional Kinematics.....	36
2.3.2 Theoretical Demonstration.....	38
2.4 Chapter Summary.....	46
Chapter 3 Evaluation of Existing Inertial Profilers.....	48
3.1 Field Experiment.....	49
3.1.1 Test Sections.....	49
3.1.2 Profilers.....	50
3.1.3 Reference Measurements.....	51
3.1.4 Speed/Location Measurement.....	51
3.1.5 Test Conditions.....	52
3.2 GPS Data Processing.....	54
3.2.1 Static GPS Measurements.....	54
3.2.2 Local Coordinates.....	55
3.2.3 Speed and Acceleration.....	55
3.2.4 Diagnostics.....	56
3.3 Results.....	56
3.3.1 Summary.....	56
3.3.2 Transverse Profile Variations.....	59
3.3.3 Constant-Speed Operation.....	62
3.3.4 Coasting.....	66
3.3.5 Braking.....	67
3.3.6 Throttling.....	75
3.3.7 Stop-and-Go Operations.....	76
3.3.8 Operation from a Dead Stop.....	85
3.3.9 Longitudinal Distance Measurement.....	87
Chapter 4 System Description.....	89
4.1 System Overview.....	90
4.1.1 Nominal Inertial Profiler.....	90
4.1.2 Three-Dimensional Kinematics.....	90
4.1.3 Longitudinal Distance Measurement.....	91
4.1.4 Diagnostics.....	92
4.1.5 Signal Timing.....	92

4.2 Physical Layout	92
4.2.1 Outer Pods	96
4.2.2 Center Pod	97
4.2.3 Upper Instrumentation Rack.....	97
4.2.4 Other Sensors.....	98
4.3 Sensors.....	98
4.4 Signal Flow.....	101
4.5 Nominal System Performance.....	102
4.5.1 Stationary Testing.....	102
4.5.2 Agreement to the Reference	104
4.5.3 Repeatability.....	106
Chapter 5 Error Suppression Algorithms	108
5.1 Profile Calculation Algorithms.....	109
5.2 Test Conditions.....	111
5.3 Basic Temporal Algorithm	114
5.4 Temporal Mean Removal	120
5.5 Temporal High-Pass Filtering, Pre-Integration	122
5.6 Local Suppression	125
5.7 Adaptive High-Pass Filtering	127
5.8 Basic Spatial Algorithm	132
5.9 Spatial High-Pass Filtering, Pre-Integration.....	135
5.10 Timer Distortion and Height-Sensor Reflection.....	137
5.11 Summary.....	143
Chapter 6 Sensor Augmentation.....	145
6.1 The Kalman Filter.....	146
6.1.1 Linear Kalman Filter	146
6.1.2 Extended Kalman Filter.....	148
6.1.3 Multi-Rate Kalman Filter	150
6.1.4 Kalman Smoother.....	150
6.2 Coordinate Reference Frames	152
6.3 System Equations	154
6.3.1 Angular Rate.....	155
6.3.2 Linear Acceleration	156
6.3.3 Sensor Drift	157
6.3.4 GPS Position and Velocity	157
6.3.5 GPS Pitch and Roll.....	159

6.3.6 Discrete System Equations	159
6.4 Sensor Errors	160
6.4.1 Allan Variance	160
6.4.2 Rate Gyroscopes	161
6.4.3 GPS Outputs	164
6.4.4 Tuning.....	165
6.5 Implementation for Profile Calculation	168
6.6 Results	170
6.6.1 Kalman Filter.....	171
6.6.2 Kalman Smoother.....	174
6.6.3 Kalman Smoother with Height-Sensor Reflection.....	178
6.6.4 Kalman Smoother with a Constant Attitude Reference	180
6.6.5 Kalman Smoother with a Constant Height and Attitude Reference.....	182
Chapter 7 Conclusions and Recommendations	184
7.1 Summary.....	184
7.2 Contributions	189
7.3 Suggestions for Future Research	190
7.3.1 Practical Implementation.....	190
7.3.2 Three-Dimensional Surface Measurement	190
7.3.3 Alternative Measurement Concepts	191
7.3.4 Computational Efficiency.....	191
Appendices	193
Bibliography	208

List of Figures

Figure 1.1 GM Research Road Profilometer [27]	3
Figure 1.2 Measurement of profile with a surveyor's rod and level	4
Figure 1.3 Inertial measurement of profile (after Huft [36])	5
Figure 1.4 Block diagram of an inertial profiler [27]	6
Figure 1.5 Accelerometer tilted due to braking	9
Figure 2.1 Golden-Car Model [68]	18
Figure 2.2 NHS IRI distribution, 2018	19
Figure 2.3 Profiles, urban bridge encounter	20
Figure 2.4 Image, urban bridge encounter	21
Figure 2.5 Image, deteriorated bridge joint	21
Figure 2.6 Roughness profiles, urban bridge encounter	21
Figure 2.7 IRI gain for profile slope	25
Figure 2.8 Portion of the IRI captured versus wavelength	27
Figure 2.9 Accelerometer spectral content	31
Figure 2.10 Spectral density of floating-reference-height and height-sensor signals	32
Figure 2.11 Slope spectral density of profile and its components	33
Figure 2.12 Floating-reference-height signal	34
Figure 2.13 Floating reference height, height sensor, and complete profile	35
Figure 2.14 Effect of filter type on a raw profile trace	36
Figure 2.15 Body-fixed rotations in pitch and roll	37
Figure 2.16 Inverted pendulum model	39
Figure 2.17 Acceleration components	40
Figure 2.18 Deceleration pulse	41
Figure 2.19 Measured and actual vertical acceleration	41
Figure 2.20 Height-sensor and floating-reference-height signals	42
Figure 2.21 Simulated profile measurement	43
Figure 2.22 Short-interval roughness profile, simulated braking	43
Figure 2.23 Profile measurement with and without braking	44
Figure 2.24 Test speed profile	45

Figure 2.25 Simulated profile measurement error, long braking pulse	45
Figure 3.1 Section starting point	50
Figure 3.2 GPS system set-up	52
Figure 3.3 Short-interval roughness profiles of transversely inconsistent localized roughness....	61
Figure 3.4 Short-interval roughness profiles of transversely inconsistent localized roughness....	61
Figure 3.5 Agreement in IRI between inertial profilers and the reference values versus travel speed	63
Figure 3.6 Raw profile traces measured by Profiler 4 at 48 km/hr	64
Figure 3.7 Raw profile traces measured by Profiler 4 at 16 km/hr	64
Figure 3.8 Comparison of IRI values in passes with coasting and at constant speed	67
Figure 3.9 Speed profile for a pass with braking.....	68
Figure 3.10 Longitudinal acceleration profile for a pass with braking	69
Figure 3.11 Raw profile trace with braking at 0.28 g, Profiler 4	70
Figure 3.12 Raw profile trace with braking at 0.28 g, Profiler 5	70
Figure 3.13 Raw profile trace with braking at 0.28 g, Profiler 6	70
Figure 3.14 Raw profile trace with braking at 0.28 g, Profiler 3	71
Figure 3.15 High-pass filtered traces from passes with and without braking	72
Figure 3.16 Short-interval roughness profiles for passes with braking.....	73
Figure 3.17 Speed profile for a pass with forward acceleration.....	76
Figure 3.18 Speed profile for a pass with a stop	77
Figure 3.19 Acceleration profile for a pass with a stop.....	78
Figure 3.20 Elevation profile measured by Profiler 2 with a stop.....	79
Figure 3.21 Elevation profile measured by Profiler 1 with a stop.....	80
Figure 3.22 Elevation profile measured by Profiler 4 with a stop.....	80
Figure 3.23 Elevation profile measured by Profiler 5 with a stop.....	81
Figure 3.24 Elevation profile measured by Profiler 3 with a stop.....	81
Figure 3.25 Short-interval roughness profiles, Profiler 2 with a stop	82
Figure 3.26 Short-interval roughness profiles, Profiler 2 with and without a stop	83
Figure 3.27 Short-interval roughness profiles, Profiler 3, with and without a stop	85
Figure 3.28 Elevation profile measured at constant speed, from a dead stop, and through a stop	86
Figure 3.29 Roughness profile measured at constant speed from a dead stop, and through a stop	87
Figure 4.1 Measurement system, side view.....	93
Figure 4.2 Measurement system, rear view	93
Figure 4.3 Lower sensor rack, top view	94

Figure 4.4 System schematic, top view	95
Figure 4.5 Right sensor pod.....	96
Figure 4.6 Center sensor pod.....	97
Figure 4.7 Short-interval roughness profile produced by a bounce test.....	104
Figure 4.8 Leftward tracking error	105
Figure 4.9 Agreement score versus lateral tracking error	106
Figure 4.10 Repeatability score versus average lateral separation.....	107
Figure 5.1 Stop-and-go run speed profiles	112
Figure 5.2 Braking run speed profiles	113
Figure 5.3 Short-interval roughness profile measured under favorable conditions	114
Figure 5.4 Basic temporal profile calculation algorithm.....	115
Figure 5.5 Accelerometer signal, 10.7-second-long stop	117
Figure 5.6 Integrated accelerometer signal, 10.7-second-long stop.....	118
Figure 5.7 High-pass filtered profile, 10.7-second-long stop.....	118
Figure 5.8 Short-interval roughness profile, 10.7-second-long stop	119
Figure 5.9 Temporal profile calculation algorithm with high-pass filtering	123
Figure 5.10 Local suppression algorithm applied at low speed	125
Figure 5.11 Adaptive high-pass filter cut-off frequency and wavelength.....	128
Figure 5.12 Adaptive high-pass filtering algorithm, spatial backward pass	130
Figure 5.13 Basic spatial profile calculation algorithm.....	133
Figure 5.14 Spatial high-pass filtering, pre-integration.....	136
Figure 5.15 Timer adjustment versus speed	139
Figure 5.16 Height-sensor and floating-reference-height signals, timer distortion.....	140
Figure 5.17 Height-sensor and floating-reference-height signals, timer distortion and height-sensor reflection.....	142
Figure 6.1 Process model signal flow, after Hol [110].....	155
Figure 6.2 GPS antenna offset, rear view	158
Figure 6.3 Allan deviation, rate gyroscope	162
Figure 6.4 Allan deviation, GPS height.....	164
Figure 6.5 Normalized autocorrelation, GPS height	164
Figure 6.6 Sensor signal flow for profile computation.....	169
Figure 6.7 Drift in Kalman filter output, 10.7-second-long stop.....	173
Figure 6.8 Kalman filter corrections during drift, 10.7-second-long stop.....	174
Figure 6.9 Drift in Kalman smoother output, 10.7-second-long stop	175
Figure 6.10 Short-interval roughness profile comparison, Kalman filter	176

Figure 6.11 Short-interval roughness profile comparison, Kalman smoother	177
Figure B.1 Left side view	198
Figure B.2 Right side view	198
Figure B.3 Lower sensor rack	199
Figure B.4 Rear view	199
Figure B.5 Rotational encoder mounting hardware	200
Figure B.6 Right sensor pod, underside, lower cover removed	200
Figure B.7 Right sensor pod, upper cover removed	201
Figure B.8 Center sensor pod, cover removed	201
Figure B.9 Forward camera and lane tracker camera	202
Figure B.10 Front left GPS antenna (pitch rover)	202
Figure B.11 Left front laser	203
Figure B.12 Vehicle interior	203
Figure B.13 DAS exterior	204
Figure B.14 DAS, power supply, and GPS receivers	204
Figure B.15 Vehicle interior with outer hardware stowed	205

List of Tables

Table 2.1 FHWA IRI ratings	19
Table 2.2 Model coefficients for four sample roads.....	24
Table 2.3 Sample cases for analysis	25
Table 2.4 Thresholds for 0.5 percent error in IRI.....	27
Table 2.5 Long-wavelength thresholds for 0.5 percent error in IRI.....	28
Table 2.6 Short-wavelength thresholds for 0.5 percent error in IRI.....	28
Table 3.1 Participating profilers	50
Table 3.2 High-pass filtering	51
Table 3.3 Test conditions	53
Table 3.4 Static measurement noise	54
Table 3.5 Agreement scores, long waveband, Profiler 4, left	65
Table 3.6 Range of speeds, deceleration, and coating onset location	66
Table 3.7 Effects on short-interval roughness profiles, braking from 48-24 km/hr.....	74
Table 3.8 Effects of average deceleration on short-interval roughness profiles	75
Table 3.9 Effects of peak deceleration on short-interval roughness profiles	75
Table 3.10 Contamination of profile around stops	84
Table 4.1 System sensors	99
Table 5.1 Stop-and-go run characteristics and designations	112
Table 5.2 Braking run characteristics and designations	113
Table 5.3 Results for the basic temporal algorithm.....	119
Table 5.4 Results for temporal mean removal.....	121
Table 5.5 Results for temporal high-pass filtering	124
Table 5.6 Results for local suppression combined with temporal high-pass filtering.....	127
Table 5.7 Results for adaptive high-pass filtering.....	131
Table 5.8 Results for adaptive high-pass filtering with a backward pass	132
Table 5.9 Results for the basic spatial algorithm	135
Table 5.10 Results for the spatial algorithm with pre-integration high-pass filtering.....	137
Table 5.11 Results for stops and the near stop, timer distortion	140
Table 5.12 Results for stops and the near stop, timer distortion and height-sensor reflection....	142

Table 6.1 Kalman filter tuning approach.....	165
Table 6.2 Results for the Kalman filter	172
Table 6.3 Results for the Kalman smoother	176
Table 6.4 Results for the Kalman smoother with height-sensor reflection	180
Table 6.5 Results for the Kalman smoother with a constant attitude reference	181
Table 6.6 Results for the Kalman smoother with a constant height and attitude reference	183
Table 7.1 Cross correlation to the reference test run for selected conditions.....	188
Table A.1 Filter coefficients.....	195

List of Appendices

Appendix A Digital Filtering Technical Notes	193
Appendix B Measurement System Photos	198
Appendix C Linearized System Equations	206

List of Abbreviations

AASHTO	American Association of State Highway and Transportation Officials
CAN	Controller Area Network
CORS	Continuously Operating Reference Stations
CPU	Central Processing Unit
DAS	Data Acquisition System
DOF	Degree of Freedom
DOT	Department of Transportation
FHWA	Federal Highway Administration
FLHP	Federal Lands Highway Program
GCARS	Golden-Car Average Rectified Slope
GM	General Motors
GPS	Global Positioning System
HPF	High Pass Filter
HPMS	Highway Performance Monitoring System
IIR	Infinite Impulse Response
IMU	Inertial Measurement Unit
INS	Inertial Navigation System
IRI	International Roughness Index
ISO	International Organization for Standardization
LPF	Low Pass Filter
MAP-21	Moving Ahead for Progress in the 21st Century
NHS	National Highway System
PI	Proportional Integral
PSD	Power Spectral Density
PTRN	Pre-Transform Ride Number
RMS	Root Mean Square
RN	Ride Number
RTCM	Radio Technical Commission for Maritime
RTK	Real-Time Kinematic
RTS	Rauch-Tung-Striebel
SAE	Society of Automotive Engineers
TPM	Transportation Performance Management

List of Notations

α	exponential constant for adaptive filtering
β	sharpness coefficient
γ	cross correlation amplitude adjustment
δ	slowly time-varying bias
θ_{gps}	GPS pitch inclination
λ	wavelength, longitude
λ_{-3dB}	wavelength for 3 dB reduction in cascaded filter
λ_0	reference longitude
λ_c	cut-off wavelength
μ	Golden-Car Model normalized unsprung mass
μ_p	mean value for filtered profile p
ν	wave number
ν_0	reference wave number
ρ_{pq}	normalized cross correlation for profiles p and q
σ	standard deviation
σ_A	Allan deviation
τ	time constant
ϕ	latitude
ϕ_0	reference latitude
ϕ_{gps}	GPS roll inclination
ψ	heading angle change
ω	angular frequency
ω_a	analog (angular) cut-off frequency
ω_n	angular natural frequency
Δt	time interval
Δt_0	reference (maximum) time interval
Δt_{Adj}	adjusted time interval
Δx	distance interval
Ω	raw sensor output for Allan variance analysis
$\bar{\Omega}$	cluster average for Allan variance analysis
c_r	rotational damping

d	disturbance signal
dE	movement eastward
dF	displacement forward
dL	displacement leftward
dN	movement northward
e	error signal
f_{-3dB}	frequency for 3 dB reduction in cascaded filter
f_c	cut-off frequency
f_{ls}	low-speed cut-off frequency
h_{rc}	rotation center height
h_p	profiler height relative to the rotation center
k	sample number
k_r	rotational stiffness
l_p	profiler longitudinal position relative to the rotation center
l_y	GPS antenna lateral offset
l_z	GPS antenna vertical offset
m	mass
p, q	profiles stored at a constant distance interval
t	time
t_s	start time
v_0	reference speed
v_{set}	PI controller set speed
w	road elevation spectral model exponent
x_{off}	distance offset
B	moving average base length
B_A	bias instability
C	Golden-Car Model normalized suspension damping
D	denominator
$G(v)$	road elevation spectrum
$G'(v)$	road slope spectrum
G_0	reference road spectrum elevation coefficient
G_a	road spectrum spatial acceleration coefficient
G_e	road spectrum elevation coefficient
G_s	road spectrum slope coefficient
H	transfer function for spatial frequency
H_0	reference height above sea level
K_1	Golden-Car Model normalized tire stiffness
K_2	Golden-Car Model normalized suspension stiffness

K_A	rate random walk
K_I	integral gain
K_P	proportional gain
L	pavement section length
L_{cm}	center of mass height in relation to the rotation center
N	number of samples
N_A	angle random walk
Q_A	quantization
$R(\phi_0)$	Earth radius at the reference latitude
R_A	ramp instability
R_{pq}	cross correlation for profiles p and q
S	spectral density function
T	duration, total time
V	Golden-Car Model forward speed

Kinematics

Superscripts on scalar and vector quantities denote the reference frame.

θ	Euler pitch angle
ϕ	Euler roll angle
ψ	Euler yaw angle
$\vec{\omega}_{a/b}$	angular rate vector, frame a relative to frame b
ω_x	angular rate about the longitudinal axis
ω_y	angular rate about the lateral axis
ω_z	angular rate about the vertical axis
$\Omega_{b/n}$	skew symmetric matrix corresponding to the angular rate vector
$\vec{a}_{a/b}$	acceleration vector, frame a relative to frame b
\vec{a}_p	acceleration vector, profiler reference point
a_{xp}	profiler reference point longitudinal acceleration
a_{yp}	profiler reference point lateral acceleration
a_{zp}, a_{zref}	profiler reference point longitudinal acceleration
a_{xpeak}	peak longitudinal acceleration
\vec{f}	specific force vector, expressed in frame a
f_z	specific force vertical component
\vec{g}^a	gravity vector, expressed in frame a
g	acceleration due to gravity
h	height sensor reading

$\vec{p}_{a/b}$	profiler reference point position, frame a relative to frame b
$\vec{r}_{a/b}$	position vector, point a relative to point b
r_{xp}	profiler reference point longitudinal position
r_{zp}, r_{zref}	profiler reference point vertical position
r_{zr}, r_{zroad}	road surface vertical position
$\vec{v}_{a/b}$	velocity vector, point a relative to point b
v_h	horizontal speed
v_x, v_{xp}	profiler reference point longitudinal speed
v_{zp}	profiler reference point vertical speed
x	longitudinal distance
C^{nb}	direction cosine matrix, frame b to frame n
C_{ij}^{nb}	direction cosine matrix element, row i , column j , frame b to frame n

Kalman filtering notation

k	time step
nm	number of measurements
ni	number of inputs
nn	number of process noise terms
ns	number of state variables
u_k	input vector
v_k	measurement noise vector
w_k	process noise vector
x_k	state vector
$\hat{x}_{j k}$	state estimate at time step j , given information up to time step k
y_k	measurement vector
A_k	state transition matrix, linearized state transition matrix
B_k	input matrix
H_k	observation matrix, linearized observation matrix
K_k	Kalman gain matrix
L_k	RTS fixed-interval smoother blending matrix
N	number of time steps
$P_{j k}$	state covariance estimate at time step j , given information up to time step k
Q_k	process noise covariance matrix
R_k	measurement noise covariance matrix
V_k	linearized measurement noise matrix
W_k	linearized process noise matrix

Abstract

Inertial profilers can measure the longitudinal road elevation profile and the International Roughness Index (IRI) accurately when they are operated under favorable conditions. However, their performance deteriorates when they experience disturbances such as lateral and longitudinal accelerations, and when the profiler host vehicle travels very slowly or comes to a stop.

Preliminary analytical and experimental work confirmed two major sources of measurement errors. First, slowly varying bias in vertical acceleration measurements causes drift in the signals derived from them after they are integrated twice to form a component of the measured profile. When the profiler host vehicle decelerates to very low speed or comes to a stop, the drift appears directly in the profile and causes a large artificial change in elevation that is concentrated over a small travel distance. Second, the inertial sensors experience dynamic changes in pitch and roll orientation as the profiler host vehicle reacts to driver inputs, such as braking and steering. Tilt of the sensitive axis causes contamination of the accelerometer signal by inputs along other axes. After double integration, this appears as errors in vertical curvature in the profile over the region where the braking or steering occurred. The errors reduce the accuracy of longitudinal profiles on urban road networks and low-speed roadways, and render the measurements of IRI unusable at important locations, such as intersections.

This research proposed two solutions for addressing these measurement errors. First, the research investigated data processing algorithms that reduce measurement errors without the need for adding sensors to the typical inertial profiler design. These solutions combine specialized processing algorithms with standard filtering techniques to mitigate artificial roughness caused by drift and misalignment. Since no additional hardware is required, these algorithms offer low-cost options for immediate implementation within the existing fleet. The algorithms do not offer a complete solution, because they mitigate large upward biases in roughness measured at stops at the cost of reducing the validity of measured profile at low speed.

Second, the research proposed and tested the use of additional sensors to improve profile measurement at low speed, during braking, and at stops. The augmented system includes inertial and GPS measurement of profiler kinematics. A multi-rate extended Kalman filter combines the

inertial sensors with the GPS outputs to reduce drift and errors associated with profiler host-vehicle tilt. Use of a Rauch-Tung-Striebel smoother improves the mitigation of drift.

A custom measurement system was designed and built for this research to enable an experimental evaluation of the proposed solutions. The performance of the error suppression algorithms and sensor augmentation proposed in this research was evaluated using the results from several test runs collected under challenging conditions, including operation at low speed, braking, and operation through a stop. For all test runs, performance is quantified using standard measures for accuracy of longitudinal profile and IRI used by road agencies for pavement network quality assurance and pavement network management.

Use of inertial measurement in three dimensions and GPS measurement of profiler height and orientation is shown to give the best performance. The recommended processing algorithm integrates an additional mode of operation into the Kalman filter that applies an alternative measurement model at stops. Nearly equivalent performance was observed when the GPS outputs were replaced by artificial signals. This version of the system offers an option for measurement in urban canyons.

Chapter 1

Introduction

1.1 Motivation

State and Federal highway departments collectively manage a network of roads that represents a huge public investment. The U.S. public road system comprises more than 4 million centerline miles of road, which supported 3 trillion vehicle-miles of travel in 2014 [1]. In 2016, Federal, state and local highway funding was \$219.0 billion, and it had exceeded \$200 billion each year since 2010 [2].

Most state and Federal highway agencies use pavement roughness as a measure of the quality of roads. Roughness measurements are used to monitor the ride quality of their road networks, prioritize pavement rehabilitation and reconstruction projects, and to select pavement preservation strategies [3]. Many agencies also use roughness measurements for construction quality control and assurance, and adjust the value of paving contracts based on the roughness of the finished surface [4]. In addition, the Federal Highway Administration (FHWA) Highway Performance Monitoring System (HPMS) requires states to submit roughness data for a large portion of their Federal aid highway network, including the National Highway System (NHS) [5]. In turn, these data influence the allocation of billions of dollars in funding for roads through the FHWA's Highway Economic Requirements System [6,7].

Roughness is not measured directly for these applications. Instead, the roughness of a particular segment of road is calculated from a measurement of longitudinal elevation profile [8]. Longitudinal elevation profile is a record of road surface elevation relative to an arbitrary datum, which is stored as a function of distance along the pavement. Hereafter, longitudinal elevation profile is referred to as *profile*. By far, the most common scale for quantifying the roughness of a profile is the International Roughness Index (IRI), and the most common device for measuring profile is the inertial profiler [3,9,10].

A greater emphasis on the quality of pavement roughness measurements has been provoked recently by the adoption of Federal legislation: Moving Ahead for Progress in the 21st Century (MAP-21). The Act requires an asset management plan for the entire NHS, and requires states to meet minimum standards for pavement performance or lose flexibility in the use of their highway funds [11,12]. The IRI had been selected as a “tier 1” measurement of pavement condition, and would therefore be implemented immediately as the primary indicator of pavement performance [10,13]. States are now required to report the IRI on an expanded NHS network under the National Highway Performance Program [5].

Under ideal conditions, inertial profilers have demonstrated the capability to measure profile with sufficient accuracy and repeatability for the engineering applications described above. However, horizontal acceleration of the profiler host vehicle combined with changes in its orientation introduces artificial roughness into measured profiles [14]. This occurs when profilers operate on curves, or when safe piloting of the profiler host vehicle requires rapid changes in speed or stop-and-go driving [15].

Urban pavements pose a particular challenge to inertial profilers, because they include signal lights, stop signs, railroad crossings, and heavy traffic. Obtaining valid measurement of roughness in urban areas is particularly important, since MAP-21 expands the 264,000-km NHS by more than 96,000 km, and most of the newly designated roads are in urban areas [16]. Further, more than two thirds of the 3-trillion vehicle miles traveled on the U.S. road system in 2018 occurred on urban roadways [17].

Many low-speed rural roads also pose a challenge to inertial profilers. For example, the Federal Lands Highway Program (FLHP) includes 276,000 km of road built within parks, forests, wildlife refuges, Indian reservations, and other locations with difficult terrain [18]. In addition, the FHWA’s design guidance for roads built under the FLHP calls for “context sensitive” road design, which requires respect for the land, preservation of wildlife, and minimization of the effect of the road system on existing features [19]. As such, these roads often include tight horizontal curves and aggressive grade changes.

This research will systematically define the limitations of current inertial profiling technology and develop and validate improvements to the technology needed for obtaining valid profile measurements that are not sensitive to horizontal acceleration or pitch and roll of the profiler host vehicle. Since several hundred, and possibly more than one thousand, inertial

profilers are in service in the U.S. for measurement of profile and road roughness, the technology improvements must be cost effective and augment the design of conventional inertial profilers.

1.2 Problem Description

1.2.1 Background

The inertial profiler was invented in the early 1960s at the General Motors (GM) Corporation. A research laboratory within GM created the “Profilometer,” shown in Figure 1.1, to measure road profiles with “reasonable flexibility and speed” for use as realistic vertical disturbance inputs to vehicles on a driving simulator [20,21]. Previous devices that measured road roughness efficiently produced output based on measurement of vehicle response or relative measurements from the device chassis to the road [22]. These devices did not offer a flat frequency response to the true profile [23]. Engineers interested in undistorted profiles obtained them using high-precision rod and level surveys, because the level provides a consistent reference from which to measure the relative elevation of the road [24-26]. However, the measurement process was “very time consuming and requires painstaking care” [22].

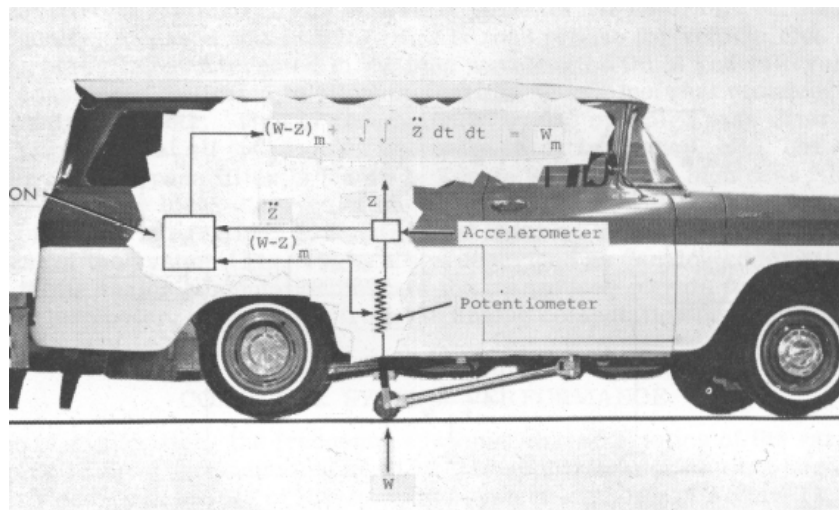


Figure 1.1 GM Research Road Profilometer [27]

Shortly after GM introduced the first inertial profiler to the pavement community, the Bureau of Public Roads initiated a research project with the Michigan Department of Transportation (DOT) to duplicate the GM design and evaluate the technology for measurement of “bridge and pavement roughness.” [28] In parallel, a number of state DOTs began to evaluate

the technology and adapt it for pavement management applications [29-32]. Early study showed that inertial profilers could efficiently reproduce profiles measured by high-precision rod and level surveys over a broad waveband, although they could not detect road grade or gradual grade changes [27,28]. Users did not find the measurement principle of inertial profilers intuitive [33], and the need to cover large road networks safely and efficiently challenged inertial profilers' ability to establish a valid inertial reference with difficult operational conditions. Nevertheless, the relative efficiency of inertial profilers and their ability to reproduce the true profile over a broad waveband under favorable operational conditions led to their widespread use for monitoring road roughness.

1.2.2 Measurement Principle

Inertial profiles measure the elevation of the road surface along a given wheel path (or multiple wheel paths) as a function of longitudinal distance. To do so, they combine the same three ingredients that make up a profile measured by a surveyor's rod and level: (1) a reference elevation, (2) the height of the road relative to the reference elevation, and (3) a measure of longitudinal distance [34]. Figure 1.2 illustrates this measurement concept for a rod and level. The level establishes a constant reference elevation (r_{zref}). At each location along a given segment of road, the reading on the rod ($r_{zref} - r_{zroad}$) indicates the vertical distance to the road beneath the reference elevation. Longitudinal distance is measured independently, often with a graduated steel tape. When profile is measured for analysis of pavement roughness, both elevation and distance (x) are reported relative to an arbitrary origin, although the final profile is often offset vertically and horizontally to place the origin at the start of a road section of interest.

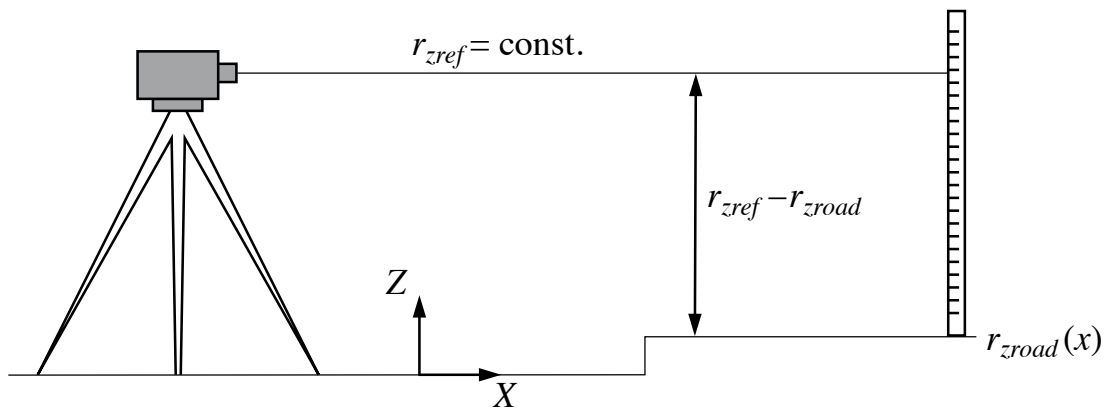


Figure 1.2 Measurement of profile with a surveyor's rod and level

The purpose of inertial profilers is to efficiently record profile, and they are often mounted to conventional over-the-road vehicles to facilitate safe operation in live traffic. An inertial profiler records the elevation of a reference point on a host-vehicle chassis and the height of the road surface relative to the reference point as the vehicle passes over a road section of interest. The profile is calculated as follows:

$$r_{zroad}(x) = r_{zref}(x) - (r_{zref}(x) - r_{zroad}(x)) \quad (1.1)$$

Figure 1.3 illustrates the principle of operation for an inertial profiler with sensors mounted to a reference point forward of the front bumper of a vehicle. Unlike the rod and level, the elevation of the reference point fluctuates as the profiler host vehicle responds to the roughness of the road and to other disturbances. A vertically oriented accelerometer, mounted to the profiler’s reference point, provides a record of its motion. Integrating twice produces a record of $r_{zref}(x)$. This “accelerometer-established inertial reference” is often called a *floating-reference-height* signal [35].

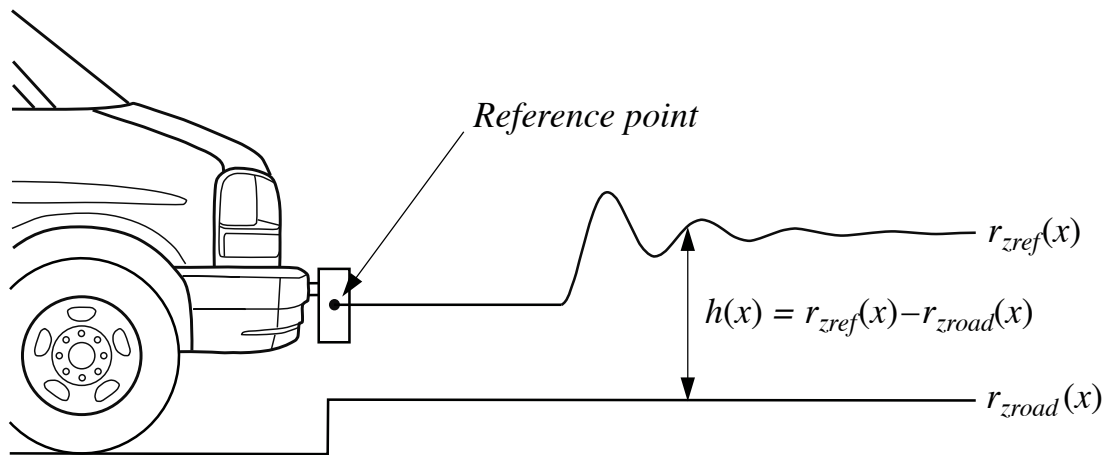


Figure 1.3 Inertial measurement of profile (after Huft [36])

A ranging sensor, often called a *height sensor* in this context, provides the relative measurement $r_{zref}(x) - r_{zroad}(x)$ to the road surface. Unlike the original GM design shown in Figure 1.1, which used a potentiometer connected to a road follower wheel, most inertial profilers sense the vertical distance from the (floating) profiler reference point to the road surface using laser triangulation sensors.

In some implementations the calculation of profile is performed in the time domain:

$$r_{zroad}(t) = \iint a_{zref}(t) dt dt - h(t) \quad (1.2)$$

Where $a_{zref}(t)$ and $h(t)$ are the signals from the accelerometer and height sensor, respectively. The temporal profile is resolved to a spatial profile in a subsequent processing step using an independent measurement of distance versus time. In other implementations the sensor signals are digitized with a constant longitudinal spacing, or resolved to the spatial domain before the profile is calculated [37,38]:

$$r_{zroad}(x) = \iint (a_{zref}(x)/v_x^2) dx dx - h(x) \quad (1.3)$$

Where v_x is the longitudinal speed of the profiler host vehicle. The term in the integrand is the spatial vertical acceleration of the profiler reference point.

Figure 1.4 presents a block diagram used to explain the principle of operation of the first inertial profiler [27]. The figure illustrates the signal flow from the actual profile, W (i.e., $r_{zroad}(x)$ in Figure 1.3), to the measured profile. The figure also provides straight-line approximations of the temporal frequency content at each stage of the process for a simple model of the profiler host vehicle described as a mechanical filter with a “natural frequency of ω_n ”, and idealized sensor and filter performance.

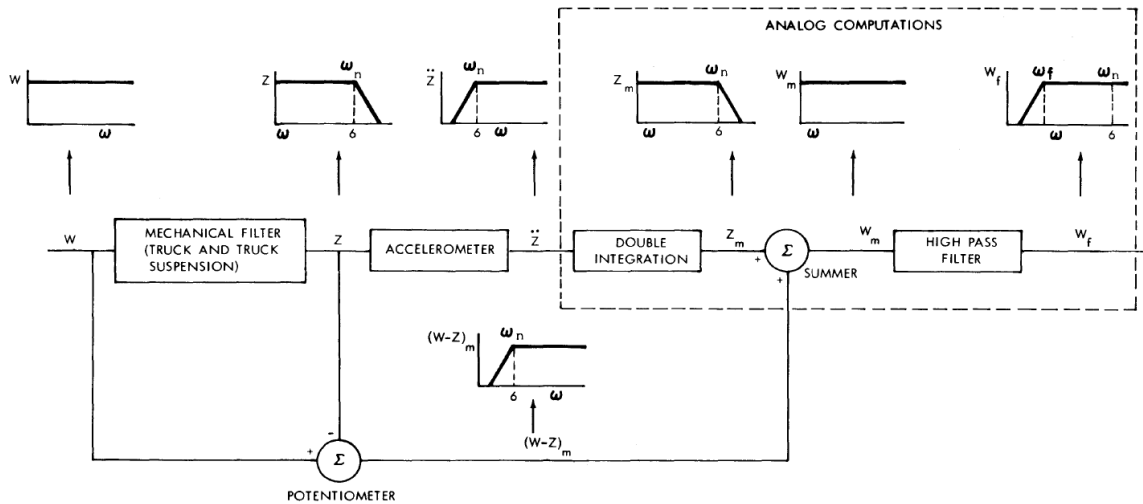


Figure 1.4 Block diagram of an inertial profiler [27]

As shown in Figure 1.4, the profile serves as the excitation to the host vehicle. The time history of vertical position of the profiler reference point (r_{zref}) is determined by the dynamic response of the profiler host vehicle. The response is detected by a vertically oriented

accelerometer, and the vertical position of the profiler reference point is recovered by integrating the accelerometer output twice. The height sensor, which is shown as the “potentiometer” in the figure, provides the vertical distance from the profiler reference point to the road. In theory, the profile is reproduced when the two signals are combined. In early profilers, a high-pass filter was applied to the measured profile to avoid exceeding the voltage capacity of the analog components.

Although Figure 1.4 illustrates the measurement principle used by inertial profilers, it omits several details that are relevant to this research. For example, the functions enclosed within the box marked “analog computations” are performed digitally in most modern inertial profilers, and filtering is performed at multiple stages in the measurement process. In addition, the frequency content of the vehicle response is much more complex, and the frequency response of the height-sensor and accelerometer signal overlap. Chapter 2 examines these issues using field measurements.

1.2.3 Measurement Errors

Two mechanisms cause errors in the measurement of the floating-reference-height signal. These impose a limitation on the measurement of the very-long-wavelength (i.e., low-frequency) portion of the profile. The first is system noise. At progressively lower frequencies, the actual vertical acceleration diminishes in relation to noise in the instrumentation and the resolution of the system [39]. Although grade changes and long-wavelength roughness typically correspond to large changes in elevation their contribution to the vertical acceleration measured on a profiler host vehicle is very small relative to other disturbances.

Second, offsets caused by tilt of the accelerometer from true vertical and other sources of drift appear in the output signal [20,31,36]. In typical inertial profilers the accelerometers are rigidly mounted to the host-vehicle sprung mass. A combination of road grade, cross slope, imprecise mounting, and quasi-static inconsistency in vehicle attitude all cause accelerometer misalignment. When the error in the accelerometer readings is nearly constant over a long time interval, the error in the floating reference height after double integration grows in proportion to the square of time [36].

Early inertial profilers applied analog high-pass filters to the accelerometer signals, in part to eliminate the waveband that was contaminated by these two error sources [28,29]. High-

pass filtering also limited the output of profilers to the waveband of interest for vehicle dynamic response. In modern implementations profilers apply high-pass filtering with a specific spatial frequency response in mind, and the most common cut-off corresponds to a wavelength of 91.44 m [40]. The 91.44-m wavelength limit is a vestige from an early stage in the history of inertial profiler development, “which at 100-mph car velocity produce(s) input frequencies to the car below the natural frequencies of all current road vehicle suspensions” [20]. Use of the 91.44-m cut-off value has prevailed as a standard, since at practical travel speeds it retains content that affects ride comfort, suspension stroke, and dynamic tire load fluctuations. For typical combinations of road grade, cross slope, road roughness level, profiler host-vehicle properties, and host-vehicle speed, the high-pass filter eliminates the content that is contaminated by low signal strength in the accelerometer and slowly fluctuating or constant accelerometer misalignment.

Some accelerometer misalignment occurs because of excessive rigid-body motion of the host-vehicle sprung mass (i.e., pitch and roll response to roughness) and errors caused by operator-induced disturbances (e.g., braking, steering corrections for lane keeping). These alignment errors are a serious source of drift for two reasons. First, since inertial profilers used for pavement management must operate in live traffic, they experience the road at speeds near the prevailing traffic speed. Therefore, misalignment errors caused by profiler host-vehicle dynamic responses map to the same range of wavelengths in the measured profile that affect the IRI. Second, the dynamic component of accelerometer tilt typically occurs in response to, or at least in conjunction with, horizontal acceleration that further contaminates the accelerometer readings.

Sayers and Karamihas [34] described errors in accelerometer readings caused by braking, and Karamihas et al. [14] expanded the discussion to include lateral acceleration and demonstrated the problem experimentally. The discussions are summarized here using an example in the pitch plane. Figure 1.5 shows the side view of an accelerometer that is tilted due to braking. In the figure, the Z_w axis is aligned with gravity, and the X_w axis is perpendicular to gravity and parallel to the longitudinal plane of symmetry of the profiler host vehicle. These axes exist within a frame of reference called the *wander frame*. (See Chapter 6.)

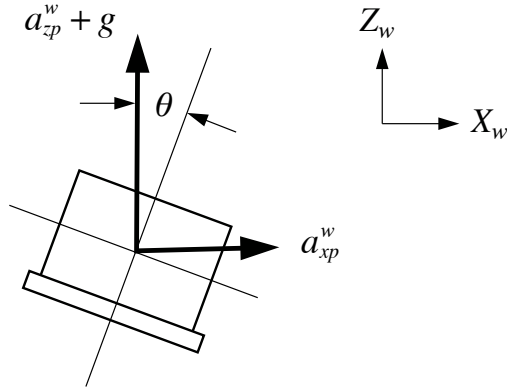


Figure 1.5 Accelerometer tilted due to braking

In this example, the accelerometer is “servo” type, and it reads vertical acceleration equal to 1 g when it is at rest. Typically, the 1 g offset is removed. As such, an ideal sensor would read a_{zp}^w , which is the vertical acceleration of the profiler reference point in the direction aligned with gravity. Equation (1.4) provides the reading obtained by the misaligned accelerometer, which is fixed in the vehicle body.

$$a_{zp}^b = a_{xp}^w \sin(\theta) + (a_{zp}^w + g) \cos(\theta) - g \quad (1.4)$$

Where g is the acceleration due to gravity, a_{xp}^w is the longitudinal acceleration (negative for braking), and θ is the pitch angle. The pitch angle defines the misalignment of the sensitive axis of the accelerometer compared to true vertical.

The error in the accelerometer reading is:

$$a_{zp}^b - a_{zp}^w = a_{xp}^w \sin(\theta) + (a_{zp}^w + g)(\cos(\theta) - 1) \quad (1.5)$$

Note that the projection of vertical acceleration onto the sensitive axis of the accelerometer (the second term) causes an error in proportion to $\cos(\theta) - 1$. This term grows very slowly with misalignment. In contrast, the projection of horizontal acceleration onto the sensitive axis of the accelerometer (the first term) grows in proportion to longitudinal acceleration magnitude and in approximate proportion to misalignment angle θ for practical situations. Since θ itself increases with longitudinal acceleration, this term is very sensitive.

The analysis by Karamihas et al. [14] addressed accelerometer misalignment in pitch due to braking and accelerometer roll due to lateral acceleration. However, it did not address higher-

frequency variations in accelerometer misalignment and horizontal acceleration caused by road disturbances. In addition, the literature has not offered an analysis of the kinematics presented in Equations (1.4) and (1.5) in light of dynamic vehicle response. That is, the effect of misalignment on profile depends on the time history of vertical and horizontal acceleration experienced by the system, the profiler host vehicle's misalignment in response to it (and the associated lag), and the manner in which the "error" signal maps to profile. This is addressed in Chapter 2.

1.3 Literature Review

The existing literature offers several options with the potential to reduce or eliminate the influence of profiler host-vehicle misalignment on profiles measured in live traffic. These fall into four categories:

1. Suppression of measurement errors in inertial profile computation and processing algorithms.
2. Augmentation of inertial profiler sensors with additional measurements, such as profiler host-vehicle attitude.
3. Estimation of profile from vehicle response measurements.
4. Measurement of profile without the use of an accelerometer-established floating reference.

This section presents a brief review of published work on each approach.

1.3.1 Error Suppression

Walker and Becker [15] developed a method of suppressing profile measurement errors that occur when a profiler host vehicle slows below a given speed or comes to a complete stop. When the speed is sufficiently low, the profile calculation algorithm is modified in two ways. First, the apparent progression of time is reduced over the interval of low-speed operation so that the double-integrated accelerometer signal grows less rapidly. Second, the change in elevation between readings in the computed profile is limited to a preset value. This method did not completely eliminate profile measurement errors observed in areas of low-speed operation and stops, but it greatly reduced the severity of the artificial roughness that is typically observed.

Gagarin et al. [41] studied operational conditions that affect the accelerometer-established floating reference height for inertial profilers, including alignment errors, cross-axis contamination by horizontal acceleration, and frequency response. The research simulated errors in measured profile and roughness on roads with horizontal and vertical curvature using CarSim, and developed estimates of the expected error in IRI associated with various combinations of travel speed, horizontal road curvature, and vertical road curvature.

1.3.2 Sensor Augmentation

Direct correction of accelerometer alignment errors requires measurement of host-vehicle orientation and off-axis acceleration. Dembski et al. [42,43] presented kinematic equations for errors to inertial profiler readings caused by pitch and roll in a description of a terrain severity measurement system. The system was implemented using a gyroscopically enhanced rate sensor for measurement of orientation. Demić et al. [44] presented the kinematic equations for a system that uses two body-mounted tri-axial accelerometers for indirect measurement of the change in body pitch, roll, and yaw on a trailer that would house an inertial profiler. Gagarin et al. [41] proposed the use of tri-axial accelerometers and gyroscopes for measurement of true vertical acceleration. Past developers of inertial profiling systems have also suggested the use of gyroscopic stabilization to help avoid host-vehicle alignment errors [31,45,46], although the associated cost prevented the implementation of such a system. In an effort to improve the low-frequency performance of inertial profilers by modulation, Pong [46] mounted four accelerometers to a disk that rotated in the roll plane.

Kern and Ferris [47] and Wagner et al. [48] incorporated an inertial measurement unit (IMU) and global positioning system (GPS) receiver into a road and terrain measurement system. This system used Kalman filtering to estimate host-vehicle position and orientation from GPS and IMU signal, and fused the vehicle position estimate with the floating reference height from the inertial profiler using a weighted average. Liu et al. [49] replaced the inertial reference in the system described by Dembski with an IMU and GPS receiver for estimation of host-vehicle position via Kalman filtering. Liu et al. [49] also demonstrated a “Kalman smoother”, which post-processed the signals and considered readings collected fore and aft of a position of interest. This improved the kinematic estimates and eliminated discontinuities.

Collectively, these references suggest that combining inertial and GPS measurement of profiler host-vehicle kinematics have the potential to improve the measurement of profile on paved roads.

1.3.3 Estimation Using Vehicle Response

Several authors have presented indirect methods of profile measurement by observing or estimating road profile from measured vehicle responses using linear models of vehicle vertical vibration response.

Qin et al. [50] presented the transfer function for calculating the power spectral density (PSD) function for a road profile from the PSD function for unsprung-mass vertical acceleration using a linear quarter car model. Wang et al. [51] proposed calculation of road profile spectral density using the signal from a dynamic tire pressure sensor and linear transfer functions. The method assumed a proportional relationship between tire vertical deflection and tire pressure, and the transfer function between tire pressure and axle acceleration was measured empirically. Outputs from an embodiment of the system were provided for various types of localized roughness. Tomiyama et al. [52] back-calculated road profile from a linear quarter-car model using measured sprung-mass and unsprung-mass vertical acceleration. The velocity and position associated with each degree of freedom were obtained by integrating the measured acceleration signals.

Nguyen [53] used a Luenberger observer with a linear quarter-car model to infer the floating-reference-height signal from the signal provided by the height sensor. Vehicle parameters were obtained with system identification using impulse response and step response tests, and observer parameters were obtained with system identification using testing on roads with known profile. Harris et al. [54] presented the theoretical development and simulated examples for inferring road profiles from vertical accelerations measured above and below the suspensions on both sides at a given axle position. The method proposed combinatorial optimization for obtaining parameters for a 4-degree-of-freedom (DOF) half-car model using measurements collected on roads with known profiles, and the same modeling framework to subsequently estimate profile on roads with unknown profiles in turn.

Yousefzadeh et al. [55] and Solhmirzaei et al. [56] presented methods of training neural networks for estimation of profiles using detailed vehicle dynamics models that were exercised over synthetic profiles. The neural network used seven inputs, including vertical accelerations at each wheel, and “roll, bounce, and pitch” of the sprung mass. The results did not show sufficient promise for road monitoring applications. First, significant effort was required to populate the underlying vehicle model (ADAMS/CAR) with parameter values and tune its response using hydraulic shaker testing. Second, the demonstration produced correlation to the reference profile measurement in the range from 0.8 to 0.95 for the waveband from 1 m to 10 m, which is below the requirements for valid measurement of IRI and addresses only part of waveband of interest.

Imine et al. [57-60] and Rabhi et al. [61-63] offer multiple publications that describe the use of sliding mode observers for estimation of road profile. The core vehicle model ranges from a 4 DOF roll plane model of a single axle position to a full three-dimensional vehicle model with longitudinal dynamics. In these publications road profile and other signals of interest are estimated based on measurements of sprung-mass vertical motion and axle relative vertical motion. The sensors used to obtain those signals are not specified. These publications present measured and observed cross plots of profile elevation versus travel distance. The plots demonstrate “fair agreement with local discrepancies” [58]. These plots do not provide an objective basis for evaluation. Subjectively, they do not appear to meet the accuracy requirements for road-monitoring applications.

Rath et al. [64] presented a simulation study of road profile and friction estimation in support of longitudinal control (anti-lock braking, traction control, etc.) and active suspension systems. The mode at the core of the method combined a non-linear quarter car with a model of vehicle longitudinal dynamics. The quarter-car model included non-linear suspension elements; and the longitudinal dynamics model included tire rolling losses, aerodynamic drag, tire-road friction, wheel spin dynamics, and driveline dynamics.

1.3.4 Non-Inertial Systems

Only one type of device used in practice for network pavement evaluation directly measures profile without an inertial reference and operates in live traffic. This is based on a concept proposed by Still and Jordan [65], in which several ranging sensors are mounted to a longitudinal beam that is mounted to a host vehicle or trailer. The device used a 5-m-long beam

and four sensors. Relative to the leading sensor, the remaining three were 0.107 m, 2.14 m, and 4.28 m rearward. In this system, sensor pairs provide measurements of slope relative to reference beam. For reference, the height and orientation of the beam is derived by dead reckoning.

The irregular spacing of the sensors was needed to increase the waveband of the final profile. Still presented results that showed reproduction of a survey profile in the wavelength range from 0.5 m to 390 m. However, the existing commercial embodiment of this device uses modern ranging sensors and a different geometric layout. Yi and Rong-Gui [66] presented the theoretical development of a similar system with five sensors.

1.3.5 Assessment

The methods for obtaining profile reviewed here are very diverse, and many originate with terrain measurement or vehicle dynamic evaluation and control as the intended application. As such, the relative accuracy of each method or device is not presented in a way that addresses the specific requirements of road profiling for pavement evaluation. Chapter 2 addresses this issue.

A majority of the estimation approaches described in the literature have only been developed theoretically or tested using computer simulations. In addition, while many of them reproduce a portion of the profile spectrum or the visible content in a raw elevation trace, it is not clear whether the details of the profile are sufficiently captured to support the needs of the pavement community. Further, only two of the estimation methods addressed system performance during horizontal acceleration.

This research emphasizes sensor augmentation and improvements to profile computation algorithms. This approach was selected for two reasons: (1) the potential for application of the results to in-service profilers, given the large investment made in the existing fleet used for pavement evaluation in the U.S.; and (2) the potential to support other functions in pavement monitoring, such as the measurement of transverse profile, grade, and cross slope.

1.4 Problem Definition

Inertial profilers have demonstrated reproduction of the true longitudinal road elevation profile in the waveband of interest for vehicle dynamic response (i.e., roughness) when they are operated under favorable conditions. However, they are limited in their ability to measure

aspects of the profile related to roughness when the host vehicle accelerates longitudinally, accelerates laterally, or comes to a stop. These weaknesses have hindered the application of inertial profilers on urban road networks and on ramps and other roads with aggressive changes in horizontal and vertical alignment. This research developed and tested inertial profiler design modifications that address errors in profile measurement caused by adverse operational conditions.

This research investigated data processing algorithms that suppress measurement errors without the need for adding sensors to typical in-service profilers. These algorithms combine standard filtering techniques with an enhancement of the Walker and Becker [15] error suppression algorithm. The recommended algorithms mitigate errors in profile measured during stops using only the nominal set of sensors found on a typical production inertial profiler. However, the reduction in artificial roughness measured during a stop requires the elimination of valid profile content at low travel speed.

This research also investigated an inertial profiler design that incorporates additional sensors to eliminate errors in measured vertical acceleration caused by misalignment and drift in the floating-reference-height signal that appears after double integration. The augmented system includes body-fixed measurement of profiler acceleration and rotation rate in three dimensions (i.e., “inertial sensors”). This provides the means to resolve the component of profiler reference point acceleration into the direction aligned with gravity. The augmented system also includes GPS measurement of profiler host-vehicle height, vertical velocity, pitch inclination, and roll inclination. An extended Kalman filter with a backward pass for smoothing combines the inertial sensors with the GPS outputs to eliminate drift in the floating reference height. Special provisions are included for incorporating the height sensor into the estimate of floating reference height when the profiler host-vehicle forward speed is close to zero.

1.5 Dissertation Organization

Chapter 2 presents technical background in support of the engineering approach. This includes an introduction to the IRI and roughness profiles, a definition of the waveband of interest for roughness measurement, and a description of a method for assessing profile accuracy. The chapter also demonstrates the accelerometer alignment problem using a simple dynamic

model, and presents kinematic equations in support of the approach taken to eliminating profile measurement errors.

Chapter 3 describes a field experiment that demonstrated the effect of operator-induced disturbances on profiles and roughness measured with existing commercial inertial profilers and discusses the results in detail.

Chapter 4 describes a custom-built inertial profiler that was designed and fabricated to support the experimental evaluation of profiler design modifications proposed for reducing measurement error. This system includes the nominal sensors that appear on a typical commercial profiler and several additional sensors to support the measurement of three-dimensional kinematics and drift removal via Kalman filtering. The chapter describes an experimental assessment of the accuracy and repeatability of profile measured by the system using the nominal sensors under ideal operational conditions (i.e., at constant speed).

Chapter 5 presents error suppression algorithms proposed in this research for application to inertial profilers without adding sensors to the typical commercial design. These algorithms emphasize the reduction of errors in measured roughness during stop-and-go operations, but do so at the expense of profile measurement accuracy at low travel speed. The chapter proposes error suppression algorithms designed for both temporal and spatial profile data collection architectures. The performance of each algorithm is compared to the performance of baseline algorithms with no error suppression. Performance is also evaluated in terms of expectations for adequate profile measurement accuracy.

Chapter 6 proposes the use of an augmented sensor set to improve the measurement of the floating reference height. This design uses a multi-rate, extended Kalman smoother to derive an estimated floating-reference-height signal from inertial and GPS measurement of profiler host-vehicle kinematics. The chapter presents alternative versions of the proposed design to account for cases when GPS outputs are unavailable. The performance of each design is compared to the baseline system without additional sensors or error suppression algorithms. Performance is also evaluated in terms of expectations for adequate profile measurement accuracy.

Chapter 7 summarizes the results, presents conclusions and suggestions for future work, and reviews the contributions made by this research.

Chapter 2

Technical Background

This chapter presents the technical background and describes preliminary analysis conducted to support the research. The first section reviews standard profile analysis methods and establishes techniques for quantifying profile measurement errors. The second section examines the signals that contribute to profiles measured by inertial systems, and demonstrates the role of high-pass filtering in the profile calculation process. The third section demonstrates the contamination of measured profile caused by accelerometer misalignment using a simple dynamic model. It presents three-dimensional kinematic equations for deriving true vertical acceleration from the output of body-fixed sensors.

2.1 Profile Measurement Requirements

This research requires objective comparison of profiles measured in different passes by the same device, calculated using alternative algorithms from raw data obtained in the same pass, or measured by two different devices. This document reports differences in measured roughness in terms of changes to average IRI values over a pavement segment of standard length and the peak roughness within a pavement segment using roughness profiles. Agreement between profile traces is quantified using cross correlation of profiles that have been filtered to emphasize content that affects the IRI.

This section presents technical background needed to interpret the comparisons of measured profiles and roughness.

2.1.1 International Roughness Index (IRI)

The IRI is a general pavement roughness indicator designed to estimate the relative level of vehicle vibration caused by the unevenness (i.e., roughness) within the profile [34]. The index is based on a 2-DOF quarter-car simulation of a broadly representative vehicle's response to the profile [67]. The IRI is calculated using four steps [68].

1. Convert the elevation profile to slope profile using a finite difference between adjacent points.
2. Smooth the profile by applying a moving average with a base length of 250 mm. This step approximates the envelopment of short-duration profile features by the tire.
3. Pass the smoothened profile through the Golden-Car Model using a simulated forward speed of 80 km/hr. The Golden-Car Model is a linear quarter-car simulation with standard vehicle properties. (See Figure 2.1.) The Golden-Car Model predicts the relative velocity between the sprung mass and unsprung mass. The output signal is provided in terms of spatial velocity (e.g., m/km), rather than temporal velocity (e.g., m/s).
4. Calculate the average rectified value from the Golden-Car Model output signal.

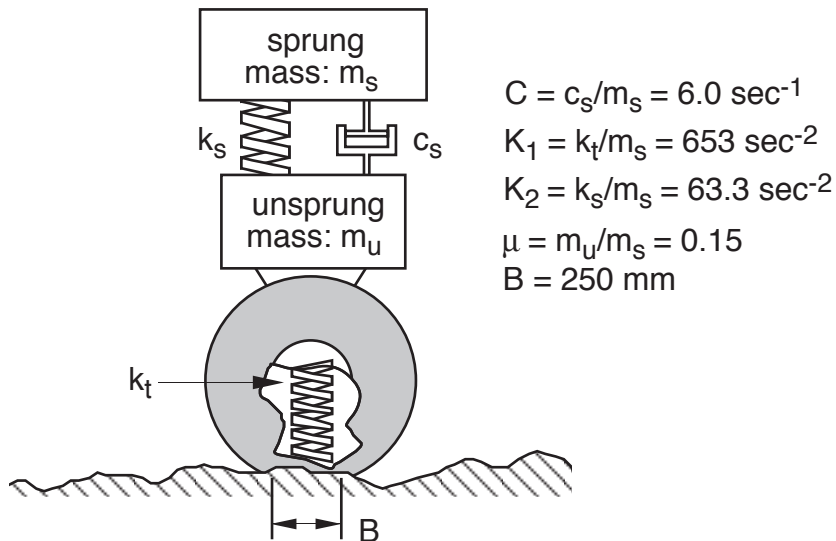


Figure 2.1 Golden-Car Model [68]

2.1.2 The IRI Scale

The calculation of IRI as described above can be performed for a section of road of any length. However, when profile is measured over long sections of roadway, an IRI value is often reported using 160.9-m-long segments [3,13]. The FHWA Transportation Performance Management (TPM) system defines a *pavement section* as having a nominal length of 160.9 m within their reporting requirements [5]. When it is appropriate, this research quantifies the effect of profile measurement errors by the bias they impose on the average IRI within a 160.9-m-long segment of profile.

The IRI scale starts at 0 for a perfectly smooth road and increases with roughness of the road, with no limit at the upper end of the scale [69]. The IRI for a given length of profile is typically expressed in in/mi or m/km. This is often interpreted as the accumulated absolute suspension stroke normalized by travel distance, which is mathematically equivalent to the average absolute spatial velocity across the suspension. The FHWA TPM system assigns the following ratings to pavement sections based on their IRI value: (1) good (< 1.50 m/km), (2) fair (1.50 m/km to 2.68 m/km), and (3) poor (> 2.68 m/km). Table 2.1 lists the IRI ranges for various qualitative categories used by the FHWA, including those used prior to the TPM [70]. In both eras, the poor category was considered “less than acceptable.”

Table 2.1 FHWA IRI ratings

Rating	TPM IRI Range (m/km)	Pre-TPM for Interstate (m/km)	Pre-TPM for non-Interstate (m/km)
Very Good	—	< 0.95	< 0.95
Good	< 1.50	0.95-1.50	0.95-1.50
Fair	1.50-2.68	1.50-1.89	1.50-2.68
Mediocre	—	1.89-2.68	2.68-3.47
Poor	> 2.68	> 2.68	> 3.47

Figure 2.2 shows the distribution of IRI values for NHS pavement sections that appeared within the 2018 FHWA HPMS submittal. The FHWA provided the data used to create this distribution. These data included IRI values, segment length, estimated traffic, and other items for 3,093,742 NHS pavement sections.

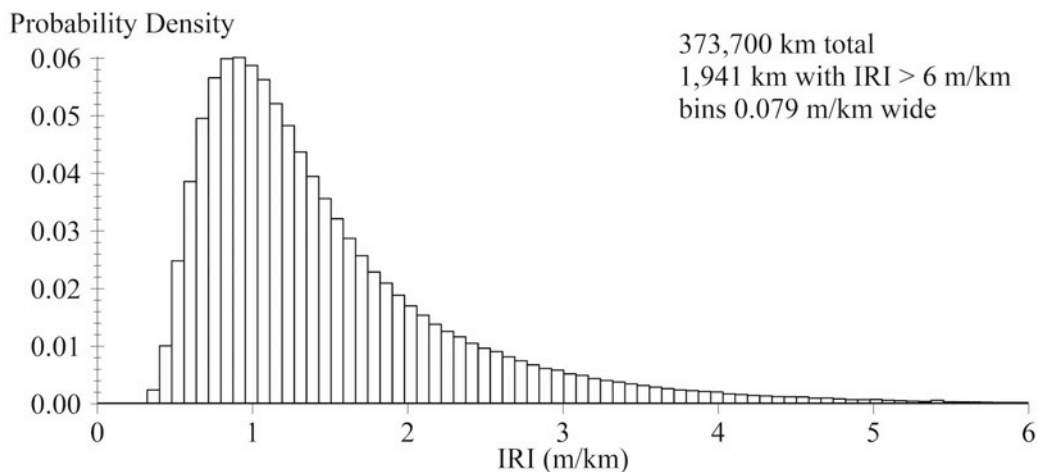


Figure 2.2 NHS IRI distribution, 2018

The IRI values that contributed to the distribution in Figure 2.2 were weighted by segment length, although a wide majority of pavement sections were 160.9 m long. The IRI values were not weighted by traffic. The distribution includes IRI values from a total length of 373,700 km, including 236,325 km (63.24 percent) in the good category, 99,545 km (26.64 percent) in the fair category, and 37,800 km (10.12 percent) in the poor category.

2.1.3 Roughness Profiles

A short-interval roughness profile displays the spatial distribution of roughness within a pavement section, and provides a means to quantify the severity of localized roughness [71]. Typically, roughness profiles are used to identify localized roughness caused by construction defects, built-in features, and pavement distress [72-74]. Figures 2.3 through 2.6 provide examples.

Figure 2.3 shows profiles from the left and right wheel path on a state route in an urban area. The horizontal axis shows the distance along the route using the state's distance referencing system. The profile is high-pass filtered to make sources of roughness that affect the IRI more visible. The range shown in Figure 2.3 includes a utility cover in the left wheel path and a bridge. Figure 2.4 provides an image of the bridge. A joint in the center of the bridge is deteriorated, particularly in the right wheel path. (See Figure 2.5.)

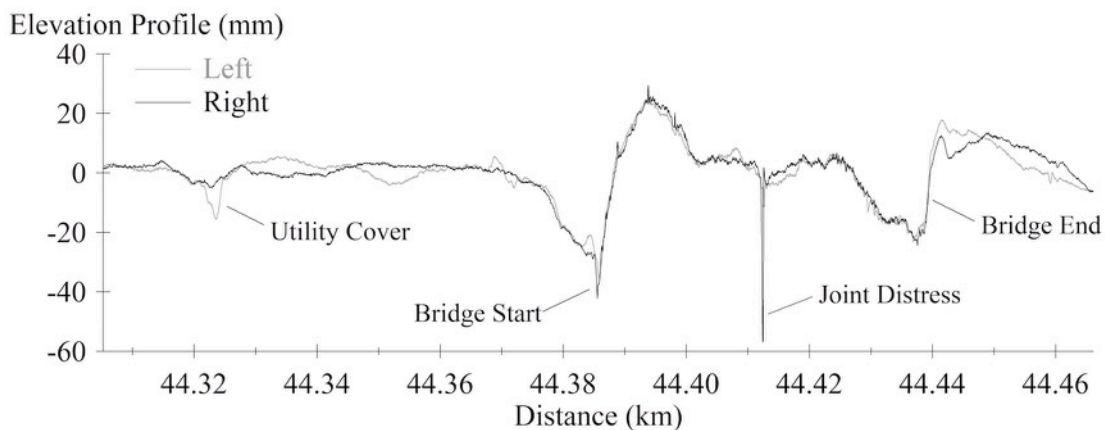


Figure 2.3 Profiles, urban bridge encounter



Figure 2.4 Image, urban bridge encounter



Figure 2.5 Image, deteriorated bridge joint

Figure 2.6 shows the short-interval roughness profile for both wheel paths using a base length of 7.62 m. Each point in the roughness profiles represents the IRI averaged over a 7.62-m pavement segment ranging from 3.81 m upstream to 3.81 m downstream. The roughness profiles are calculated as follows: (1) Scale the trace produced by Steps 1 through 3, above, of the IRI calculation procedure to the desired units (e.g., m/km). (2) Rectify the trace (i.e., take the absolute value of every point). (3) Apply a moving average to the rectified trace with the desired base length.

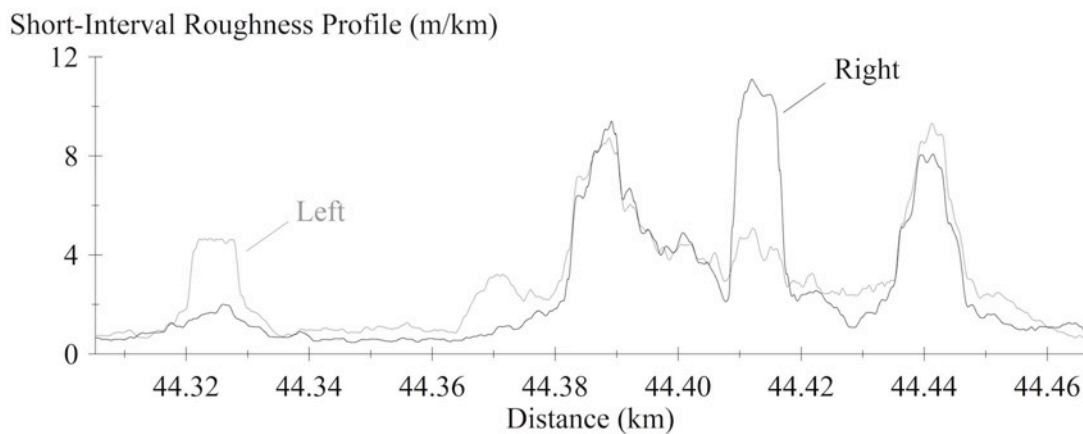


Figure 2.6 Roughness profiles, urban bridge encounter

Over the 160.9-m-long pavement section shown in Figure 2.3, the left profile had an IRI of 2.934 m/km and the right profile had an IRI of 2.637 m/km. The short-interval roughness profile demonstrates that the utility cover, joint distress, and the interfaces between the bridge deck and the surrounding pavement contribute heavily to the average roughness. For example, the short-interval roughness profile from the right wheel path rises to a peak value of 11.16 m/km at the distressed joint. The sub-segment of profile corresponding to this point represents about 4.8 percent of the overall length shown. As such, it accounts for about 0.53 m/km of the average IRI for the 160.9-m-long pavement section.

In many cases, such as stop-and-go operations, profile measurement errors appear as severe artificial roughness at a specific location. In this research, the peak value of the short-interval roughness profile is used to quantify the effects of localized measurement errors on overall measured roughness. In this document, *short-interval roughness profile* refers to a profile of roughness using the IRI, and averaged over a base length of 7.26 m.

2.1.4 Waveband of Interest

This section establishes a frequency range of interest for profile measurement. A previous study established a waveband of interest for profile measurement with an emphasis on roads with high travel speeds [75]. This section presents an update of that work with consideration of unique spectral content that exists on low-speed, recreational roadways.

The calculations use linear analysis to combine idealized spectral density functions for a range of road types with the frequency response function for the IRI algorithm. The spectral density functions include limit cases for measured profiles, in which either long-wavelength content or short-wavelength content make up a large share of the roughness. To capture a broad range of vehicle responses, the analysis examines modifications to the IRI algorithm for a range of speeds, as well as sprung-mass acceleration and dynamic tire load variation from the underlying Golden-Car Model.

2.1.4.1 Spectral Models

Andr n reviewed several spectral models of single-track road profiles proposed in the literature [76]. These models idealize measured road spectral density functions using simple functions with an assumed shape. For example, the International Organization for

Standardization (ISO) recommends fitting the following function to the profile elevation spectrum [77]:

$$G(\nu) = G(\nu_0) \left(\frac{\nu}{\nu_0} \right)^{-w} \quad (2.1)$$

Where $G(\nu)$ is the fitted function, ν is wave number, $G(\nu_0)$ is the spectral density at a reference wave number ν_0 , and w is an exponent that determines the function slope with logarithmic scaling. Fitting is done with a straight-line approximation to the spectrum with log-log scaling.

When the exponent w is equal to 2, the spectrum of slope, $G'(\nu)$, is constant:

$$G'(\nu) = (2\pi\nu_0)^2 G(\nu_0) = G_s \quad (2.2)$$

To account for the change in characteristic slope over the log-log spectrum, some have proposed a spectral shape made up of a combination of white noise sources. La Barre [80] proposed one such model for European roads:

$$G'(\nu) = G_0 \left[1 + \left(\frac{\nu_0}{\nu} \right)^2 \right] \quad (2.3)$$

Where G_0 and ν_0 are constants within the model. At low wave numbers, white noise spatial acceleration dominates this function, and at high wave numbers, white noise slope dominates this function. The break point between the two is determined by the value of ν_0 . A study of European roads found that the break point to be about 0.0656 cycles/m for “rigid constructions” and 0.164 cycles/m for “flexible constructions.” In terms of wavelength, this is 15.2 m and 6.1 m, respectively.

This analysis uses a model proposed by Sayers [81] that combines three sources of white noise:

$$G(\nu) = G_e + \frac{G_s}{(2\pi\nu)^2} + \frac{G_a}{(2\pi\nu)^4} \quad (2.4)$$

Where G_e represents the contribution of white noise elevation, G_s represents the contribution of white noise slope, and G_a represents the contribution of white noise spatial acceleration. This

was selected with the expectation that the arithmetic combination of terms with exponents of 0, 2, and 4 would provide enough flexibility to capture the variations described above.

Sayers [82] provided coefficients for several in-service roads that cover a diverse range of spectral shape, and recommended four representative cases as standard simulation inputs. (See Table 2.2.)

Table 2.2 Model coefficients for four sample roads

Description	G_a 1/(m•cycle)•10 ⁻⁶	G_s m/cycle•10 ⁻⁶	G_e m ³ /cycle•10 ⁻⁶
Normal	0	20	0
Asphalt with Long Waves	7	20	0
Rough (Short Waves)	0	100	1
Limit Roughness	0	300	8

“Limit roughness” represents the sample in which the largest proportion of content comes from the high wave-number (short-wavelength) range. “Asphalt with long waves” represents the sample in which the largest proportion of content comes from the low wave-number (long-wavelength) range, with a ratio of G_a to G_s of 0.35 m⁻². Note that, in the slope domain, the Sayers model is:

$$G'(v) = \frac{G_e}{(2\pi v)^{-2}} + G_s + \frac{G_a}{(2\pi v)^2} \quad (2.5)$$

Comparison of Equation (2.5) to Equation (2.3) (the La Barre model) yields:

$$\frac{G_a}{G_s} = (2\pi v_0)^2 \quad (2.6)$$

For “flexible constructions” (i.e., wavy asphalt) this is a ratio of 1.06 m⁻².

For this research, a limited number of low-speed, recreational roadway profiles were analyzed to identify a new limit case. These roadways are built in areas with limited opportunity to select or alter road grade, and are meant for travel at low speed. These roads exhibited values of the ratio of G_a to G_s of 1.42 m⁻² to 11.12 m⁻², with a quarter of the values above 8 m⁻².

The linear analysis of wavelength sensitivity below examines the cases listed in Table 2.3. “Very wavy” corresponds to low-speed, recreational roads; “standard” corresponds to La Barre’s observations for flexible constructions; and “choppy” corresponds to an extreme among the observations made by Sayers.

Table 2.3 Sample cases for analysis

Description	G_a/ G_s (m^{-2})	G_e/ G_s (m^2)
Very wavy	8	0
Standard	1.06	0
White noise slope	0	0
Choppy	0	0.08

2.1.4.2 Frequency Response

Figure 2.7 shows the temporal frequency response of the IRI algorithm in terms of slope (spatial velocity across the suspension) as a function of slope spectral density. Figure 2.7 presents an alternative axis showing wavelength, which corresponds to the standard Golden-Car simulation speed for the IRI of 80 km/hr.

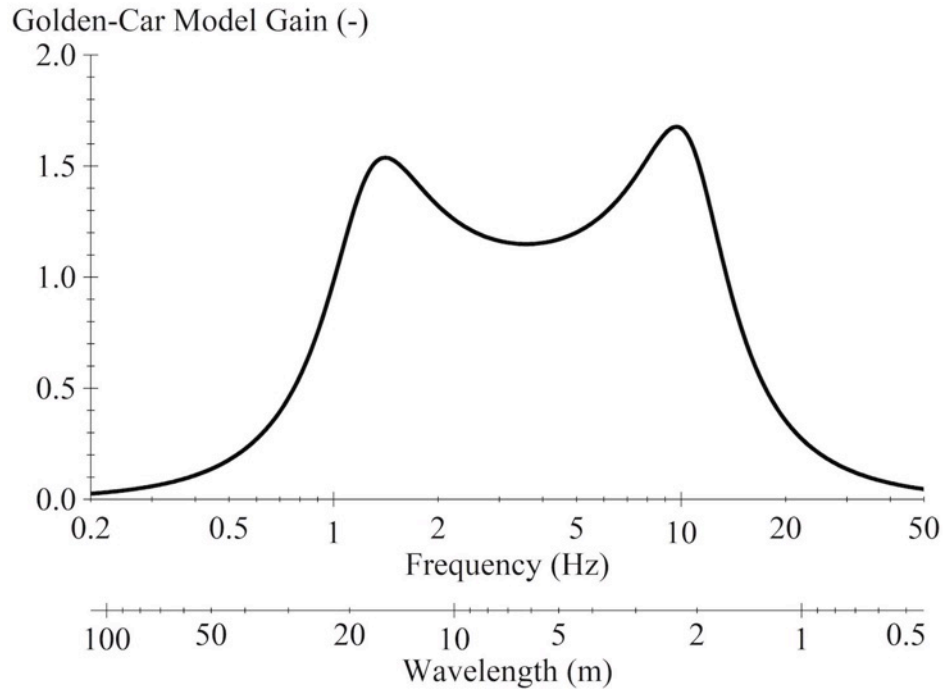


Figure 2.7 IRI gain for profile slope

The frequency response function shown in Figure 2.7 includes contributions from two linear filters. First, the moving average has a transfer function that is a fixed function of wavelength (λ). In terms of wave number (ν):

$$H_{MA}(\nu) = \frac{\sin(\pi B\nu)}{\pi B\nu} \quad (2.7)$$

Where:

$$v = 1/\lambda \quad (2.8)$$

Second, the Golden-Car Model response transfer function for suspension stroke is:

$$H_{GCSS}(\omega = 2\pi vV) = \frac{K_1 \omega^2}{D} \quad (2.9)$$

Where V is simulated travel speed, ω is angular frequency, and the denominator (D) is:

$$D = \mu \omega^4 - (K_1 + K_2(1 + \mu)) \omega^2 + K_1 K_2 + jC \omega (K_1 + \omega^2(1 + \mu)) \quad (2.10)$$

So, in the wave-number domain, the signal used to calculate the IRI is:

$$G_{IRI}(v) = |H_{MA}(v)|^2 |H_{GCSS}(v)|^2 G'(v) \quad (2.11)$$

Where $G'(v)$ is slope spectral density from the road profile. For a Gaussian signal with zero mean, the average rectified value of the output signal is proportional to the standard deviation, which is the square root of integral of the output spectrum, G_{IRI} .

Figure 2.8 shows the normalized cumulative response of the IRI calculation for the “Standard” road identified in Table 2.3. The range of wavelengths up to 20.13 m produces an estimate of the IRI that is 95 percent of the value for the entire waveband, and wavelengths up to 36.30 m capture 99.5 percent of the total. Figure 2.8 also shows an accumulation of the IRI running downward from the long-wavelength end of the spectrum. In this case, wavelengths down to 1.85 m capture 95 percent of the overall IRI value and wavelengths down to 1.12 m captures 99.5 percent.

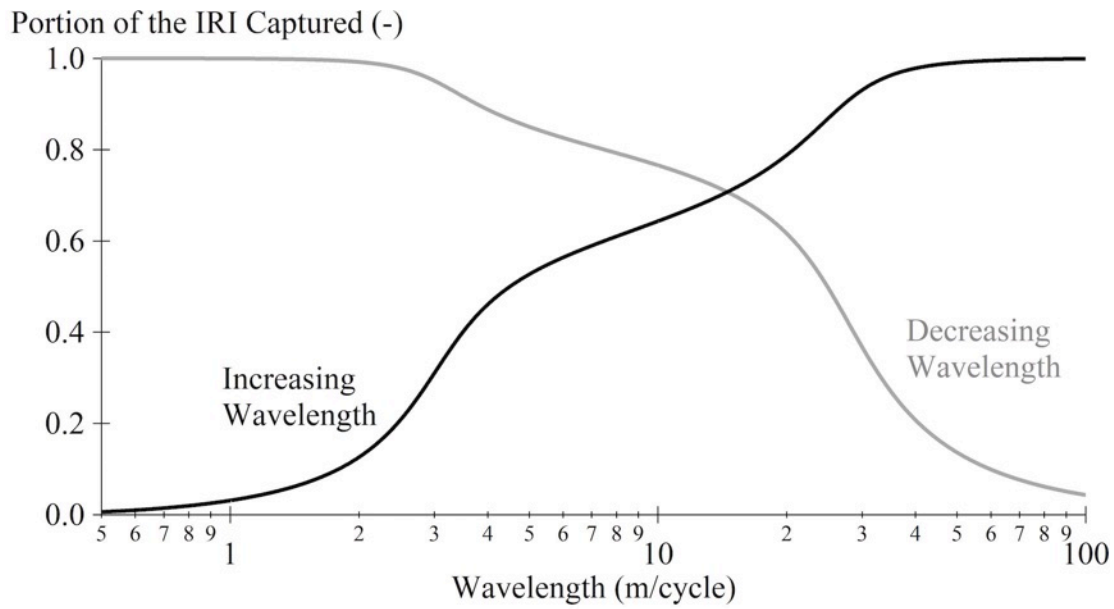


Figure 2.8 Portion of the IRI captured versus wavelength

2.1.4.3 Wavelength Thresholds

Table 2.4 presents the wavelength thresholds that correspond to capture of 99.5 percent for the overall IRI value for the four sample roads listed in Table 2.3. (The range defined by these thresholds corresponds to a total error of 1 percent.) These were derived using the methodology described in section 2.1.4.2.

Table 2.4 Thresholds for 0.5 percent error in IRI

Sample Case	Very Wavy	Standard	White Noise Slope	Choppy
Long Wavelength (m)	42.88	36.30	20.43	18.79
Short Wavelength (m)	1.47	1.12	0.96	0.61

Alternatives to the IRI using lower speeds are also currently under consideration, because roughness measurements based on profile are increasingly performed on low-speed and urban roadways. Alternatives at higher speeds are also under consideration, because prevailing speeds on limited access freeways are much higher than 80 km/hr. When the Golden Car is simulated at other speeds, the temporal frequency axis in Figure 2.7 remains unchanged, but the wavelength axis shifts (leftward) in proportion to speed. In terms of spectral content, a change in speed changes the features of the road that affect the response. Further, as speed decreases the moving average attenuates a progressively larger portion of the content that affects the Golden Car [83].

To help ensure valid measurement of profile for the IRI and other indices tied to vehicle response, the analysis was extended to include: (1) Golden-Car Average Rectified Slope (GCARS) at 40 km/hr, GCARS at 120 km/hr, and Ride Number (RN). RN is a profile-based index with an empirical link to panel ratings of user satisfaction with pavement ride quality [84,85].

Tables 2.5 and 2.6 provide the results. Note that RN filters the profile in a manner similar to the IRI to emphasize the waveband of interest, and accumulates root mean square (RMS) of the resulting signal. The RN algorithm casts the RMS value into a 0-to-5 scale using a non-linear transformation. The results in Tables 2.5 and 2.6 pertain to the pre-transform RN value (PTRN).

Table 2.5 Long-wavelength thresholds for 0.5 percent error in IRI

Index	Wavelength (m)			
	Very Wavy	Standard	White Noise Slope	Choppy
GCARS ₁₂₀	65.58	59.63	30.53	29.23
GCARS ₄₀	19.88	14.75	10.42	8.45
PTRN	16.55	11.82	8.65	5.80

Table 2.6 Short-wavelength thresholds for 0.5 percent error in IRI

Index	Wavelength (m)			
	Very Wavy	Standard	White Noise Slope	Choppy
GCARS ₁₂₀	2.37	1.80	1.36	0.86
GCARS ₄₀	0.68	0.59	0.57	0.42
PTRN	0.38	0.34	0.34	0.14

For measurement of IRI, the waveband of interest is 0.61 m to 42.9 m. The analysis above shows that accommodation of other applications of profile related to vehicle response (i.e., general roughness measurement) requires a waveband from 0.14 m to 65.58 m.

2.1.5 Objective Trace Comparison

This research quantifies agreement between profiles using a standard method that is based on cross correlation [86,87]. In this application, two profiles are cross-correlated after they are filtered to emphasize the frequency content of interest.

2.1.5.1 Cross Correlation

For two measures of road profile over a finite length L , the cross-correlation function is estimated as:

$$R_{pq}(x_{off}) \approx \frac{1}{L} \int_0^L p(x)q(x + x_{off})dx \quad (2.12)$$

Inputs p and q are each measurements of road profile as a function of distance x . The cross correlation function, R , exists as a continuous function of the offset distance x_{off} between the profiles. Since the profile is sampled at discrete intervals, the integral must be replaced by a summation:

$$R_{pq}(i\Delta x) \approx \frac{1}{N} \sum_{k=1}^N p(x_k)q(x_{k+i}) \quad (2.13)$$

Where the subscripts indicate discrete sample numbers, recorded at a distance interval of Δx . The number of samples, N , is the value needed to cover the overall length of interest.

Equation (2.13) has two weaknesses when applied to road profiles. First, it yields a cross correlation function in units of elevation squared. A more desirable rating system is normalized to produce a value of 1 for perfect correlation:

$$\rho_{pq}(i\Delta x) = \frac{1}{\sigma_p \sigma_q} \sum_{k=1}^N (p(x_k) - \mu_p)(q(x_{k+i}) - \mu_q) = \frac{1}{\sigma_p \sigma_q} \sum_{k=1}^N \hat{p}(x_k) \hat{q}(x_{k+i}) \quad (2.14)$$

Where the hats over the symbols “ p ” and “ q ” indicate that the profiles are offset vertically to have a mean value of zero. The values σ_p and σ_q represent the standard deviation of profiles p and q , respectively. Equation (2.14) produces a -1 to 1 rating of the correlation, and only produces a value of 1 when the shape of both profiles are exactly the same and they are synchronized.

A second weakness is that differences in overall roughness are not penalized by the standard cross correlation function. Two profiles that have the exact same shape but very different amplitudes would be rewarded with a perfect rating by Equation (2.14). To compensate for this, the following factor is applied to the normalized cross correlation function:

$$\gamma = \frac{\min(\sigma_p, \sigma_q)}{\max(\sigma_p, \sigma_q)} \quad (2.15)$$

This adjustment factor diminishes the value of correlation when the standard deviations of the profiles are not equal.

This research quantifies the agreement between profiles for a given waveband as follows:

$$\text{Agreement score} = \rho_{\max} \cdot \gamma \quad (2.16)$$

Where ρ_{\max} is the maximum correlation coefficient over the range of offsets included in the calculations.

2.1.5.2 Filtering

Repeatability and agreement to a reference measurement are quantified by cross correlating the output of the IRI filter. That is, the IRI algorithm (Steps 1 through 3 in Section 2.1.1, above) is applied to each profile, and the resulting signals are cross-correlated. A minimum threshold value for cross correlation of 0.92 is adopted from American Association of State Highway and Transportation Officials (AASHTO) R56-14 [87]. This threshold corresponds to adequate roughness measurement accuracy in production applications. AASHTO R56-14 also requires repeatability of 0.98 for systems used to make reference measurements [87]. Similarly, Karamihas recommended a threshold value of 0.98 for a “research class” profiler [86].

For diagnostic purposes, profiles are cross-correlated using slope in three additional wavebands: (1) a long waveband, (2) a medium waveband, and (3) a short waveband. The profiles are converted to slope using a finite difference, then are filtered to pass content in the wavelength ranges from 0.14 m to 1.6 m, 1.6 m to 8 m, and 8 m to 65.6 m for the short, medium, and long wavebands, respectively. Collectively, these three bands cover the range of interest identified above. The range was split into three bands for their diagnostic value, and to avoid cases in which a portion of the waveband dominates the mean square of the slope profile. Appendix A describes the high-pass (HPF_{B3x2}) and low-pass (LPF_{B3x2}) filters used to isolate the long, medium, and short wavebands. Cut-off wavelength settings (λ_c) correspond to the limits for each range provided above.

2.2 Signal Flow

This section examines sensor signals from a long profile measurement collected under favorable conditions. The discussion shows the relative contribution of the height-sensor signal and the floating-reference-height signal to the overall profile, and that they interact heavily over a portion of the frequency range of interest. The discussion also explains why high-pass filtering is a necessary part of the profile measurement process, and presents an example of the effect of filter type on the profile.

2.2.1 Signal Interaction

Figure 2.9 shows the spectral content of a profiler accelerometer signal measured at 107 km/hr over 4 km of limited-access highway. These data were collected on an interstate highway (I-94 eastbound starting near milepost post 161) by a profiler mounted near the center of the wheelbase on a minivan. The test section included several patched transverse cracks and patched potholes. The influence of vehicle dynamic response is apparent in the signal. For example, the spectral density includes elevated content due to sprung-mass resonant response at near 1 Hz to 2.5 Hz and elevated content due to unsprung-mass resonant response at 10 Hz to 20 Hz.

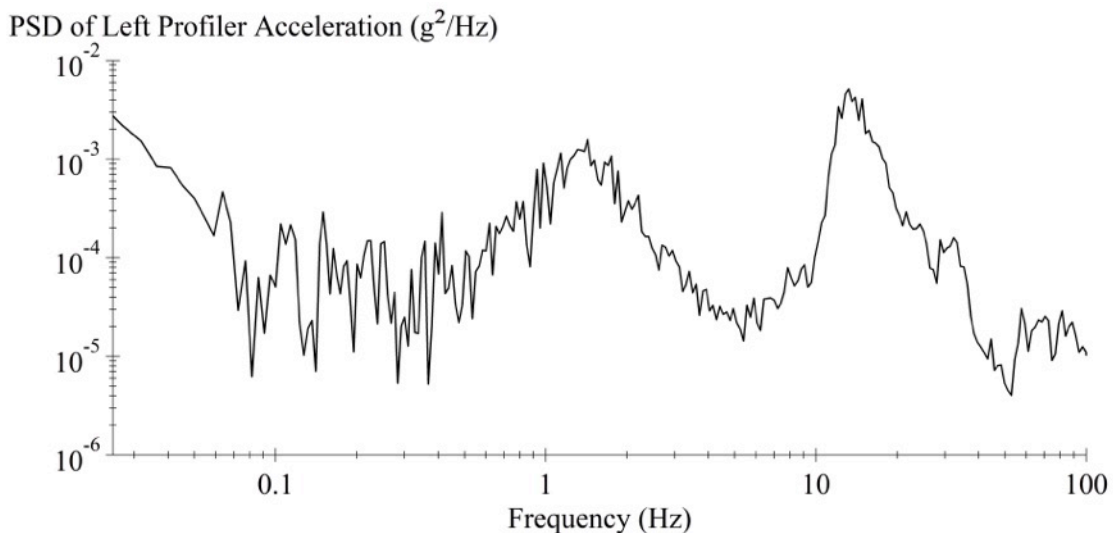


Figure 2.9 Accelerometer spectral content

As described in Section 1.2, the raw accelerometer signal is transformed to the floating-reference-height signal using the following steps:

1. Resample the signal as a function of travel distance with a constant distance interval.
2. Divide each value in the signal by the square of forward speed to convert temporal acceleration to spatial acceleration.
3. Integrate the spatial acceleration twice in the distance domain.

The floating-reference-height signal is a record of the fluctuations in vertical position of the profiler reference point as it progressed along the pavement section. The height sensor records changes in relative vertical distance between the floating reference height and the road. Subtracting the height-sensor signal from the floating-reference-height signal produces the profile. Figure 2.10 shows the spectral content of the two signals for the 4-km-long pavement section. The figure shows that when these signals are combined, the contribution from the accelerometer will dominate the low-frequency (i.e., long-wavelength) portion of the profile and the height sensor will contribute the most heavily to the high-frequency (i.e., short-wavelength) portion of the profile.

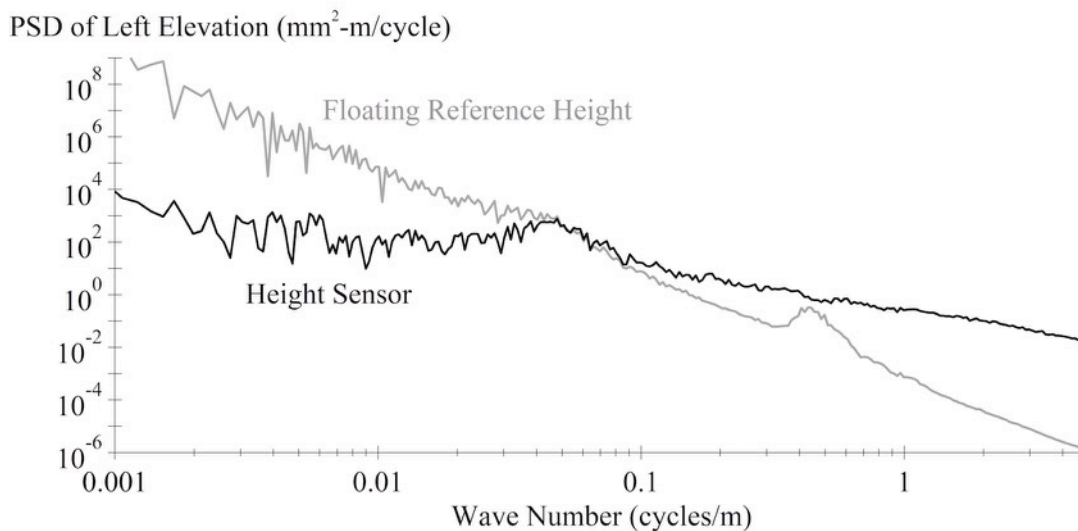


Figure 2.10 Spectral density of floating-reference-height and height-sensor signals

To help illustrate this further, Figure 2.11 provides the spectral content of the two signals and the complete profile in terms of slope. The profile slope spectrum is often used in lieu of elevation spectrum to reduce the vertical range on the ordinate axis, so that more details are visible [81,88]. The floating-reference-height signal contributes most of the content to the complete road profile for wavelengths greater than 50 m, whereas the height sensor contributes most to the profile for wavelengths below 1.6 m.

At the host-vehicle speed, 10 Hz to 20 Hz corresponds to the range of wave numbers from 0.34 cycles/m to 0.67 cycles/m. In this range, the amplitude of the height-sensor signal and floating-reference-height signal are the same order of magnitude, although the fluctuations in the floating-reference-height signal are larger. In this frequency range, the profiler reference point's motion is in phase with the changes in profile elevation. The height-sensor signal is out of phase. As a result, the complete profile has more content in this range than either of the component signals.

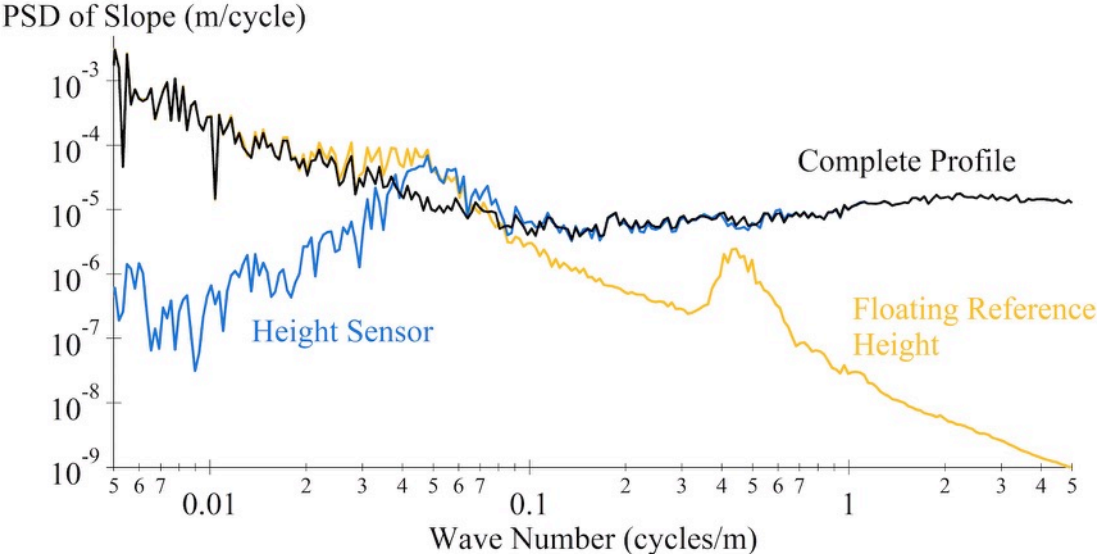


Figure 2.11 Slope spectral density of profile and its components

The range of wave numbers from 0.034 cycles/m to 0.084 cycles/m corresponds to frequencies of 1 Hz to 2.5 Hz at the host-vehicle speed. In this range, the profiler reference point's motion is out of phase with changes in profile elevation. Due to resonant response of the host vehicle associated primarily with sprung-mass motion, the amplitudes of the floating-reference-height and height-sensor signals are much larger than the complete profile. When they are combined to compute the complete profile, much of the content within the two sensors is cancelled. In this frequency range, small errors in either of the sensor signals relative to their amplitude may appear as very large errors in the resulting profile. As such, an error in one sensor signal associated with host-vehicle sprung-mass dynamics, such as accelerometer misalignment, may affect profile measurement accuracy disproportionately.

2.2.2 High-Pass Filtering

The accelerometer signal that produced Figures 2.9 through 2.11 included a small overall bias, and its average value was 0.000834 g. This may have been caused by a legitimate net vertical acceleration over the 4 km of travel. However, the average acceleration may also have been caused by a slight error in calibration (once the 1 g offset was removed), slight errors in the orientation of the accelerometer on the host-vehicle chassis, or a prevailing level of tilt from true vertical caused by the overall grade or cross slope of the road. In this measurement, the average acceleration was less than 0.55 percent as large as the variance. When the signal is integrated twice to establish the elevation time history of the accelerometer, the presence of the net acceleration will superimpose a parabolic rise in elevation of more than 73 m. This did not exist on the test section.

Figure 2.12 shows the floating-reference-height signal established by integrating the raw accelerometer signal twice. In addition to the artificial parabolic rise in vertical position, the signal includes very long wavelength fluctuations. At sufficiently low frequencies the dynamic response of the vehicle diminishes, and the accelerometer follows a path that is parallel to the road surface. Under ideal conditions, this portion of the signal would approximate the second rate of change of road elevation under the accelerometer. Instead, this portion of the signal is often contaminated by operator-induced disturbances, such as steering corrections for lane keeping and adjustment to the throttle for regulating speed. In addition, very long wavelength changes in road elevation associated with road geometric design and the prevailing land topography (i.e., grade changes) cause slow changes in accelerometer alignment.

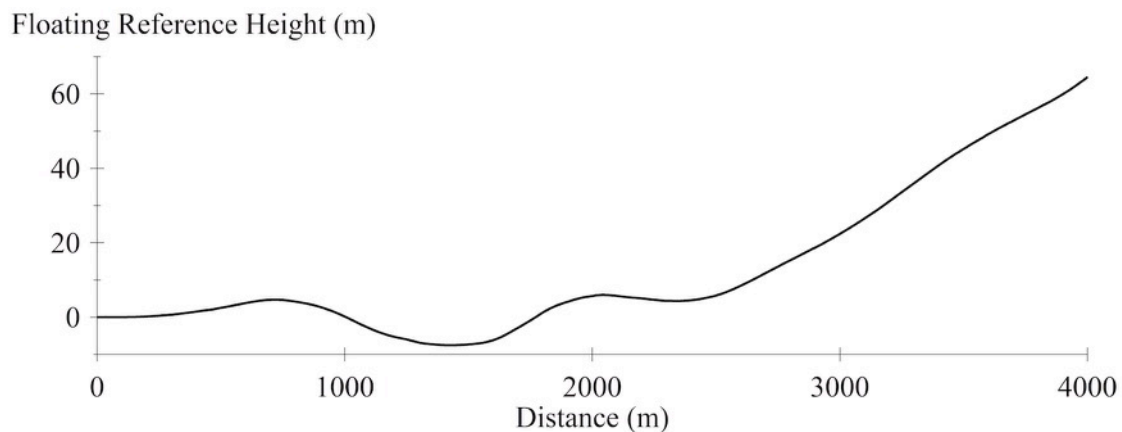


Figure 2.12 Floating-reference-height signal

Profilers typically apply high-pass filters to suppress the contaminated portion of the floating-reference-height signal. Figure 2.13 shows the floating-reference-height signal that results when a third-order Butterworth filter is applied with a cut-off wavelength of 91.44 m. (See HPF_{B3} in Appendix A.) The figure shows the accompanying height-sensor signal and the complete profile. Note that the high-pass filter determines the long-wavelength content within the floating-reference-height signal, which in turn strongly affects the long-wavelength content in the computed profile.

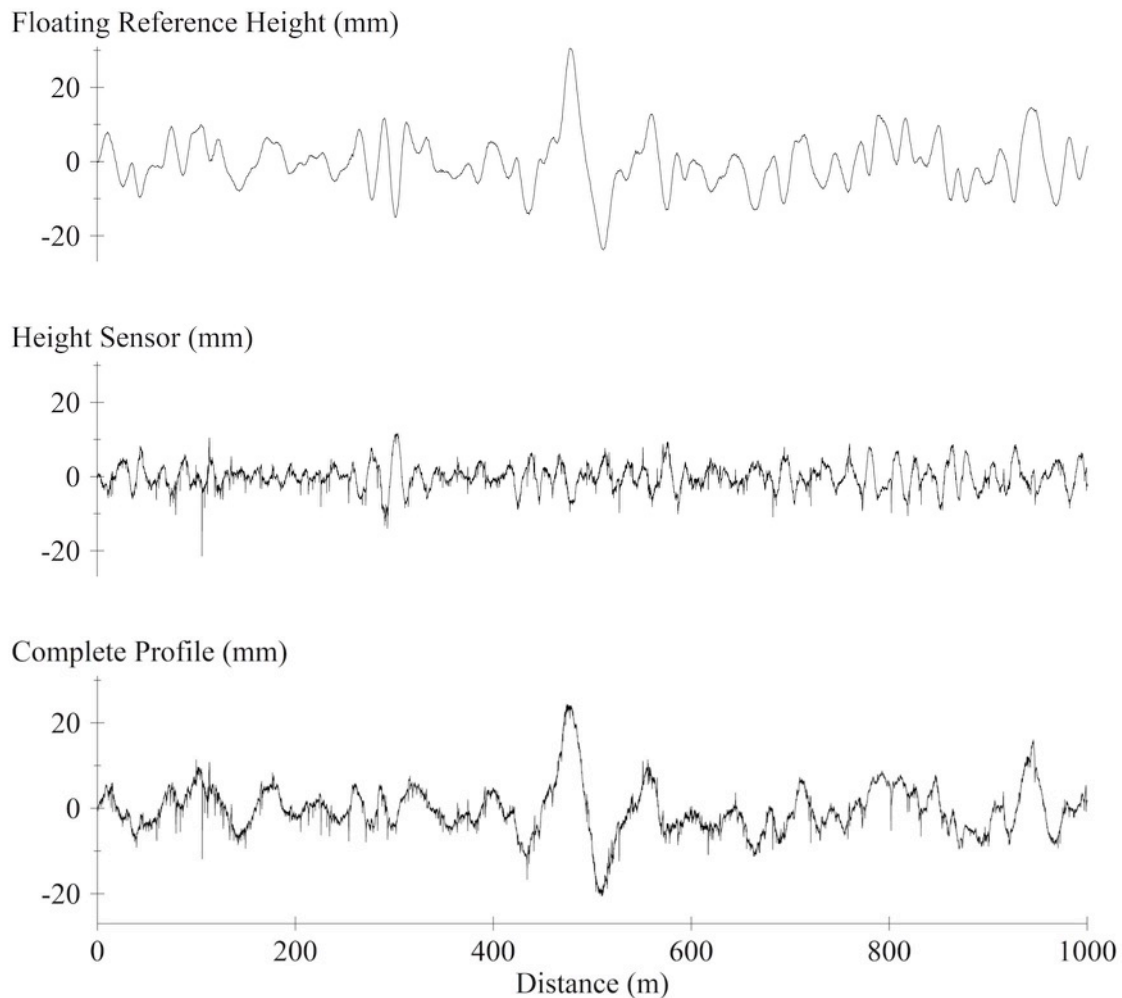


Figure 2.13 Floating reference height, height sensor, and complete profile

Many inertial profilers apply the high-pass filter to sensor signals in real time using a recursive algorithm [89,90]. In most cases, recursive digital filters impose a non-linear phase shift. Typically, the phase shift is greatest near the cut-off wavelength. This was the case for the

complete profile shown in Figure 2.13. Figure 2.14 compares the complete profile to a profile processed from the same sensor signals with a bi-directional high-pass filter. The bi-directional filter applies equivalent filtering in the forward and reverse direction to cancel phase shift. (See Appendix A, HPF_{B3x2}.) The deep cracks and short-duration features are aligned in the two profiles. However, the conventional filter distorts the long-wavelength content. For example, the dip near the center of the profile produced without phase shift by the bi-directional filter appears as a bump using the conventional filter.

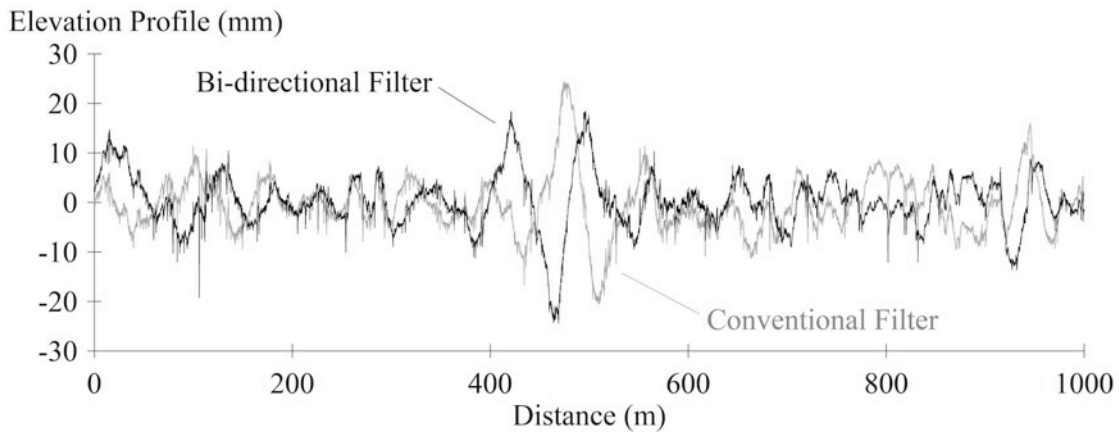


Figure 2.14 Effect of filter type on a raw profile trace

2.3 System Kinematics and Dynamics

2.3.1 Three Dimensional Kinematics

Chapter 1 presented expressions for the errors in vertical acceleration measured on-board a typical inertial profiler due to misalignment of the host-vehicle body in two dimensions. Equations (2.17) present the full expressions for vehicle-fixed accelerations that would be measured by servo-type accelerometers fixed on the profiler as it experiences rotations about the vehicle-fixed axes in pitch (θ) then roll (ϕ).

$$\begin{aligned}
 a_{xp}^b &= a_{xp}^w c_\theta - (a_{zp}^w + g) s_\theta \\
 a_{yp}^b &= a_{xp}^w s_\theta s_\phi + a_{yp}^w c_\phi + (a_{zp}^w + g) c_\theta s_\phi \\
 a_{zp}^b &= a_{xp}^w s_\theta c_\phi - a_{yp}^w s_\phi + (a_{zp}^w + g) c_\theta c_\phi - g
 \end{aligned} \tag{2.17}$$

Where s and c represent sine and cosine functions, respectively, of the angle that appears in the subscript. Equations (2.17) express vehicle body-fixed vertical (a_{zp}^b), longitudinal (a_{xp}^b), and lateral (a_{yp}^b) acceleration in terms of vertical acceleration along an axis system aligned with gravity (a_{zp}^w) and horizontal components in a plane perpendicular to gravity (a_{xp}^w and a_{yp}^w). Equations (2.17) include removal of a 1-g offset from the recorded value of a_{zp}^b .

As shown in Figure 2.15, pitch is represented as a rotation about the host-vehicle lateral axis (Y_w). The subscript “w” denotes the wander axis system, which corresponds to the Society of Automotive Engineers (SAE) intermediate axis system [91]. The alignment of the Y_w axis follows the vehicle’s yaw motion, but remains perpendicular to a vertical axis aligned with gravity. Roll is represented by a subsequent rotation about the body-fixed longitudinal axis (X_b). True vertical acceleration along the axis aligned with gravity is a_{zp}^w .

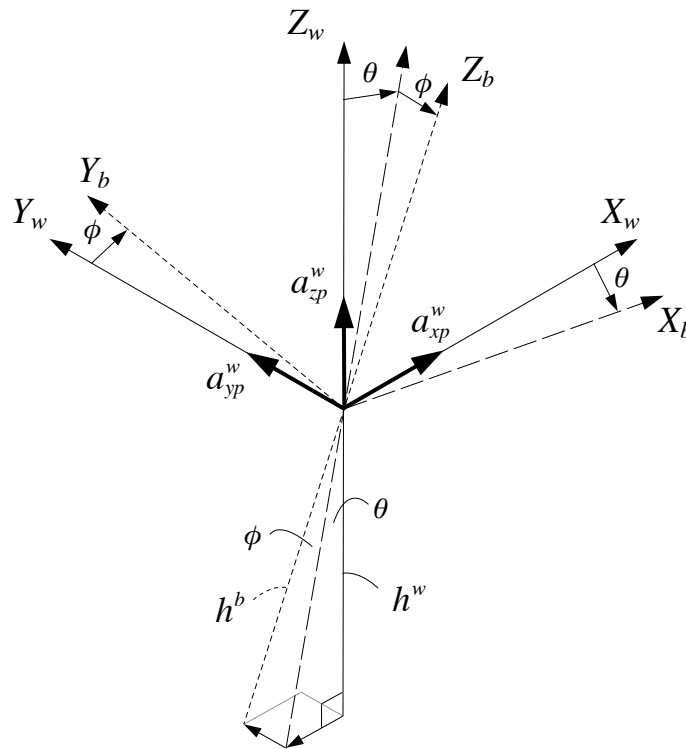


Figure 2.15 Body-fixed rotations in pitch and roll

Figure 2.15 also shows the effect of changes in host-vehicle orientation on the range to ground measured by the height sensor. For a perfectly flat, smooth ground plane the measured

range to ground along the body-fixed vertical axis (h^b) increases relative to the vertical projection along a truly vertical axis (h^w):

$$h^b = \frac{h^w}{c_\theta c_\phi} \quad (2.18)$$

When the road surface is not flat and smooth, lateral and longitudinal translation of the height-sensor footprint introduces additional spurious content into the height-sensor signal. In practice, the lateral and longitudinal translation is more important than the cosine error.

The signal $a_{z_p}^w$, rather than $a_{z_p}^b$, is required to accurately establish the floating reference height. Two strategies for obtaining this are possible:

1. Correction of $a_{z_p}^b$ to $a_{z_p}^w$ using measurements of $a_{x_p}^w$ and $a_{y_p}^w$:

$$a_{z_p}^w = \frac{a_{z_p}^b + g - a_{x_p}^w s_\theta c_\phi + a_{y_p}^w s_\phi}{c_\theta c_\phi} - g \quad (2.19)$$

2. Correction of $a_{z_p}^b$ to $a_{z_p}^w$ using measurements of $a_{x_p}^b$ and $a_{y_p}^b$:

$$a_{z_p}^w = -a_{x_p}^b s_\theta + a_{y_p}^b c_\theta s_\phi + (a_{z_p}^b + g) c_\theta c_\phi - g \quad (2.20)$$

Either approach requires measurement of profiler orientation (pitch and roll). Estimates of horizontal acceleration may be obtained by observing changes in wheel rotation (for $a_{x_p}^w$) and a combination of forward speed and yaw rate or steering angle ($a_{y_p}^w$). Since the profiler is mounted on the sprung mass of the host vehicle, horizontal acceleration measured or estimated at the vehicle's footprint (i.e., the wander frame) may not be sufficient. Measurement of body-fixed lateral and longitudinal acceleration requires additional sensors that are not commonly available on existing profilers. However, the approach shown in Equation (2.20) was selected, because direct measurement of the acceleration inputs was possible and orientation could be derived in a manner similar to a common strap-down navigation system.

2.3.2 Theoretical Demonstration

Figure 2.16 shows a planar inverted pendulum model with 1 degree of freedom that demonstrates the errors caused by accelerometer misalignment. The model represents the host

vehicle as an inverted pendulum attached to a trolley with prescribed longitudinal motion $x(t)$. Although this model is very simple, it includes a degree of freedom that permits the body on which the profiler is mounted to change its alignment in response to horizontal acceleration. Collectively, the host-vehicle properties m (mass), h_{rc} (rotation center height), L_{cm} (center of mass height in relation to the rotation center), k_r (rotational stiffness resisting rotation), and c_r (rotational damping) define the host vehicle's dynamic response to horizontal acceleration. The dimensions h_p and l_p describe the profiler's position on the host vehicle in relation to the rotation center.

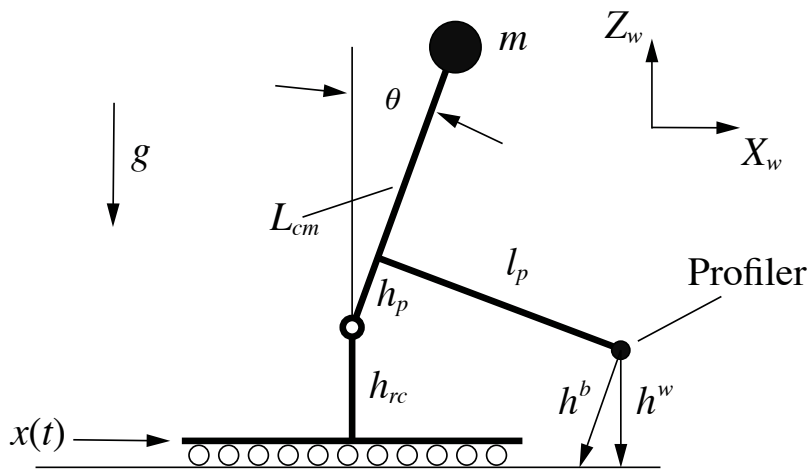


Figure 2.16 Inverted pendulum model

When the trolley experiences deceleration, the pendulum (i.e., the host-vehicle body) changes its orientation and changes its alignment by an angle θ . This has two consequences. First, the relative height of the profiler compared to the road surface measured by the misaligned height sensor is slightly larger than the true value:

$$h^b = \frac{h^w}{c_\theta} \quad (2.21)$$

Second, as shown in Figure 2.17, the measured components of vertical and horizontal acceleration are cross-contaminated. The true acceleration magnitude of the profiler, a_p , includes a contribution from an absolute vertical component a_{zp}^w , which is desired for robust measurement of the inertial platform, and an absolute horizontal component a_{xp}^w . The same vector also breaks down into a “body-fixed” vertical component a_{zp}^b , which is measured by a typical profiler, and a

body-fixed horizontal component a_{xp}^b . Figure 2.17 illustrates the equations above visually and shows the difficulty in applying corrections to vertical acceleration using on-board measurements of horizontal acceleration.

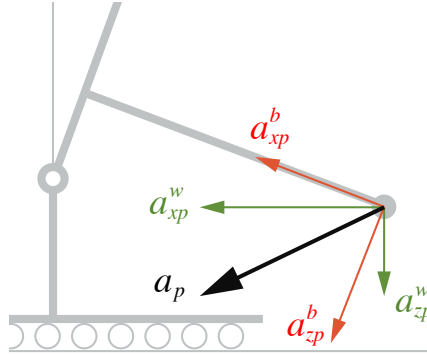


Figure 2.17 Acceleration components

For prescribed motion of the trolley base, the equation of motion for the pendulum alignment angle is:

$$\ddot{\theta} - \frac{g}{L_{cm}} s_{\theta} + \frac{k_r}{mL_{cm}^2} \theta + \frac{c_r}{mL_{cm}^2} \dot{\theta} + \frac{\ddot{x}(t)}{L_{cm}} c_{\theta} = 0 \quad (2.22)$$

Where:

$$a_{xp}^b = \ddot{x}c_{\theta} + h_p\ddot{\theta} - l_p\dot{\theta}^2 \quad (2.23)$$

$$a_{zp}^b = \ddot{x}s_{\theta} - h_p\dot{\theta}^2 - l_p\ddot{\theta} \quad (2.24)$$

$$h^b = \frac{(h_{rc} + h_p c_{\theta} - l_p s_{\theta})}{c_{\theta}} \quad (2.25)$$

And kinematic transformation of the same type that was applied in Equations (2.17) and (2.18) provide expressions for a_{zp}^w , a_{xp}^w , and h^w .

Figures 2.18 through 2.21 show the response of the trolley operating on a perfectly flat, smooth surface during the following deceleration pulse:

$$\begin{aligned} \ddot{x}(t) &= -a_{xpeak} \sin(2\pi(t - t_s)/T); 2 \leq t \leq 3 \text{ sec} \\ \ddot{x}(t) &= 0; t < 2 \text{ sec}, t > 3 \text{ sec} \end{aligned} \quad (2.26)$$

Where a_{xpeak} is the peak deceleration value of 0.4 g, T is the duration of the pulse (1 second), and t_s is the start time (2 seconds). Figure 2.18 shows the pulse and the measurement of longitudinal acceleration that would be obtained by an accelerometer fixed in the profiler host-vehicle body, which includes the influence of changes in orientation and the projection of gravity and true vertical acceleration onto its measurement axis.

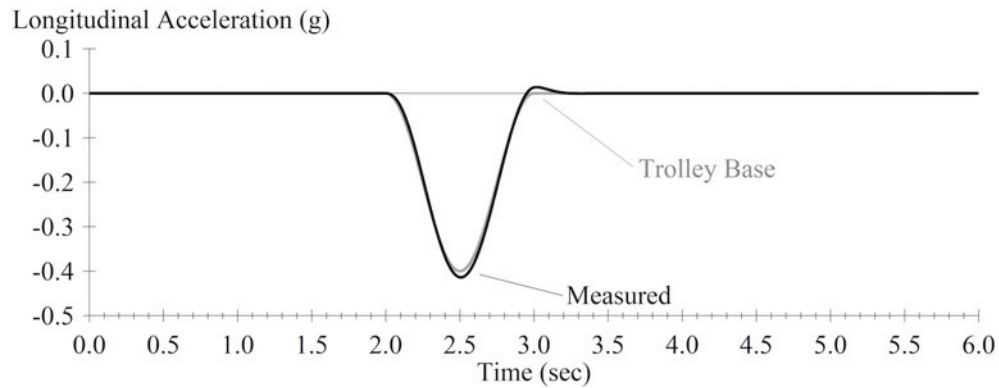


Figure 2.18 Deceleration pulse

Figure 2.19 shows the ideal measurement of vertical acceleration and the measurement that would be obtained by an accelerometer fixed in the profiler host-vehicle body. Again, the measurement by the sensor fixed in the profiler host vehicle is affected by its change in orientation. Both signals include the initial downward acceleration at the onset of the pulse, followed by a rebound and damped oscillation. However, the accelerometer fixed to the profiler host-vehicle body includes a downward bias due to the projection of longitudinal deceleration onto its sensitive axis.

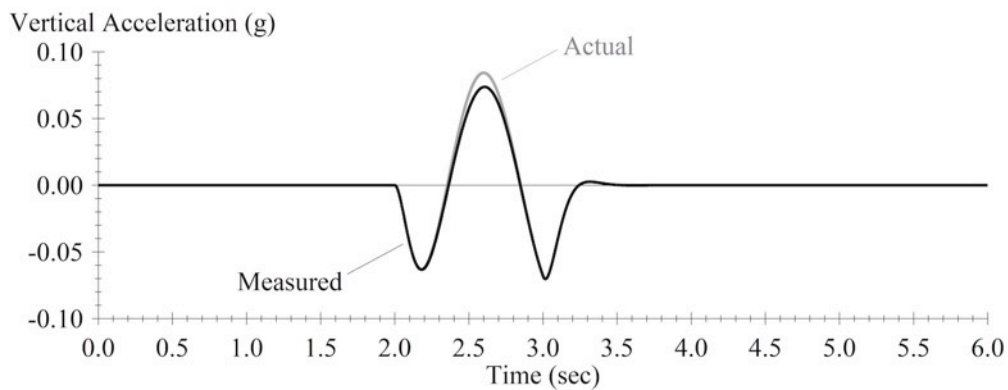


Figure 2.19 Measured and actual vertical acceleration

Figure 2.20 shows the floating reference height derived from the accelerometer and the signal measured by the height sensor for the sensors fixed to the profiler. The error in the height-sensor signal is very small, because the change in orientation (θ) is so small that the cosine term is very close to 1. This trace correctly shows that as the profiler pitches forward the simulated profiler height sensor drew about 50 mm closer to the road surface and subsequently recovered to its nominal position.

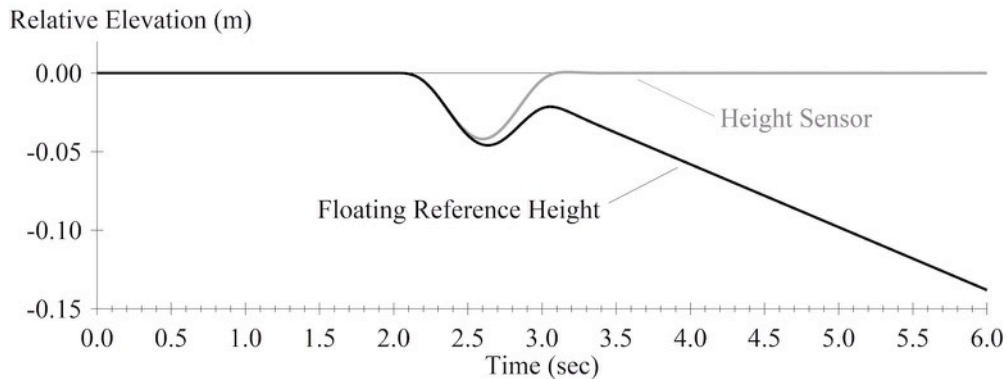


Figure 2.20 Height-sensor and floating-reference-height signals

In Figure 2.20, the floating-reference-height signal is obtained by double-integrating the accelerometer signal. It should show downward motion of the profiler followed by a recovery to its nominal position. Since the simulated road is perfectly flat, the floating-reference-height signal and the height-sensor signal should cancel. They do not, because the floating-reference-height signal includes downward curvature during the deceleration pulse. The curvature is the result of the downward bias in the accelerometer signal after double integration. Since the bias was caused by contamination of the vertical acceleration measurement, it is not canceled by the height-sensor signal.

Figure 2.21 shows the profile calculated using sensors fixed in the profiler host-vehicle body. The final profile is calculated by: (1) subtracting the height-sensor signal from the floating-reference-height signal, and (2) applying a high-pass filter. Misalignment of the accelerometer and cross contamination of its readings caused the profile to include an artificial bump over 5 mm high. The severity of the bump depends on the severity of the deceleration pulse, but its width depends on travel speed. Figure 2.21 shows the profile for deceleration from 22 m/s to 20 m/s, which is a small net speed change. A profiler with ideal sensors that provide

true vertical acceleration and true vertical range between the profiler and the road would produce a flat profile.

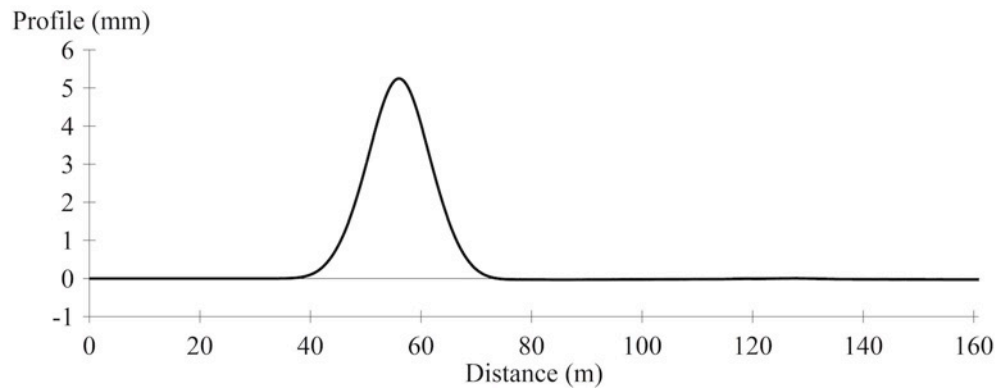


Figure 2.21 Simulated profile measurement

The severity (and shape) of the bump also depends on a combination of the dynamic properties of the profiler host vehicle and the duration of the pulse. This is because the error in vertical acceleration is equal to the product of the sine of the orientation angle and the longitudinal acceleration at every instant. Therefore, a lag between the application of longitudinal acceleration and the response may reduce the error.

For the specific conditions illustrated in Figures 2.18 through 2.21, the artificial bump causes the 160.9-m section that contains it to have an IRI value of 0.038 m/km, rather than the correct value of 0. This is not a large value, but the deceleration pulse was very short, and the net speed change was low. Further, the erroneous roughness is localized. Figure 2.22 shows the short-interval roughness profile.

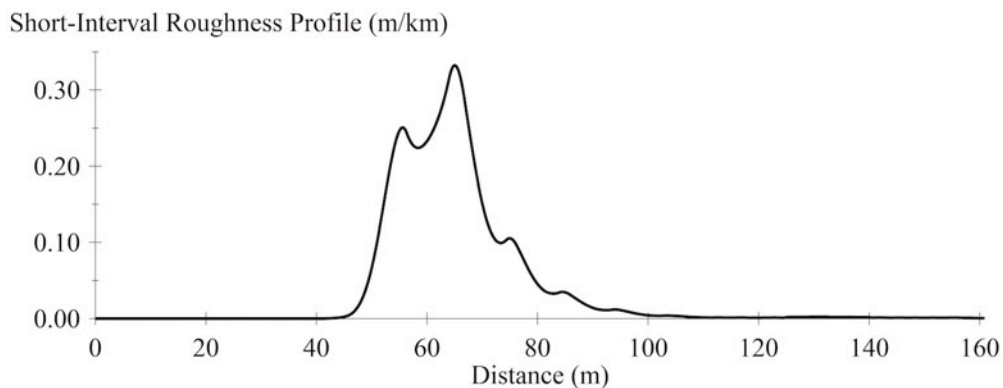


Figure 2.22 Short-interval roughness profile, simulated braking

An upward bias in roughness of 0.038 m/km does not necessarily occur when the artificial bump is superimposed on a profile with actual roughness. The artificial bump may cancel if some negative content (i.e., a dip) appears in the location where the deceleration occurred.

Forward acceleration of the host vehicle also superimposes an artificial bump onto the measured profile. During forward acceleration, the vehicle pitches rearward. The combination of positive longitudinal acceleration (a_{xp}^w) and negative pitch (θ) causes a temporary negative bias in the measured vertical acceleration. (See the first term after the equal sign for a_{zp}^b in Equation (2.17).) After double integration, this appears in the profile as a bump.

Figure 2.23 shows a pair of field profile measurements from a previous research project that illustrates the introduction of an artificial bump into the profile when the host vehicle experiences a deceleration pulse [14]. The figure shows a profile measured at constant speed and another profile that included deceleration with the speed profile shown in Figure 2.24. The vehicle decelerates from about 79 km/hr to about 37 km/hr, including about 3.75 seconds of deceleration over 0.25 g. This type of deceleration event may occur in an urban environment if the profiler is cut off or suddenly encounters slower moving traffic.

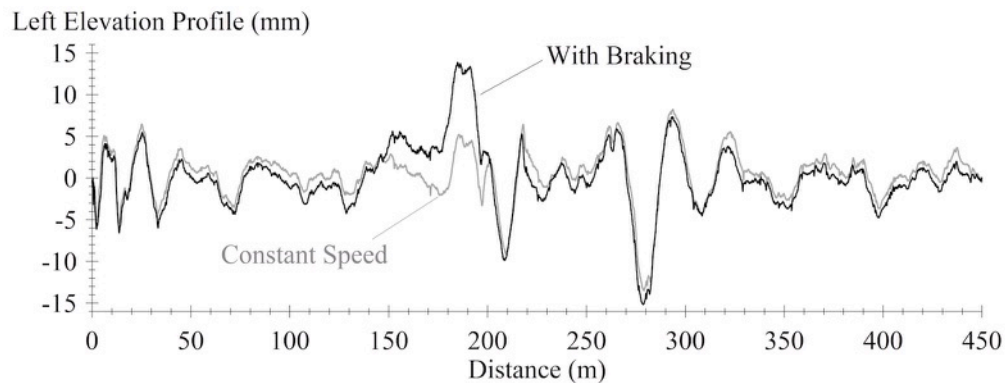


Figure 2.23 Profile measurement with and without braking

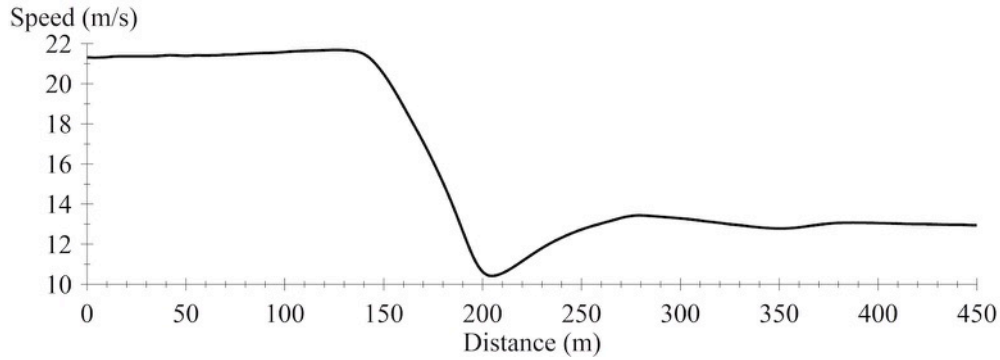


Figure 2.24 Test speed profile

The deceleration causes the same qualitative erroneous profile content predicted by the kinematic analysis and modeling described above. In particular, the projection of rearward longitudinal acceleration onto the sensitive axis of the accelerometer causes a temporary downward bias in measured vertical acceleration. This in turn causes localized downward curvature in the floating-reference-height signal after double integration, which appears in the final profile. Once the profile is high-pass filtered, the localized downward curvature appears as an artificial bump.

Figure 2.25 shows the profile produced by the trolley simulation for a deceleration pulse similar to that shown in Figure 2.24. (Note that, while the vehicle properties used are realistic, they are merely estimates.) The measured roughness induced by misalignment in the simulated profiler during deceleration is similar in shape and magnitude to the additional roughness that appears in the test data during deceleration. The range of deceleration appears from 50 m to 120 m in Figure 2.25, and from 135 m to 205 m in Figure 2.23.

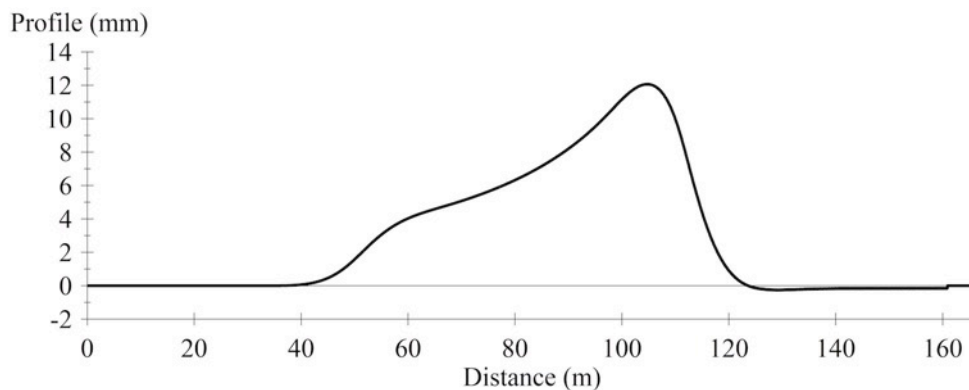


Figure 2.25 Simulated profile measurement error, long braking pulse

In the simulation, the braking event adds 0.055 m/km of roughness to a perfectly smooth 160.9-m-long section. At lower initial speeds, the severity of the roughness for the same deceleration history is much larger. For example, with an initial speed of 40 km/hr, the artificial bump is more than 200 mm high and adds roughness of 1.83 m/km to a 160.9-m segment. The increase occurs because: (1) at lower speed, the artificial roughness is more localized, and (2) the erroneous content maps to a range of wavelengths that affect the IRI to a greater extent.

2.4 Chapter Summary

The standard inertial profiler design uses body-fixed measurement of vertical acceleration to establish the floating reference height. Errors in the floating reference height occur during longitudinal and lateral acceleration, because the pitch and roll response of the host vehicle cause the sensitive axis of the accelerometer to tilt. As a result, the measured vertical acceleration is contaminated by acceleration along the other axes. This is a powerful source of error, because it occurs in the frequency range where the height-sensor signal and accelerometer signal interact to cancel the effect of host-vehicle vertical vibration on the computed profile. Since this frequency range is linked to vehicle vertical dynamic response, it is also in the frequency range that affects the IRI. This chapter demonstrated this error source and the resulting error in profile and the IRI analytically and provided an experimental example. Chapter 5 proposes algorithms that suppress the error caused by accelerometer tilt by removing drift in integrated accelerometer signals.

This chapter recommends the use of vertical acceleration in the direction aligned with gravity in place of body-fixed vertical acceleration to eliminate the errors caused by accelerometer tilt. The chapter presents kinematic equations for using body-fixed measurements of acceleration and orientation of the host vehicle in three dimensions to derive the true vertical acceleration. This is the motivation for the design and fabrication of the measurement system described in Chapter 4, which includes the sensors needed to support the approach. This is the core of the proposed design solutions examined experimentally in Chapter 6.

This chapter establishes 0.61 m to 42.9 m as the wavelength range of interest for the IRI, and 0.14 m to 65.58 m as the wavelength range of interest for general roughness measurement. These ranges serve as engineering requirement for the design solutions proposed in this research. The chapter recommends profile and roughness comparison as the means to assess the relative

success of each design. Roughness values are compared using the average IRI over a 160.9-m-long road section, and peak values from short-interval roughness profiles. Profiles are compared by cross correlating the output of the algorithm used to calculate IRI. Cross correlation of 0.92 is required for adequate profile agreement, and 0.98 is required to demonstrate reference-grade performance.

Chapter 3

Evaluation of Existing Inertial Profilers

This chapter describes an experiment conducted to examine the effects of potentially adverse operational conditions on the measurement of profile by high-speed inertial profilers. The experiment included staged reproductions of common operational conditions encountered while conducting network-level profile measurements on low-speed and urban roadways, such as

- operation at low speed,
- acceleration or deceleration,
- stop-and-go operation, and
- profiling from a dead stop.

Overall, the experimental plan included 24 test conditions composed of repeated runs under ideal conditions and multiple iterations of those listed above. All of these runs were performed on the low-volume loop at the MnROAD test track near Albertville, MN.

The experiment demonstrated the effect on the measurement caused by: (1) accelerometer tilting and changes in accelerometer tilt during longitudinal acceleration or longitudinal deceleration of the host vehicle, (2) limitations in accelerometer resolution, and (3) limitations in real-time and post-processing filtering procedures.

Six commercially available high-speed inertial profilers participated in the experiment. Together, these six manufacturers build most of the equipment in use for measurement of longitudinal profile for network-level pavement management in the U.S.

This chapter presents agreement between measurements by the inertial profilers operating at various speeds and reference measurements collected with an inclinometer-based rolling device that is commonly used to collect reference data for profiler certification. This chapter also presents agreement between measurements by the inertial profilers operating under ideal conditions (i.e., constant speed) and subsequent passes that include operator-induced disturbances.

Analysis of the measured profiles emphasized agreement in profile for calculation of the IRI and the spatial distribution of roughness along a test section. The analysis sought to ascertain

the range of profile in the vicinity of an operator-induced disturbance that was contaminated by measurement error. This was done using short-interval roughness profiles with an averaging base length of 7.62 m. Raw profiles, profile spectral content, and filtered profiles were also examined for elucidation of the overall effect of measurement errors on profile and the interaction of measurement errors with the high-pass filtering applied by each profiler.

The reported results do not characterize the inherent quality of each profiler manufacturer's products, or the expected performance of every profiler of a given make. Indeed, the accuracy of the profile measured in a given pass over a pavement section is heavily influenced by the quality of the profiler's sensors and electrical components, the manner in which they are mounted to the host vehicle, and the profile computation algorithm. However, accuracy also depends on properties of the host vehicle and the manner in which the profiler is operated. In particular, the sensitivity to the staged disturbances in this experiment depended heavily on the dynamics of the profiler host vehicle (center of gravity height, suspension compliance and kinematics, etc.), and the result from individual passes depended on the lateral placement of the vehicle within the lane. As such, this chapter does not identify the profilers by brand name.

3.1 Field Experiment

3.1.1 Test Sections

The testing took place on the low volume loop at the MnROAD research facility near Albertville, MN. The testing took place on a tangent section running southeast along the northern straightaway on the low volume loop. The section was 458 m long. This length was needed to observe the effects on measurement of long-wavelength content during operation at very low speed and long transient effects that occurred during acceleration and deceleration, as well as the residual effects of high-pass filter settling behavior. Most of the test section was asphalt concrete, but it included a transition to Portland cement concrete about 33.5 m upstream of the section end.

Section starting and ending locations were marked with temporary reflective tape. Diamond shaped marks were painted 45.7 cm to the right of the left track of interest to help drivers maintain the lateral position of their profiler accurately and consistently. The marks were placed about 6 m apart starting 90 m upstream of the section and extending over its length.

Figure 3.1 shows the starting tape and some of the diamond markings. Cones were placed at the right lane edge at several landmarks along the section as guides for staging specialized speed profiles. Depending on the desired speed profile, the cones appeared at locations where the driver was expected to change their speed or acceleration, or come to a stop.



Figure 3.1 Section starting point

3.1.2 Profilers

Table 3.1 lists the profilers that participated in the experiment, the mounting location on the host vehicle, the sensor type, and the lateral sensor spacing. Sensor type is known to affect profile measurement accuracy, particularly on surfaces with coarse macrotexture [75]. To minimize that error source on the results of this experiment, the test runs were performed on dense-graded asphalt with smooth macrotexture.

Table 3.1 Participating profilers

Profiler Designation	Profiler Mounting Location	Height Sensor Type	Lateral Sensor Spacing (cm)
Profiler 1	front	single point	175.3
Profiler 2	mid-wheelbase	line	175.3
Profiler 3	front	single point	172.7
Profiler 4	front	single point	167.6
Profiler 5	rear	line	167.6
Profiler 6	front	line	174.0

In the discussion of results, the term “raw profiles” refers to the profiles as they were submitted for analysis. The effects of various speed and acceleration conditions on the raw profiles depended on the type of high-pass filtering applied before data were submitted. Table 3.2 lists the type of high-pass filtering applied by each profiler.

Table 3.2 High-pass filtering

Profiler Designation	Filter Type	Cut-off Wavelength (m)
Profiler 1	none	none
Profiler 2	none	none
Profiler 3	Butterworth, 3 rd order	91.44
Profiler 4	Butterworth, 6 th order	91.44
Profiler 5	moving average, anti-smoothing	70
Profiler 6	cotangent	91.44

Profiler 4 applied a cascaded filter that applied the same sub-filters running in each direction to cancel phase shift. The data from Profiler 1 and Profiler 2 were submitted without high-pass filtering. Note that the profiles submitted “without filtering” might have included procedures for suppressing drift.

3.1.3 Reference Measurements

Reference profile measurements were collected on both wheel paths using a SurPRO 3500. The SurPRO 3500 is an inclinometer-based device that is supported by two wheels 250 mm apart. It is pushed along a test section at walking speed, and constructs a profile by accumulating changes in height using a series of slope values recorded at a constant longitudinal distance interval. This device records profile data at 25.4-mm intervals. The distance between the wheel paths was 175.3 cm. The overall IRI of the test section was 1.76 m/km in the left wheel path and 1.75 m/km in the right wheel path.

3.1.4 Speed/Location Measurement

A custom-built GPS data logging system was mounted on each profiler to collect independent measurements of the profiler’s speed and position during each run. The system included corrections provided by the Minnesota DOT’s network of continuously operating reference stations (CORS) captured via cellular modem at 1 Hz. The GPS receiver output a velocity vector record and a position record at 20 Hz. In this system, the expected position accuracy for the roving GPS receiver with the correction signal is 1 cm + 1 ppm (i.e., 1 mm per 1,000 m) of the distance between the roving receiver and the reference station. The distance to the reference station during the testing at MnROAD was a maximum of 1.6 km. The expected velocity error is 0.03 m/s RMS.

When conducting measurements, the GPS antenna and cell antenna were fixed to a high point on the vehicle (e.g., the roof) with magnetic mounts. Figure 3.2 shows an example of the set-up. The position of the GPS antenna on each host vehicle relative to the profiler's laser footprint was recorded. This, in conjunction with the lateral sensor spacing, provided a way to transform the raw measurements of antenna position to positions of the tracks followed by the left- and right-side profiler sensors.



Figure 3.2 GPS system set-up

3.1.5 Test Conditions

The experiment included several types of staged test conditions.

Constant Speed: Pass over the test section at a constant speed using cruise control if possible.

Coasting: Enter the section traveling at a constant speed. Disengage the throttle or cruise control at a designated landmark and coast to the end of the section.

Braking: Enter the section traveling at a constant speed. Apply the brakes at a designated landmark, decelerate at a targeted level to a targeted final speed, and continue at the final speed to the end of the section.

Throttling: Enter the section traveling at a constant speed. Apply the throttle at a designated landmark, accelerate to a targeted final speed, and continue at the final speed to the end of the section.

Stop-and-Go: Enter the section traveling at a constant speed. Apply the brakes at a designated landmark, slow at a targeted deceleration level to a stop as close as

possible to a second landmark, remain stopped for a designated length of time, accelerate to the initial speed, and continue to the end of the section.

Dead Stop: Stop at a designated landmark on the section (before initiating profile data collection), initiate data collection, accelerate to a target final speed, and continue at the final speed to the end of the section.

Table 3.3 lists the number of conditions of each type of test, including the designated speed, acceleration levels, deceleration levels, and stopping intervals where applicable. Each driver was asked to perform three valid passes for each test condition.

Test Type	Number	Test Conditions
Constant Speed	9	97, 80, 72, 64, 48, 40, 32, 24, and 16 km/hr
Coast	1	initial speed 72 km/hr
Braking	6	braking from 72-32 km/hr at 0.1, 0.2, and 0.3 g braking from 48-24 km/hr at 0.1, 0.2 and 0.3 g
Throttling	2	natural and heavy acceleration from 32-72 km/hr
Stop-and-Go	4	braking at 0.1 g to stop from 48 km/hr; stop for 5 sec; accelerate to 48 km/hr braking at 0.2 g to stop from 48 km/hr; stop for 5 sec; accelerate to 48 km/hr braking at 0.2 g to stop from 72 km/hr; stop for 5 sec; accelerate to 72 km/hr braking at 0.2 g to stop from 72 km/hr; stop for 1 sec; accelerate to 72 km/hr
Dead Stop	2	natural and heavy acceleration to 72 km/hr

For the Dead Stop and Throttling tests, “normal” and “heavy” acceleration was driver and vehicle dependent. Practice runs early in the experiment showed that specific acceleration levels were difficult to achieve accurately. In the Braking and Stop-and-Go tests, guide cones were placed where braking should start and end to achieve the requested change in speed and average deceleration level. In many cases, more than three passes were needed to get an acceptable set of three runs. The GPS data logger described above was monitored to provide feedback to the driver in real time or just after a given pass to help make adjustments for the next pass.

3.2 GPS Data Processing

The GPS data logging system recorded the time (GPS week and time), position (latitude, longitude, height above sea level), velocity (horizontal speed, heading, vertical speed), and diagnostics (latency, number of satellites, solution type) with real-time corrections at a rate of 20 Hz. This section describes the processing applied to the recorded data to characterize the speed profile of each run, define the location of the onset of disturbances or stops, quantify the relative strength of acceleration and deceleration pulses, or quantify duration of stops.

3.2.1 Static GPS Measurements

Static GPS readings were collected over a 50-second time interval with the receiver on the pavement surface at the test section boundaries. The receiver was placed at the intersection of each wheel path of interest with the longitudinal center of the start and end stripe.

Table 3.4 lists the standard deviation of position and speed measurements observed over the 50-second measurement interval. Noise in latitude and longitude are expressed in terms of north-south displacement and east-west displacement, respectively. Many of the probability distributions were not Gaussian. In particular, distributions of position quantities at some locations included positive excess kurtosis (i.e., thin at the center with long tails). Typically, this system applied a new position correction every 0.8-1.2 seconds. The largest step changes in position quantities and larger speed values often correspond to a recorded sample with a fresh position correction. Noise observed in the position quantities from this source was often correlated among the position signals (latitude, longitude, and height). Position and velocity was based on only 6 satellites for the measurements at the left start position. This may explain the higher noise levels for the vertical speed and height measurements relative to other positions. Data for the other positions was based on 7 or 8 satellites.

Table 3.4 Static measurement noise

Landmark	North-South Displacement (mm)	East-West Displacement (mm)	Vertical Speed (m/s)	Horizontal Speed (m/s)	Height (mm)
Left Start	3.4	4.7	0.159	0.030	19.9
Right Start	1.6	1.4	0.054	0.011	4.2
Left End	5.3	4.3	0.067	0.024	6.8
Right End	1.6	1.4	0.046	0.011	4.5

3.2.2 Local Coordinates

Measurements of latitude and longitude were transformed to local Cartesian coordinate systems with axes aligned eastward, northward, and upward. The origin was placed at the intersection of the left wheel path with the starting stripe. Locations north (dN) and east (dE) of the section origin were calculated from instantaneous readings of latitude (ϕ) and longitude (λ) as follows:

$$dN = (R(\phi_0) + H_0)(\phi - \phi_0) \quad (3.1)$$

$$dE = (R(\phi_0) + H_0)\cos(\phi)(\lambda - \lambda_0) \quad (3.2)$$

The symbols ϕ_0 , λ_0 , and H_0 denote the latitude, longitude, and height above sea level, respectively, at the test section origin. $R(\phi_0)$ is an estimate of the Earth's radius at the origin. For both test sections, this was approximately 6,368.084 km.

Data were further transformed in the horizontal plane to distance forward dF and distance leftward dL along the section. This re-oriented the horizontal axes to include an axis (with the original origin) that passed through the left-side endpoint. In particular:

$$\begin{aligned} dF &= dE \cos(\psi) + dN \sin(\psi) \\ dL &= -dE \sin(\psi) + dN \cos(\psi) \end{aligned} \quad (3.3)$$

Where:

$$\psi = \text{atan}\left(\frac{dN_{End}}{dE_{End}}\right) = -37.68 \text{ deg} \quad (3.4)$$

Subsequently, the coordinates were offset to provide the location of the left-side profiler on each vehicle instead of the position of the GPS antenna.

3.2.3 Speed and Acceleration

For data recorded during travel over the test section, readings of horizontal speed and heading were resolved to “forward” and “leftward” components using the coordinate system aligned with the test section. The forward and leftward speed signals were differentiated in time to obtain estimates of horizontal acceleration. However, the resulting signals were very noisy, in part due to system noise and in part due to vibration of the host vehicle in response to

disturbances from the road and driver inputs. In addition, the GPS system did not update its measurement of horizontal speed or heading in the first sample recorded after a new position correction. (It is believed that the 0.05-second cycle time did not provide an adequate opportunity to resolve the Doppler velocity estimate with a new kinematic correction.) As such, instantaneous readings of peak acceleration were considered inaccurate, and acceleration records were inspected, analyzed, and plotted after application of a 1-second moving average.

3.2.4 Diagnostics

The system recorded several diagnostic items, including the position type, the number of satellite ranges above the designated mask angle of 5 degrees for each waveband (L1 and L2), and standard deviation values associated with each value of latitude, longitude, and height. Very few runs were conducted with position and velocity based on fewer than six satellites, with seven to nine available for a majority of the runs. With one exception, all of the readings were recorded with the system in “integer narrow-lane ambiguity” mode, which implies that the system was confident it had eliminated carrier phase ambiguity prior to passing over the test section.

3.3 Results

3.3.1 Summary

The results of this experiment confirmed the sensitivity of inertial profilers to misalignment of the accelerometers during horizontal acceleration of the host vehicle and stops. Two operational conditions introduced artificial content into the profiles that registered as localized roughness:

1. Rapid transitions in horizontal acceleration introduced errors in curvature into the profiles at the locations where the brakes were released.
2. Stopping introduced an artificial change in elevation at the location of the stop.

The severity of localized roughness registered during braking events and stop-and-go operation depended on the type of disturbance (e.g., duration of the stop, deceleration level during braking) and the propensity of the host vehicle for misalignment in pitch or roll. Application of a high-pass filter to the measured profile spread out the influence of these errors.

Transitions in horizontal acceleration affected the long-wavelength content in measured profiles. This includes: the onset of braking, releasing the brakes, transition to coasting, heavy changes in throttle position, and operation through changes in road curvature. Operation at low speed also degraded the measurement of long-wavelength content.

Lateral tracking errors affected the reproducibility of measurements during the experiment, which confounded the interpretation of the results.

3.3.1.1 Constant-Speed Operation

Effect on profile:

- Speed affected the repeatability and reproducibility of long-wavelength profile content (8 m to 67 m). Repeatability of content that affects the IRI was higher for repeated passes above 32 km/hr than for measurements below 32 km/hr. Reproducibility was highest for comparisons of runs among the higher speeds, and lowest for comparisons or runs among lower speeds.

Effect on IRI:

- Position records from a GPS data logging system showed that lateral tracking of the profilers strongly affected their repeatability and accuracy. Over the range of speeds from 40 km/hr to 97 km/hr, inconsistency in lateral tracking affected agreement in profile and roughness more than travel speed for five of the six profilers.
- Travel speed affected longitudinal distance measurement and measured IRI in turn. In the absence of intermittent calibration of the distance measurement instrument to account for changes in travel speed, systematic differences in measurement of longitudinal distance of up to 1 percent occurred over the range of speeds from 16 km/hr to 97 km/hr.
- One of the profilers measured much lower IRI at 16 km/hr than at other speeds, and another showed greater variation at speeds of 32 km/hr and below than at higher speeds. However, three of the profilers were able to measure the IRI with the same level of accuracy and repeatability over the entire range of speeds from 16 km/hr to 97 km/hr.
- One of the profilers showed a systematic increase in IRI with travel speed over the entire range from 16 km/hr to 97 km/hr. This appears to be due to a signal processing issue that has since been addressed.

3.3.1.2 Coasting

Transition from operation with cruise control to coasting did not cause any discernable errors in profile measurement or IRI. However, the net change in travel speed and change in slip condition of the tires during coast affected measurement of longitudinal distance. For coast from 72 km/hr on an upward grade of 0.5 percent, up to 2 m of longitudinal misalignment accumulated over 235 m of travel.

3.3.1.3 Braking

Application of the brakes introduced large artificial disturbances into measured profiles. Each profiler that applied a high-pass filter spread out the effect of braking beyond the range where braking occurred. The shape, severity, and range of the errors in profile depended on the type of high-pass filtering applied by each profiler. The following observations were made:

- Errors in profile caused by braking affect the IRI most near the location where the brakes were released. This is because the change in deceleration occurs while the host-vehicle is out of alignment in pitch.
- Braking with a peak deceleration of 0.16 g or less rarely caused an increase in the measured roughness that raised the IRI of a 160.9-m section by more than 0.05 m/km, or caused an artificial area of localized roughness.
- Braking with peak deceleration of 0.26 g or more nearly always caused an artificial area of localized roughness.
- Braking with peak deceleration from 0.16 g to 0.26 g affected the measured IRI somewhat, but caused an artificial area of localized roughness in less than half of the test runs. In this range, braking was more likely to cause localized roughness in vehicles with a high center of gravity.
- Braking caused a rapid accumulation of downward bias in measured longitudinal travel distance. For the braking events included in the experiment, a reduced estimate of travel distance of 0.6 m to 1.2 m was common.

3.3.1.4 Application of the Throttle

Application of the throttle for natural and aggressive acceleration from 32 km/hr to 72 km/hr affected the long-wavelength content in measured profiles. However, no discernable errors in the measurement of IRI were observed, for two reasons. First, the acceleration

capability of the test vehicles was limited relative to their braking capacity. Second, the most rapid changes in acceleration did not occur when the vehicle was out of alignment in pitch.

3.3.1.5 Stop-and-Go Operation

Stopping during a profile measurement caused a large artificial disturbance in the profile at the location of the stop. Profiles submitted without high-pass filtering typically included a large step change in elevation at the stop. Profiles submitted with high-pass filtering included erroneous content over a wide range, often with a severe slope change at the location of the stop.

Some of the profilers applied special provisions for mitigating errors near the stop. In most cases, the severity of the error in measured IRI was reduced, but not enough to avoid the appearance of severe localized roughness. The exception was a unit that used a proprietary “stop-and-go” feature.

The unit with a stop-and-go feature registered an artificial area of localized roughness at the stop in only some of the stop-and-go runs, with a maximum severity of 3 m/km. In most of the stop-and-go runs by the other profilers severe localized roughness with a peak value of at least 6 m/km, and in some cases many times greater than that, appeared at the location of the stop. Examination of the profiles showed that an area of up to 47.3 m upstream of the stop and up to 75.6 m downstream of the stop should be marked as invalid, depending on the type of high-pass filter applied to the profile.

3.3.1.6 Dead Stop

The testing program included runs where profile was collected from a dead stop. However, all six profilers included provisions for preventing the collection of profile until a sufficient speed was reached or a sufficient distance was traveled. Limited observations showed that initiating profile data collection shortly after a stop caused less error in IRI than including the erroneous content at the stop.

3.3.2 Transverse Profile Variations

This section presents results for segment-wide IRI values and cross correlation analysis in the left wheel path over a range running from 80 m to 420 m from the start of the section and in the right wheel path over a range running from 20 m to 420 m from the start of the section.

In the left wheel path, the segment from 80 m to 420 m was relatively free of transversely inconsistent pavement features, and modest lateral tracking errors did not affect the results. Outside of these limits, “hit or miss” features appeared inconsistently in the measured profiles, such as filled core holes and transverse cracks with longitudinal wander.

In the right wheel path, the section grew progressively rough between the right wheel path of interest and the right lane edge, particularly in two locations. The first location had four narrow dips up to 1 cm deep that were located between 140 m and 160 m from the start of the section. The second location had four narrow dips up to 0.75 cm deep that were located between 295 m and 315 m from the start of the section.

The increase in roughness to the right of the right wheel path affected the observed accuracy and consistency in profile measurement, because each of the inertial profilers tracked to the right of the designated path. GPS data show a typical bias of 100 mm to 300 mm rightward of the wheel path of interest. This may have been caused by the placement of the diamond-shaped guide marks, which was rightward of the center of the driver’s seat when the profilers were properly positioned.

The GPS records showed that the IRI within the two ranges described above increased with increasing “rightward” tracking error. Figures 3.3 and 3.4 provide an example. The figures show the short-interval roughness profiles over the ranges that include the dips. The figures include the following three passes by Profiler 6, which were collected as part of the constant-speed experiment: (1) the second pass at 48 km/hr, (2) the third pass at 48 km/hr, and (3) the third pass at 64 km/hr.

In Figure 3.3, the short-interval roughness profiles from all three passes by Profiler 6 agree very well with each other and the reference profile outside of the range with the dips. The profiler tracked over a path to the right of the reference device, and measured higher roughness within the range with the dips in all three passes. The second pass at 48 km/hr and the third pass at 64 km/hr, which tracked approximately 11 cm rightward of the intended location, agree very well. However, the third pass at 48 km/hr, which tracked approximately 24 cm right of the intended location, measured much more roughness in this area.

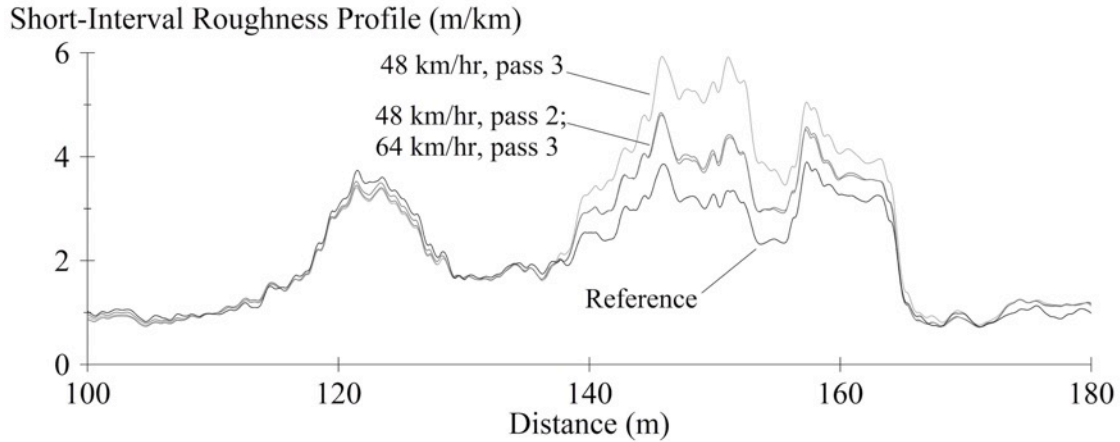


Figure 3.3 Short-interval roughness profiles of transversely inconsistent localized roughness

Figure 3.4 shows the short-interval roughness profiles over the second transversely inconsistent area. Here, the third pass at 48 km/hr and the third pass at 64 km/hr, which tracked approximately 23 cm right of the intended location, agree very well. The second pass at 48 km/hr, which tracked approximately 18 cm right of the intended location, measured less roughness in this area and was in closer agreement with the reference profile.

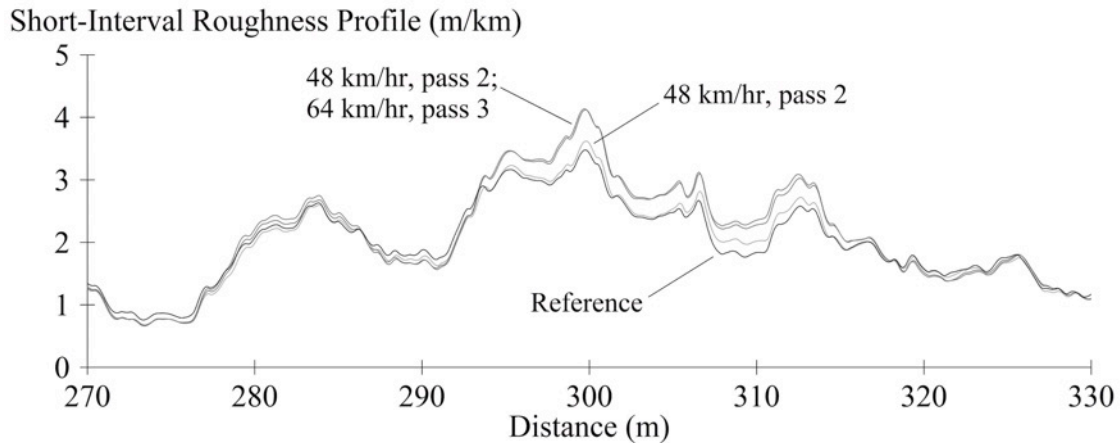


Figure 3.4 Short-interval roughness profiles of transversely inconsistent localized roughness

Figures 3.3 and 3.4 demonstrate the potential confounding effect of lateral tracking on the results. As shown, errors in roughness measurement grow with tracking error to the right in two critical portions of the test section.

3.3.3 Constant-Speed Operation

This set of runs was intended to discern the valid speed range of each profiler for constant-speed operation, and observe the change in IRI and long-wavelength profile content with travel speed. Speed profiles measured by the GPS data logging system were inspected to verify the average travel speed for each pass over the test section, and to confirm the absence of longitudinal acceleration.

3.3.3.1 IRI Agreement

Figure 3.5 shows the percentage disagreement in overall IRI over the segments of interest described above between each profiler and the reference measurement at various measurement speeds. In three passes, the profile data from the reference device in these ranges produced IRI values of 1.860 m/km, 1.884 m/km, and 1.854 m/km in the left wheel path and 1.761 m/km, 1.746 m/km, and 1.767 m/km in the right wheel path. Cross correlation of IRI-filtered profiles produced an average agreement score among the possible combination of the three passes of 0.990 for the left profiles and 0.987 for the right profiles.

Inspection of filtered profile traces, short-interval roughness profiles, and slope spectral density plots revealed the following:

Profiler 2: Inconsistency in measurement of longitudinal distance caused variation in IRI values calculated for Profiler 2. For example, in the profiles measured at 24 km/hr, the start and end tape for the first, second, and third passes appeared 461.0 m, 460.8 m, and 450.8 m apart, respectively. The “compressed” profile from the third pass registered the highest IRI value. With the exception of the third pass at 24 km/hr, Profiler 2 measured the section with increasingly smaller overall length as speed increased. This phenomenon was observed in other profilers. However, some of the other profilers re-calibrated the longitudinal distance measurement system frequently or used the section endpoints to enforce a consistent calibration in every pass.

Profiler 3: Measurements on both sides of the lane by Profiler 3 at 16 km/hr produced profiles with roughness that was uniformly reduced across the spectrum compared to measurements at other speeds. The reason for the reduction at 16 km/hr is unclear.

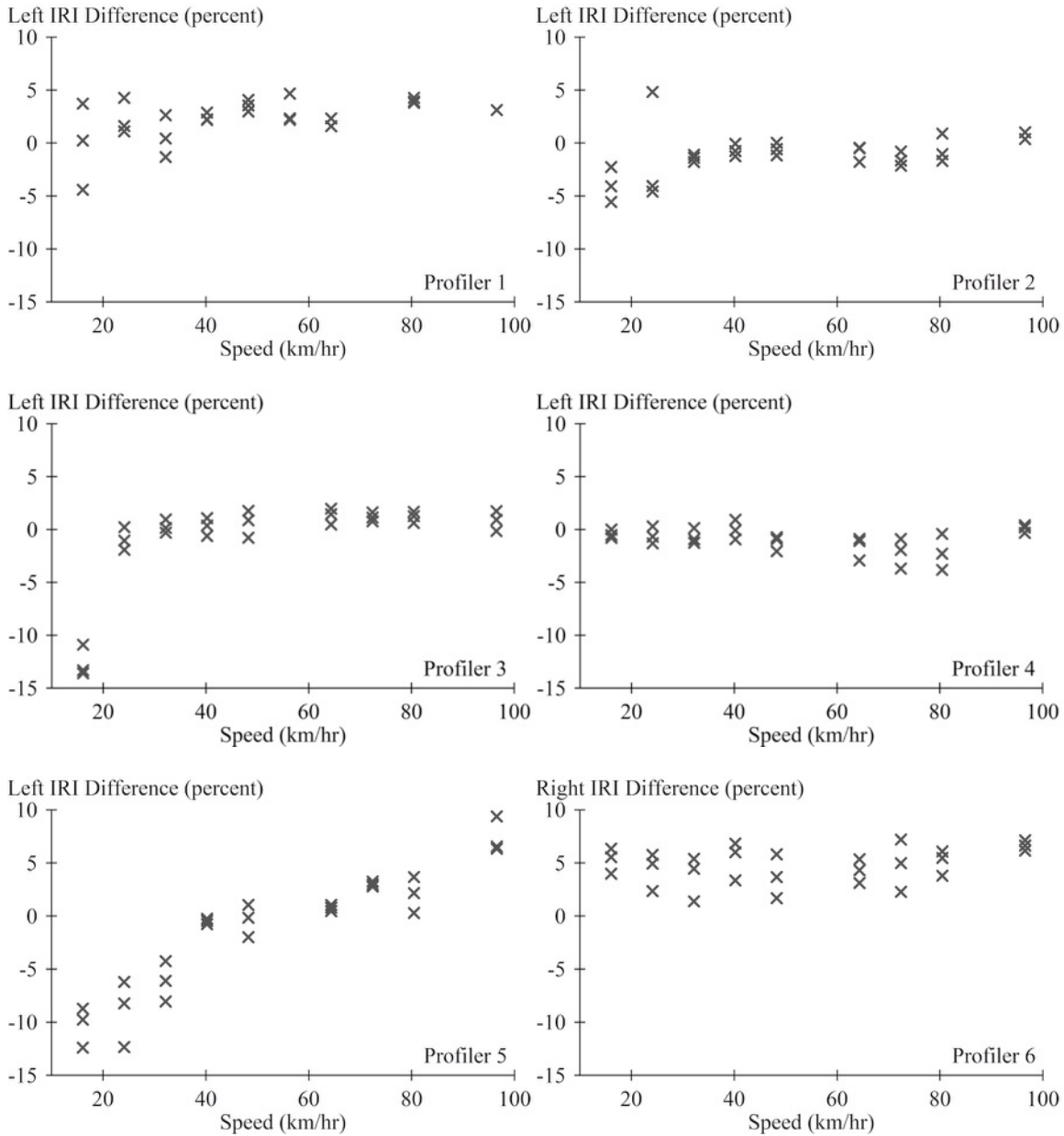


Figure 3.5 Agreement in IRI between inertial profilers and the reference values versus travel speed

Profiler 4: Some roughness variation measured by Profiler 4 was isolated near a wavelength of 1.9 m, but it was highest at 16 km/hr and 97 km/hr.

Profiler 5: Much of the change in IRI with speed by Profiler 5 occurred in a range of wavelengths of 3 m and below. Further investigation using raw sensor signals revealed that a signal timing issue that has since been addressed caused the speed-dependency for IRI values.

Profiler 6: Profiler 6 did not measure the left wheel path, and results are presented for the right wheel path. The unit tracked rightward of the wheel path measured by the reference device. The upward bias in IRI corresponds to the rightward bias in lateral position, and some of the scatter is caused by changes in tracking position.

3.3.3.2 Long-Wavelength Content

Inspection of the raw profile traces and profile traces with additional filtering applied showed that host-vehicle speed affected the long-wavelength content, particularly at low speeds (i.e., speeds below 40 km/hr). For example, Figure 3.6 shows a portion of three raw profile traces from the left side of the lane produced by Profiler 4 while traveling at 48 km/hr, and Figure 3.7 shows three raw profile traces over the same area produced by Profiler 4 at 16 km/hr. The profiles measured at 48 km/hr are much more consistent than those measured at 16 km/hr.

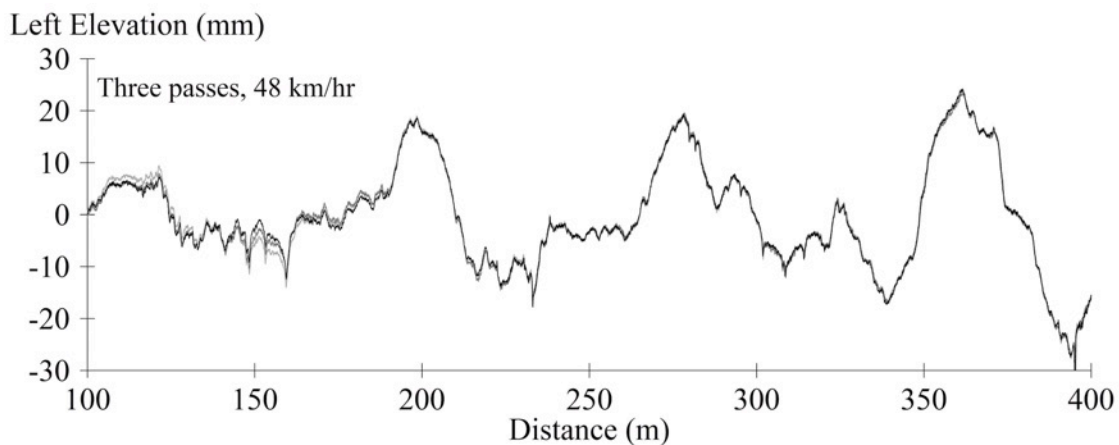


Figure 3.6 Raw profile traces measured by Profiler 4 at 48 km/hr

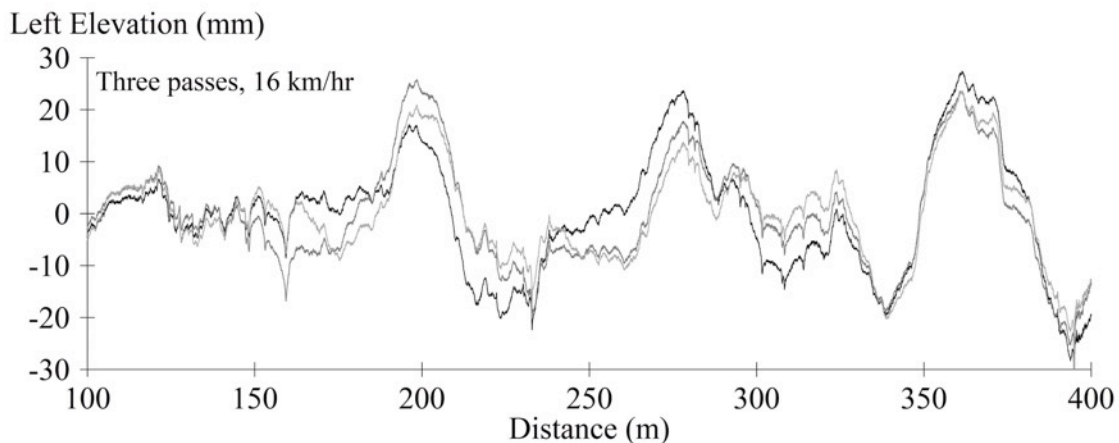


Figure 3.7 Raw profile traces measured by Profiler 4 at 16 km/hr

The inconsistency among the measurements conducted at speeds below 40 km/hr may have been caused by changes in the application of the throttle by the driver. Application and release of the throttle under manual control causes a change in pitch orientation of profilers as they travel over a test section, which tilts the sensitive axis of the accelerometer. This in turn introduces low-frequency errors into the accelerometer signal due to the projection of a component of horizontal acceleration onto the sensitive axis of the accelerometer. The reduction in vertical acceleration experienced by the profiler, and the resulting reduction in the valid portion of the accelerometer signal relative to electrical noise and measurement resolution may have also contributed to measurement error at low speed. Differences in high-pass filtering applied by each profiler strongly affected what could be observed about the long-wavelength content.

Table 3.5 presents cross correlation values for comparison of slope profiles in the long-wavelength range measured by Profiler 4 in the left wheel path. Long-wavelength content was isolated using a high-pass filter with a cut-off wavelength of 67 m and a low-pass filter with a cut-off wavelength of 8 m. This table presents the average agreement score for comparison of passes at each combination of speeds. Diagonal entries provide the average agreement score for comparisons of repeated runs at the same speed. The other entries provide the average agreement score for comparisons of repeated runs at different speeds.

Agreement scores for repeatability at a given speed (i.e., diagonal entries) are greater for measurements above 32 km/hr than for measurements below 32 km/hr. Reproducibility is highest for comparisons among the higher speeds, and lowest for comparisons among lower speeds. These observations held in nearly every case for the other five profilers.

Table 3.5 Agreement scores, long waveband, Profiler 4, left

	16 kph	24 kph	32 kph	40 kph	48 kph	64 kph	72 kph	80 kph	97 kph
97 kph	0.963	0.971	0.983	0.983	0.976	0.972	0.974	0.974	0.990
80 kph	0.942	0.954	0.976	0.984	0.986	0.987	0.992	0.992	
72 kph	0.942	0.955	0.978	0.986	0.989	0.990	0.992		
64 kph	0.941	0.955	0.980	0.985	0.992	0.991			
48 kph	0.946	0.961	0.984	0.991	0.996				
40 kph	0.953	0.966	0.988	0.991					
32 kph	0.954	0.969	0.986						
24 kph	0.958	0.964							
16 kph	0.948								

3.3.4 Coasting

These tests were intended to quantify the sensitivity of inertial profilers to the onset of host-vehicle deceleration during a transition from operation at constant speed to coasting.

Table 3.6 summarizes the passes performed by each profiler. In each run, the driver initiated coasting by disengaging cruise control while traveling at speeds of 70.3 km/hr to 74.4 km/hr. With one exception, coasting began 221.3 m to 244.2 m from the start of the section. Each host vehicle exhibited a unique level of deceleration resulting from: an upward grade of about 0.5 percent on the test section, host-vehicle rolling losses (aerodynamic drag, tire rolling losses, drivetrain and engine losses, etc.), and environmental conditions (wind speed and direction, ambient air pressure, etc.).

Table 3.6 Range of speeds, deceleration, and coasting onset location

Profiler	Passes	Initial Speed (km/hr)	Coasting Onset Location (m)	Average Decel. (g)	Final Speed (km/hr)
Profiler 1	2	72.0	222.4-222.7	0.037	54.1
Profiler 2	2	72.5-72.6	221.3-221.7	0.048	48.6-49.7
Profiler 3	2	71.9-73.0	241.0-244.2	0.046	51.2-52.9
Profiler 3	1	72.0	73.8	0.036	40.4
Profiler 4	3	70.3-71.3	226.5-236.4	0.041-0.042	49.4-51.7
Profiler 5	3	72.3-73.9	226.5-228.1	0.042-0.044	52.0-54.2
Profiler 6	3	73.2-74.4	231.5-243.7	0.036-0.043	56.2-58.2

Figure 3.8 compares left IRI values from passes with coasting to those measured at constant speeds from 56 km/hr to 72 km/hr. (Profiler 6 is excluded from the figure, because it did not measure the left profile.) These values were calculated using the profiles from the left wheel path of the test section from 80 m to 420 m from the starting point. Inspection of filtered elevation profile plots and roughness profiles confirmed that coasting most likely did not cause the variation in measured roughness. Comparison of profiles measured with coasting to those measured at constant speed showed no discernable change in profile at the location of onset of coasting. Short-interval roughness profile plots from passes with coasting included no additional localized roughness at the location of onset of coasting compared to passes at constant, but comparable speeds.

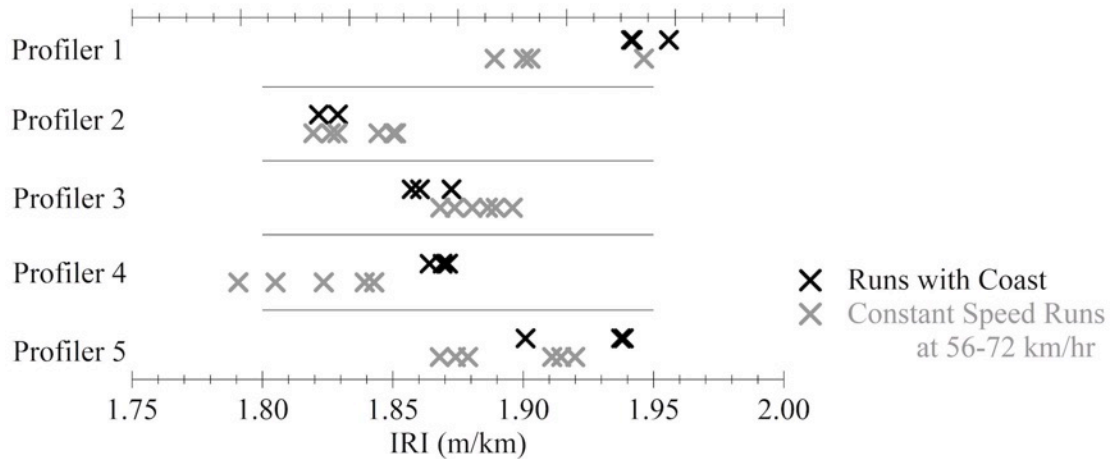


Figure 3.8 Comparison of IRI values in passes with coasting and at constant speed

No systematic effect on measured roughness caused by coasting appears in Figure 3.8. This is most likely because the change in longitudinal acceleration and vehicle pitch response of at the onset of coasting were small. As a result, any error in profile measurement they caused was smaller than other sources of variation.

3.3.5 Braking

These runs were intended to quantify the effects of host-vehicle braking on the measured profile. Passes with staged braking events were performed for deceleration from 72 km/hr to 32 km/hr and from 48 km/hr to 24 km/hr with target average deceleration values of 0.1 g, 0.2 g, and 0.3 g. This section examines the difference in measured profile and roughness of runs with braking to those at constant speed.

3.3.5.1 Characterization of Speed Profiles

The strength of the disturbance caused by braking was quantified for each run using speed profiles derived from data recorded by the GPS data logging system. Figure 3.9 shows a sample speed profile that was recorded during a pass by Profiler 4 with a target deceleration of 0.2 g from an initial speed of 48 km/hr to 24 km/hr. Like the trace in Figure 3.9, each pass with braking included four regions, which correspond to four successive modes of operation: (1) entry at a constant speed, (2) braking, (3) coasting (i.e., during the transition from using the brakes to using the accelerator) and (4) travel to the end of the section with manual control of the accelerator.

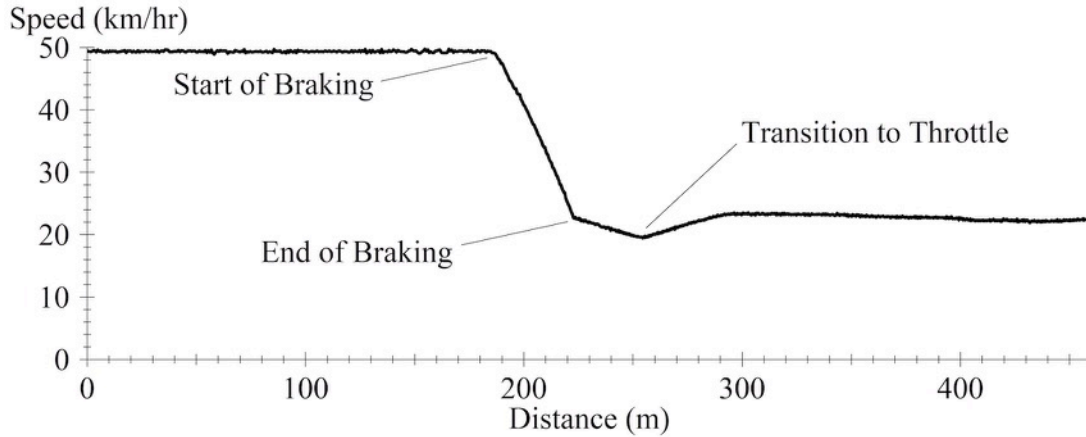


Figure 3.9 Speed profile for a pass with braking

The speed profiles provided the limits of each range shown in Figure 3.9 (i.e., the longitudinal position of each transition), and the high and low speed during each mode of operation. Post-processing of data collected by the GPS also provided the peak acceleration (or deceleration) averaged over a 1-second interval. In a few of the passes, the driver began to gently accelerate within the last 100 m of the test section. Passes were rejected if acceleration above 0.1 g was recorded over any 1-second interval within the 150 m of travel past the end of the prescribed braking event.

In this discussion, passes are identified primarily by two characteristics: (1) the average deceleration during the braking event, and (2) the highest deceleration observed during any 1-second interval within the braking event (i.e., a “peak” value). Figure 3.10 shows the longitudinal acceleration profile for the same pass presented in Figure 3.9. The acceleration trace is displayed after smoothing using a 1-second moving average. This braking pulse represents a case with relatively uniform deceleration. For this pass, the average deceleration during braking was -0.21 g, and the peak deceleration was -0.23 g.

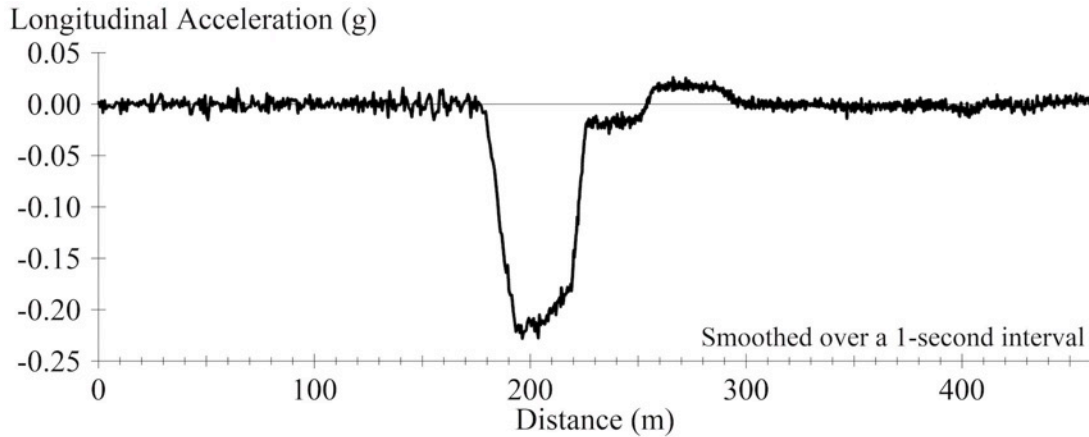


Figure 3.10 Longitudinal acceleration profile for a pass with braking

Often, the details of the acceleration profile from two passes with similar peak and average deceleration differed. For example, acceleration was heaviest at the onset of braking in some passes, and heaviest near the end of the braking event in others. In many passes, the driver elected to coast for only a short distance after the end of braking before transitioning to the throttle. Coasting over distances of up to 40 m was common, and some passes included coasting over distances of up to 85 m.

3.3.5.2 Effects on Raw Profiles

An artificial change in curvature appeared in the unfiltered profiles submitted without high-pass filtering over the range where braking occurred, which was relieved (e.g., changed direction or reduced) in the area after the end of braking. As described in Chapter 2, when the host vehicle decelerates and pitches forward simultaneously, some part of the rearward acceleration is detected by the (tilted) accelerometer. This causes a negative (i.e., downward) error in measured vertical acceleration, which appears as downward curvature in the profile after the signal is integrated twice to get the floating reference height. These observations were clearest at deceleration levels of 0.15 g and above.

High-pass filtering modified the spurious content caused by braking. Figures 3.11 through 3.14 compare profiles from a pass with braking to three passes at constant speed by the four profilers that applied high-pass filtering (Profilers 3, 4, 5, and 6). The plots show three profiles collected at 48 km/hr compared to a pass by the same profiler with braking from 48 km/hr to 24 km/hr with an average deceleration of 0.28 g and a peak deceleration in the range from 0.32 g to 0.35 g. Each plot denotes the locations of the start and end of braking.

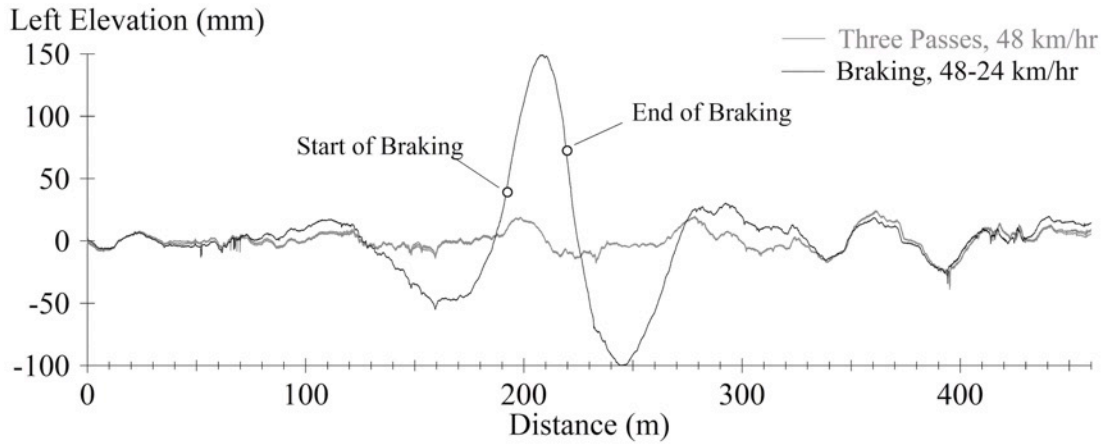


Figure 3.11 Raw profile trace with braking at 0.28 g, Profiler 4

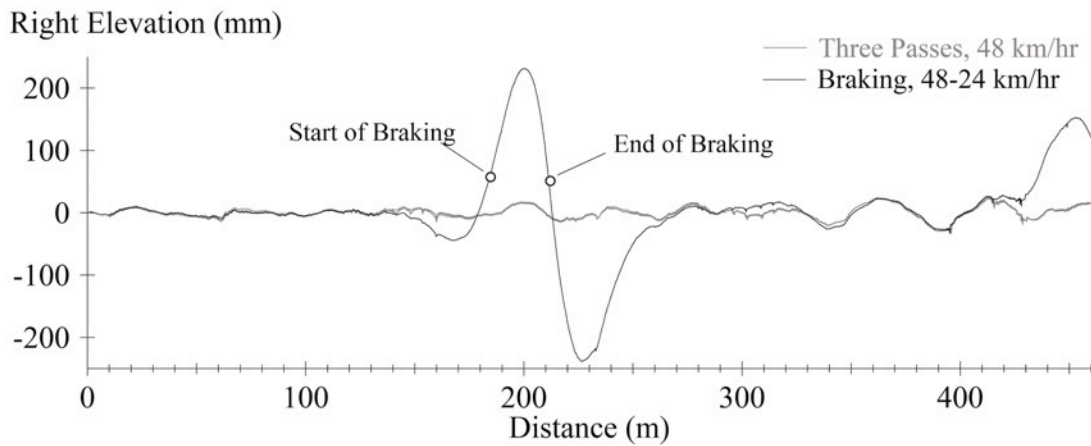


Figure 3.12 Raw profile trace with braking at 0.28 g, Profiler 5

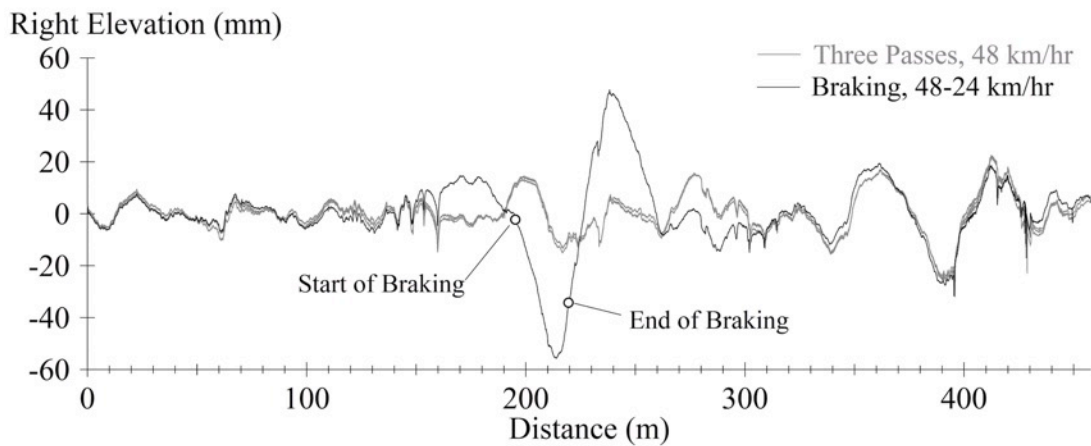


Figure 3.13 Raw profile trace with braking at 0.28 g, Profiler 6

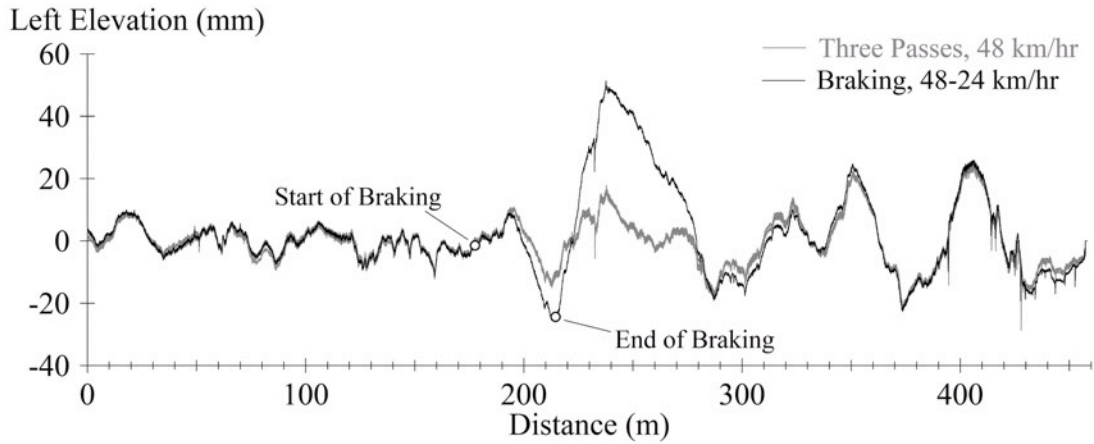


Figure 3.14 Raw profile trace with braking at 0.28 g, Profiler 3

The high-pass filtering applied by all four profilers spread out the effect of braking on the profiles outside of the areas where the brakes were applied. In each case, the braking occurred over a distance of approximately 25 m, but the effect on the elevation profile appeared over a distance of at least 130 m that started before the location where braking was applied and ended at a location past the release of the brake. For three profilers (Profilers 4, 5, and 6) braking affected the profile ahead of the start of braking and after the end. For Profiler 3, most of the effect on profile appeared in the range past the location where braking ended.

Each profiler applied a high-pass filter of a different type, and each filter spread out the effect of the braking pulse differently. The filtering applied by Profiler 4 and Profiler 5 spread out the effects of the braking symmetrically. Profiler 3 and Profiler 6 used recursive filters applied in the forward direction, and they shifted the influence of the braking pulses with a forward bias. Note that Figures 3.11 through 3.14 show the traces from the wheel path where the vertical range of the artificial content caused by braking was greatest, and very little artificial content was present on the right wheel path profiles from Profiler 3.

3.3.5.3 Effects on Short-Interval Roughness Profiles

This section examines the effects of braking on IRI using short-interval roughness profiles. Figure 3.15 shows profiles measured by Profiler 4 with and without braking after application of additional high-pass filtering to eliminate content at wavelengths above 30.48 m. This additional filtering helps to emphasize the content that affects the IRI. The figure compares the profile from a pass at a constant speed of 24 km/hr to a pass with braking from 48 km/hr to 24 km/hr with average deceleration of 0.32 g and a peak deceleration of 0.36 g. With some of the

long-wavelength content removed, the change in profile is more localized near the range where braking occurred.

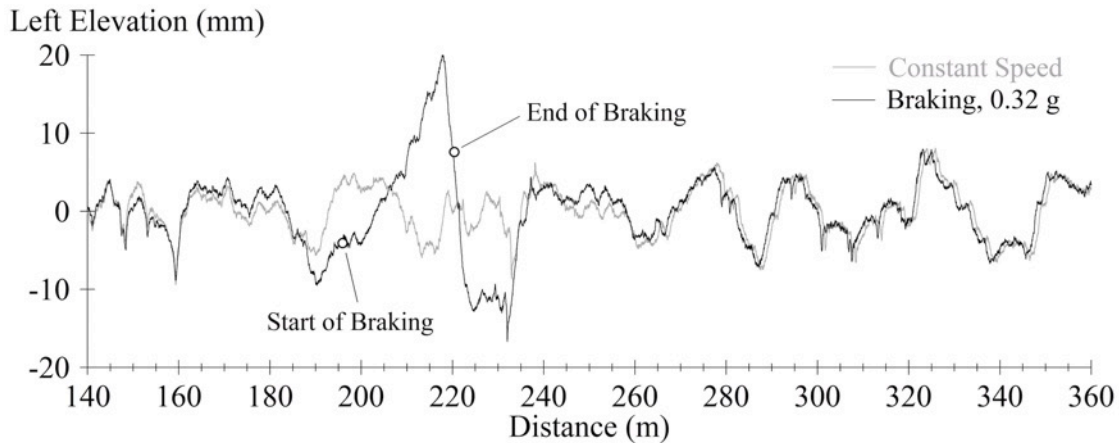


Figure 3.15 High-pass filtered traces from passes with and without braking

Figure 3.16 compares short-interval roughness profiles for runs by Profiler 4 with braking of various deceleration levels where speed decreased from 48 km/hr to 24 km/hr to a pass at a constant speed of 24 km/hr. The figure shows that the effects of braking on the IRI are localized. The braking with an average deceleration of 0.32 g began at 196.5 m and ended at 220.5 m. (This is the pass illustrated in Figure 3.15.) Additional roughness appears in the vicinity of the end of braking, but not in the location of the start of braking.

The braking terminated at the same location within 2.6 m in all three of the passes with braking shown in Figure 3.16. In each pass, additional roughness appears at a location centered just downstream of the end of braking, and the amount of roughness grows with the severity of the deceleration.

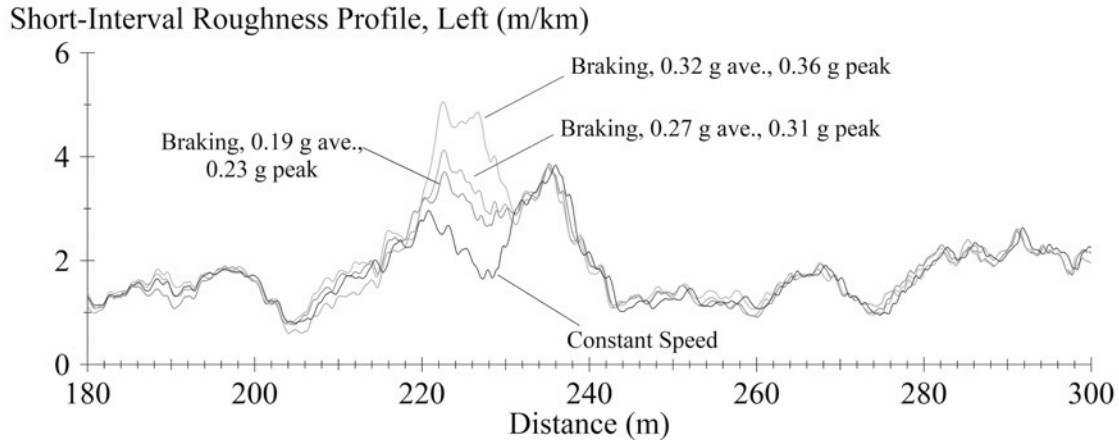


Figure 3.16 Short-interval roughness profiles for passes with braking

Collectively, the short-interval roughness profiles for passes with braking did not exhibit a systematic relationship to the severity of braking. In many cases, two passes by the same unit with braking of equal or similar severity registered differently on the short-interval roughness profile. This is due in part to the details of the speed profile and the profiler host vehicle's response to it. The precise location where the braking started and ended also varied between passes. The erroneous content in the profile caused by braking is superimposed on the actual profile. Typically, much of that content causes localized increases in slope or curvature of the profile. However, some of the erroneous content cancels out or reduces the severity of existing features within the profile.

Short-interval roughness profiles were inspected for every pass performed with braking and compared to runs performed at a constant speed. Four cases were observed:

1. Additional roughness appeared in a localized area.
2. The distribution of roughness changed, such that the roughness profile was increased over some range and decreased over another with no net change in average roughness.
3. Roughness decreased in a localized area. This occurred when the erroneous downward curvature caused by braking cancelled out existing upward curvature in the profile. (This was uncommon.)
4. No discernable change appeared in the roughness profile.

Table 3.7 summarizes the observations for the 64 passes with braking from 48 km/hr to 24 km/hr. The table sorts passes into groups by peak deceleration and into another set of groups

by average deceleration. For each group, the table provides the total number of passes, the number of passes for which the short-interval roughness profile was deemed to be altered (cases 1, 2, and 3, above), and the number of passes that included a localized increase in the short-interval roughness profile of 1 m/km or greater. Note that, when the influence of an increase in localized roughness of 1 m/km is spread out over a 160.9-m-long section, it increases the overall IRI by 0.05 m/km. Figure 3.16 presented the short-interval roughness profile for one pass with an increase of 1 m/km, and two others with a larger increase.

Table 3.7 Effects on short-interval roughness profiles, braking from 48-24 km/hr

Deceleration Range (g)		Total	Number of Passes	
Peak	Average		Altered Roughness	Localized Roughness Increase
0.09-0.16	0.05-0.13	23	4	1
0.18-0.25	0.16-0.20	16	12	5
0.26-0.43	0.22-0.40	25	23	16

When changes were observed in the short-interval roughness profiles, they consistently appeared near the end of braking. Figures 3.11 through 3.15 showed that errors in profile were spread out over a large area. However, the most severe slope changes occurred where the brakes were released. The severe slope change is the result of a rapid change in deceleration as the brakes are released together with accelerometer tilt caused by pitch. (In contrast, the change in pitch angle takes time to develop when the brakes are first applied.)

In cases with an observed localized roughness increase, the peak change appeared no more than 1.4 m in advance of the location where braking ended and no more than 13.2 m past the location where braking ended. In most cases with altered roughness, the change in the short-interval roughness profile appeared no more than 11.4 m in advance of the location where braking ended and no more than 25.1 m past the location where braking ended.

Tables 3.8 and 3.9 summarize the observations for the 75 passes with braking from 72 km/hr to 32 km/hr. Table 3.8 groups the passes by average deceleration and Table 3.9 groups the passes by peak deceleration. When changes were observed in the short-interval roughness profiles, they consistently appeared near the location where braking ended. In cases with an observed localized roughness increase, the peak change appeared no more than 10.8 m in advance of the location where braking ended and no more than 15.5 m past the location where braking ended. In most cases with altered roughness, the change in the short-interval roughness

profile appeared no more than 18.2 m in advance of the location where braking ended and no more than 31.5 m past the location where braking ended.

Table 3.8 Effects of average deceleration on short-interval roughness profiles

Average Deceleration (g)	Total	Number of Passes	
		Altered Roughness	Localized Roughness Increase
0.04-0.16	26	5	0
0.17-0.23	26	11	4
0.24-0.35	23	16	12

Table 3.9 Effects of peak deceleration on short-interval roughness profiles

Peak Deceleration (g)	Total	Number of Passes	
		Altered Roughness	Localized Roughness Increase
0.07-0.21	30	6	0
0.22-0.28	21	11	4
0.29-0.48	24	15	12

For inertial profilers that are in current use, it is necessary to mark an area of profile in the vicinity of braking as invalid, depending on the severity of braking. The boundaries of the marked area depend on the high-pass filtering applied by each profiler and the propensity of the host vehicle to respond in pitch. As a result, the boundaries would have to be determined by testing for each unit. As shown in Figures 3.11 through 3.14, this range would be quite long for engineering purposes that require valid elevation profile for wavelengths up to 91.44 m. Based on the results presented in this section, a smaller area for exclusion can be identified for valid measurement of IRI.

3.3.6 Throttling

These runs were intended to quantify the effects of forward host-vehicle acceleration on measured profile. Passes with staged events were performed for acceleration from 32 km/hr to 72 km/hr. Drivers were asked to use a “normal” level of acceleration in some passes and heavy acceleration in others.

Typically, acceleration was highest when the throttle was first applied, and it reduced near the final speed. Figure 3.17 shows the speed profile for a pass with acceleration by Profiler 5. In this pass, the acceleration began at about 0.21 g and reduced to about 0.05 g by the

end of the event with an average level of 0.12 g. This example represents a typical distribution of acceleration. The most aggressive acceleration pulse for all runs collected in this experiment began at 0.27 g and averaged 0.17 g.

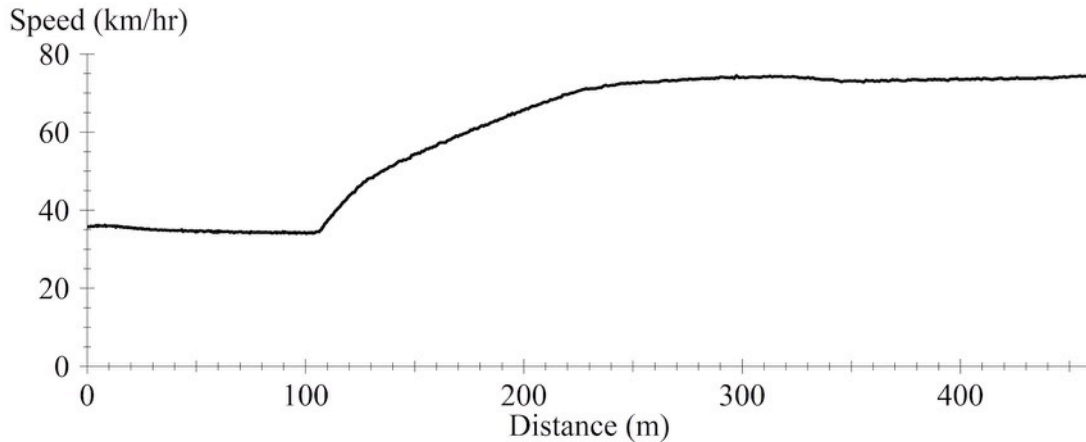


Figure 3.17 Speed profile for a pass with forward acceleration

Like the runs with braking, the staged events with acceleration caused changes to the long-wavelength content in the raw profiles. In addition, the effect of acceleration on the profile spread out over a large area, and spread out differently depending on the type of filtering applied by each profiler.

Although the raw profile plots showed the effect of acceleration, comparison of short-interval roughness profiles revealed no effects on the IRI near the onset or termination of acceleration. This indicates that the staged acceleration events did not affect profile content in the range of wavelengths that affect the IRI. Runs with throttling affected measured roughness less than runs with braking, in part because the acceleration capability of the test vehicles was limited relative to their braking capacity. Also, the most rapid changes in acceleration did not occur when the vehicle was out of alignment in pitch. Errors in profile that affect the measured roughness most happens when acceleration changes while the vehicle is at a high pitch angle.

3.3.7 Stop-and-Go Operations

These runs were intended to demonstrate errors in profile that occur when the host vehicle comes to a complete stop (e.g., due to stopped traffic, at traffic signals, etc.) and to identify the area of profile contaminated by the stop, examine the effect of deceleration level to the stop, and examine the effect of the time spent during the stop.

Passes with staged stops were performed for stops from 72 km/hr with a target deceleration level of 0.2 g and from 48 km/hr with target deceleration values of 0.1 g and 0.2 g. Stops from 72 km/hr were performed with a requested stop time of 1 second and 5 seconds, and all stops from 48 km/hr were performed with a requested stop time of 5 seconds. This section compares measured profile and IRI of runs with stops to those at constant speed.

Figure 3.18 shows a sample speed profile that was recorded during a pass by Profiler 6 with a target deceleration of 0.2 g from a target initial speed of 48 km/hr, a target stop time of 5 seconds, and acceleration back to a target speed of 48 km/hr after the stop. Figure 3.19 shows the corresponding acceleration profile. Each pass with a stop included five regions, which correspond to five successive modes of operation: (1) entry at a constant speed, (2) braking until the vehicle stops, (3) remaining stopped, (4) acceleration from a stop to the target speed, and (5) travel to the end of the section. In some passes, the end of the section was reached before the target speed was achieved.

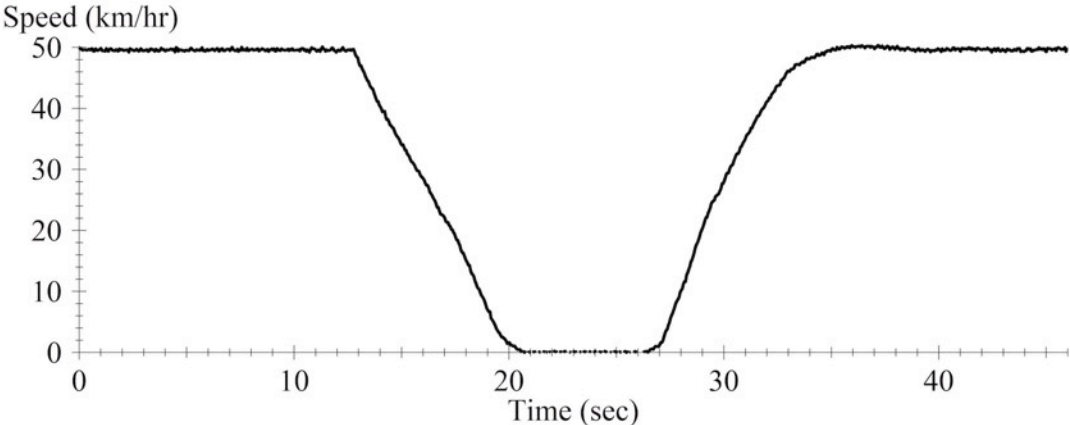


Figure 3.18 Speed profile for a pass with a stop

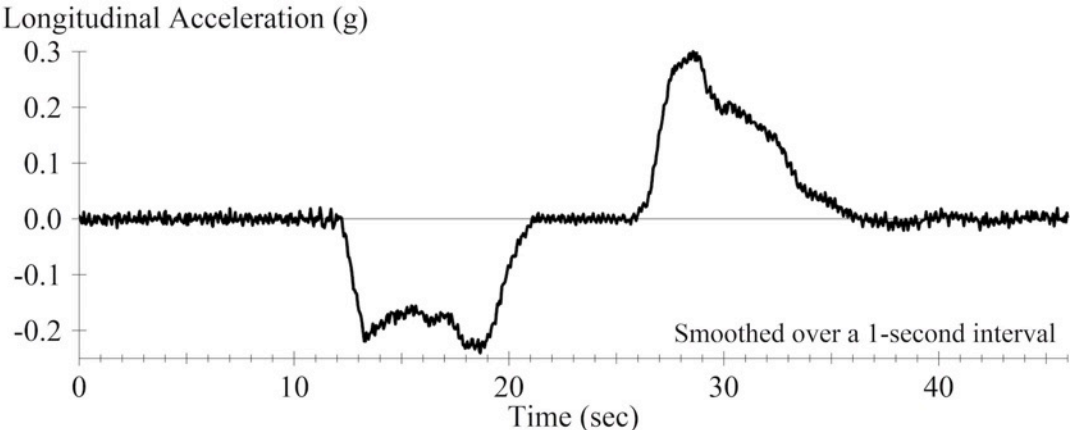


Figure 3.19 Acceleration profile for a pass with a stop

The speed and acceleration profiles provided several statistics to facilitate the analysis of the measured profiles: the locations of the start of braking, the location of the stop, the duration of the stop, the level of deceleration during braking, and the level of acceleration after the stop. The level of acceleration and deceleration were characterized by the average value and the highest value observed during any 1-second interval (i.e., a “peak” value). For the pass shown in Figures 3.18 and 3.19, the braking level averaged -0.19 g with a peak value of -0.24 g, and the acceleration level averaged 0.14 g with a peak value of 0.30 g. The stop occurred 225.3 m from the start of the section with a duration of 7.1 seconds.

Inspection of profiles and IRI distributions showed that erroneous content at or near the location of the stop accounted for most of the roughness introduced by measurement error during passes with stop-and-go events. This section demonstrates the manner in which measurement errors appeared in the profile data and the effect of those errors on the short-interval roughness profiles.

3.3.7.1 Effects on Raw Profiles

The time spent without movement during the stop introduced artificial content into the profiles beyond the effects of braking and acceleration. The accelerometer is typically not oriented precisely vertically after the profiler host vehicle comes to rest. Misalignment of the accelerometers with the direction of gravity causes a small bias in their readings which, when integrated twice, grows in proportion to the duration of the stop squared. Although there is no change in the longitudinal position during the stop, a step change in elevation is introduced at the stop as a result. This section examines the effect on profile of stops from 72 km/hr with durations of approximately 1 second.

Profilers 1, 2, and 6 submitted profiles without high-pass filtering. Raw profile traces from all three units included artificial curvature in the vicinity of the stop. Figure 3.20 shows a profile provided by Profiler 2 without high-pass filtering for a stop at a distance of 218.5 m and duration of 1.2 seconds. The disturbance introduced into the profile by the stop-and-go event includes curvature near the stop and a step change in elevation at the stop.

The upward change in elevation at the stop shown in Figure 3.20 suggests that Profiler 2 integrates the accelerometer signal in reverse. Misalignment of the accelerometer during stop is

expected to cause a negative error in the accelerometer signal, which would cause a downward change in the floating reference height after integration. (See the cosine term in Equation (1.5).) For Profiler 2, the magnitude of the step change varied, and was typically larger for cases with longer stop durations. For the pass shown in Figure 3.20, no step change appeared in the right wheel path profile, and it agreed well with passes collected at a constant speed of 72 km/hr. This means that the bias relative to 1 g in the right-side accelerometer readings was close to zero while the profiler was stopped.

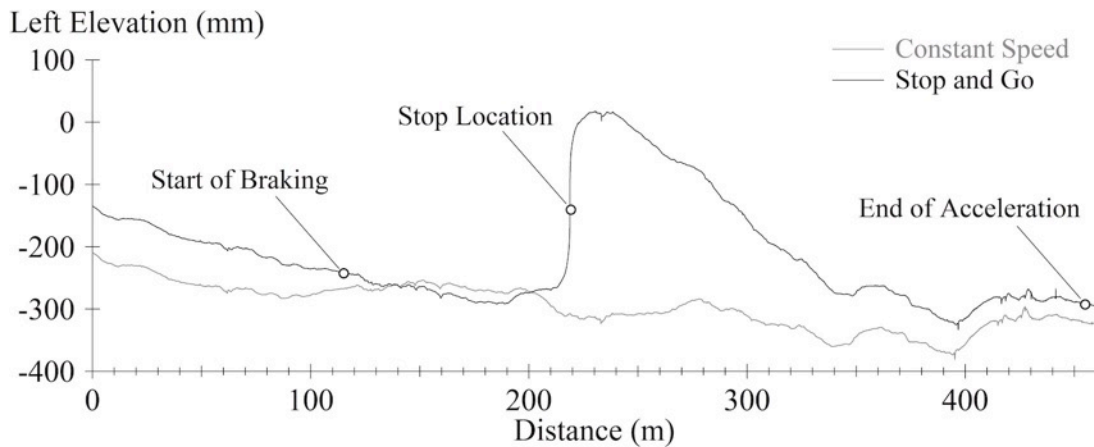


Figure 3.20 Elevation profile measured by Profiler 2 with a stop

Profiles from Profiler 1 and Profiler 6 included “sample and hold” areas surrounding the location of the stop where the profile elevation was held at a constant value over some range where the travel speed of the profiler was low. (The speed thresholds used by these profilers to enable the “sample and hold” were not known.)

Figure 3.21 shows an example from Profiler 1 for a pass with a stop at a distance of 226.6 m and duration of 0.9 seconds. A flat area is present in this profile close to 226.6 m, which corresponds to the “sample and hold” area. Although this practice eliminated the step change in elevation at the stop, the sudden change in slope at the borders of the artificially flat area introduced roughness into the profile that affected the IRI.

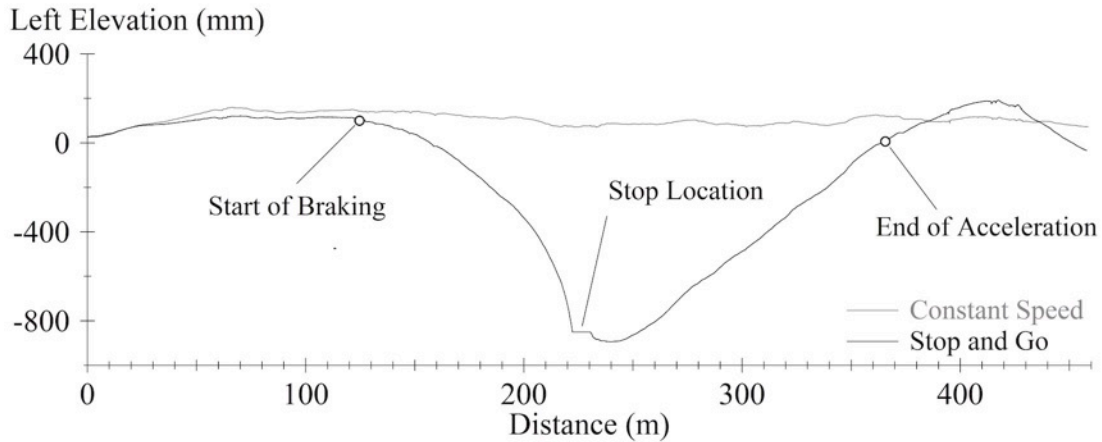


Figure 3.21 Elevation profile measured by Profiler 1 with a stop

High-pass filtering modified the spurious content differently depending on the filter type. Figures 3.22 and 3.23 show profiles submitted by Profiler 4 and Profiler 5, respectively, that were high-pass filtered. The high-pass filtering applied by these profilers spread out the effect of the stop. For the pass in Figure 3.22, the stop occurred at a distance of 205.9 m and duration of 1.5 seconds. For the pass in Figure 3.23, the stop occurred at a distance of 229.6 m and duration of 4.5 seconds. For both profilers, the high-pass filtering spread out the effect of the step change in elevation at the stop over the same distance in each direction and in proportion to the filter cut-off or base length. Profiles submitted by Profiler 6 with high-pass filtering spread out the influence of stops in a similar fashion.

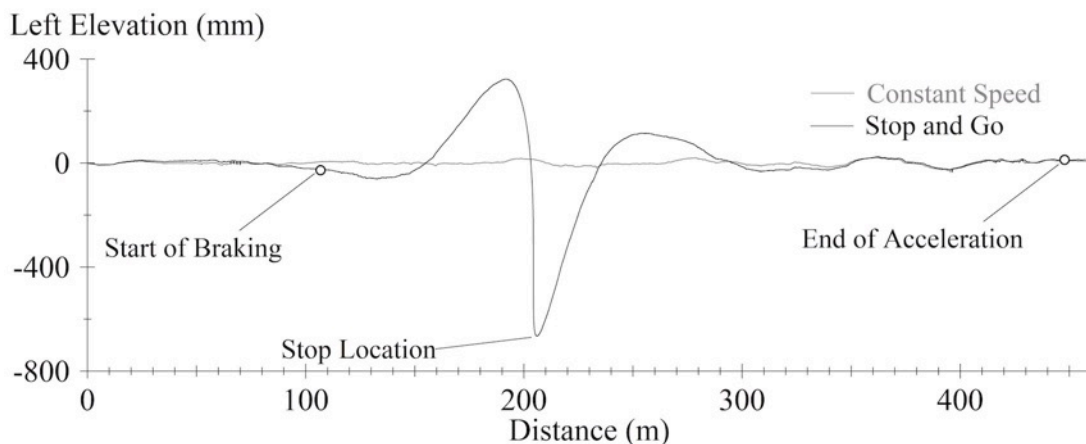


Figure 3.22 Elevation profile measured by Profiler 4 with a stop

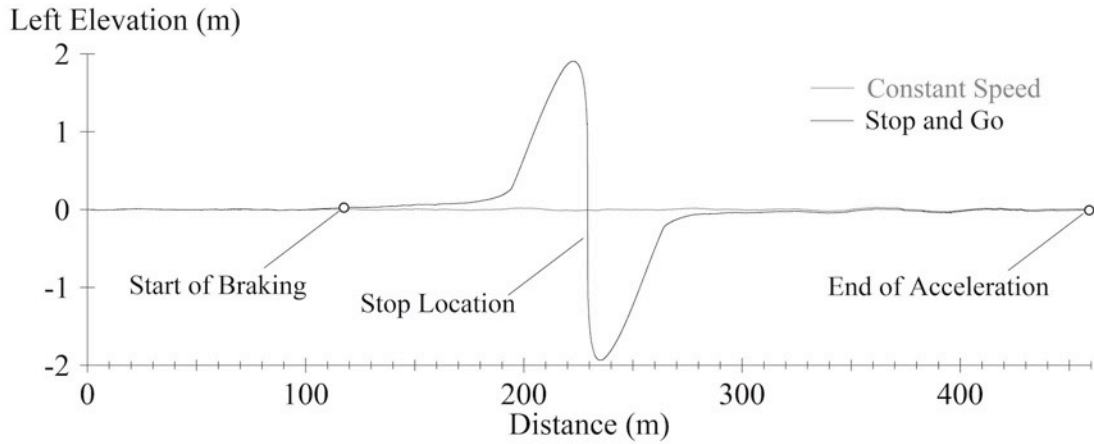


Figure 3.23 Elevation profile measured by Profiler 5 with a stop

The software in Profiler 3 included a proprietary “stop-and-go” processing feature, which is meant to reduce the measurement error caused by non-emergency stops. Figure 3.24 compares a profile measured by Profiler 3 at a constant speed of 72 km/hr to a pass with a stop from 72 km/hr at a distance of 223.6 m and duration of 1.4 seconds. The profile measured with a stop includes a small artificial disturbance where the stop occurred, but no elevation discontinuity. The stop also affected long-wavelength content in the profile. Profiler 3 applied a third order Butterworth filter with a cut-off wavelength of 91.44 m as part of the measurement process. This is a recursive filter, and it spread out the influence of the stop on the elevation profile downstream.

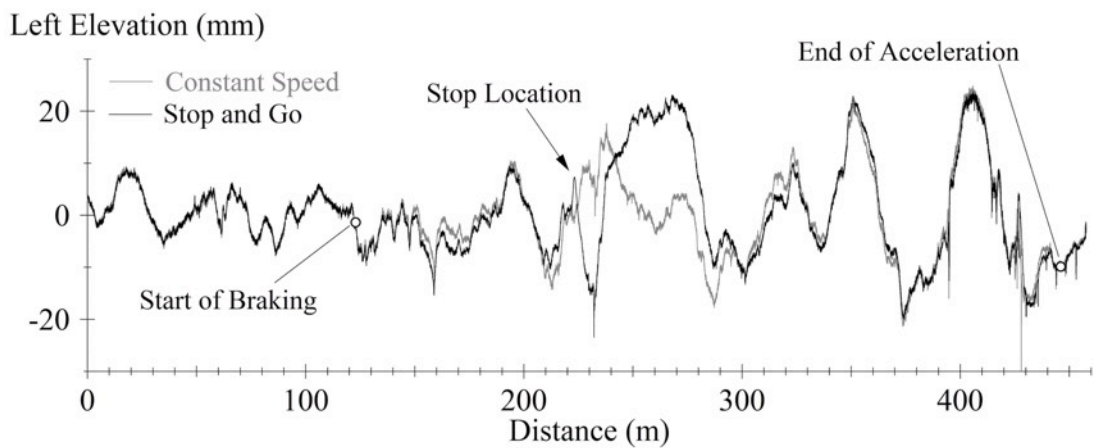


Figure 3.24 Elevation profile measured by Profiler 3 with a stop

3.3.7.2 Effects on Short-Interval Roughness Profiles

All of the profilers without provisions for error suppression (Profilers 2, 4, 5, and 6) measured severe localized roughness at stops. Figure 3.25 provides an example for Profiler 2. Figure 3.25 shows the short-interval roughness profiles for the pass by Profiler 2 shown in Figure 3.20. A narrow area of severe localized roughness appears in the left roughness profile in the vicinity of the stop with a peak value of 55.4 m/km at a distance of 221.7 m. Most of the artificial roughness is caused by the step change in elevation at the stop, with a rapid reduction in the area downstream.

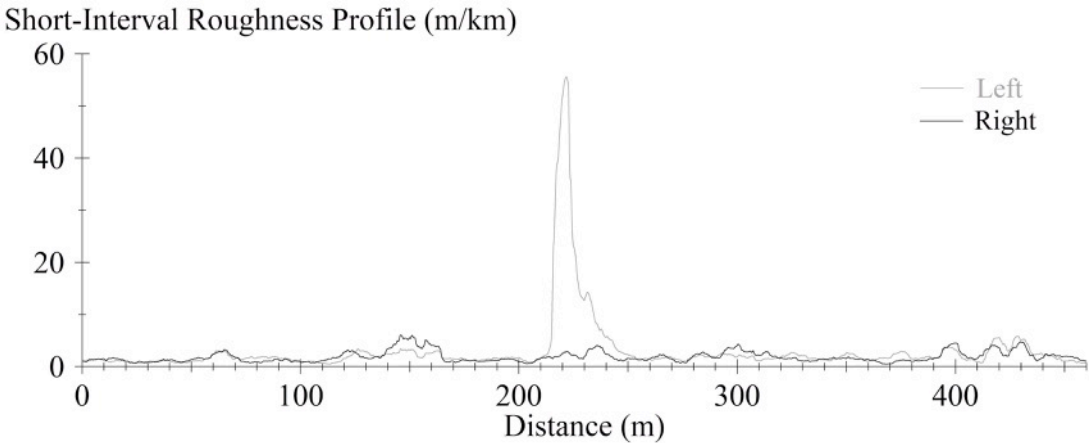


Figure 3.25 Short-interval roughness profiles, Profiler 2 with a stop

No localized roughness appeared on the right side for the run examined in Figure 3.25, because no step change in elevation was present. For this to be true, the bias in the accelerometer signal (i.e., difference from the assumed value of g) would have to be close to zero during the stop. Artificial localized roughness was present on the right wheel path profiles for the other passes with a stop by Profiler 2, and in all passes on the left side. This illustrates the somewhat arbitrary nature of the magnitude of localized roughness caused by a stop; because the accelerometer bias depends on temperature, pitch angle, roll angle, calibration error, the local level of acceleration due to gravity, etc. Storage of the accelerometer signal and height-sensor signal in the time domain is recommended to facilitate closer examination of these error sources.

Figure 3.26 compares the left wheel path short-interval roughness profile from the same pass to a pass collected at a constant speed of 72 km/hr. The vertical scale of the plot is truncated to help show the location where the pass with a stop departs from the pass at constant speed in advance of the stop, and where they begin to agree again downstream. The roughness profiles

agree up to a distance of 210 m, which is 8.5 m upstream of the stop. With the exception of a longitudinal shift caused by the braking associated with the stop, the traces agree after a distance of 256 m, which is 37.5 m past the stop. Note that the 7.62-m moving average used for plotting the short-interval roughness profile spreads out the influence of the stop by an additional 3.81 m on each side.

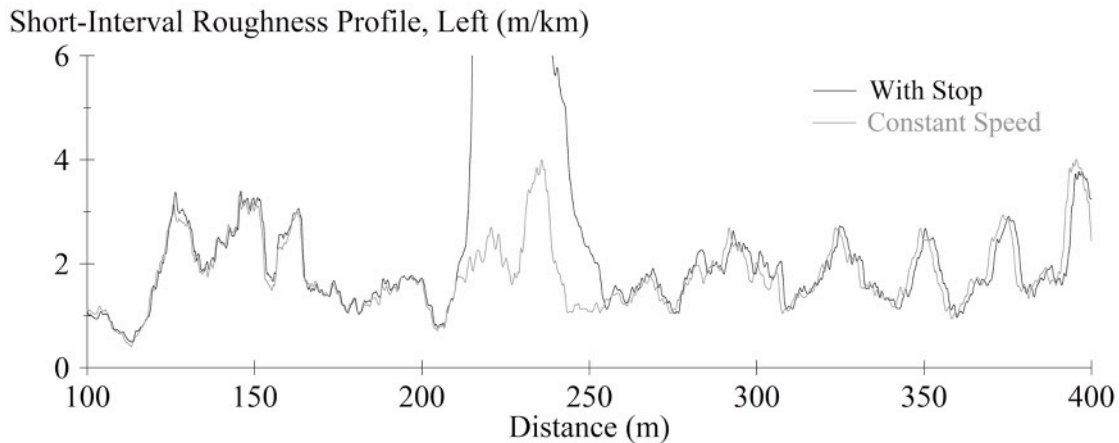


Figure 3.26 Short-interval roughness profiles, Profiler 2 with and without a stop

In the 12 passes by Profiler 2 with a stop, localized roughness appeared in the short-interval roughness profile with peak values of 48 m/km to 99 m/km on the left side and 0 m/km to 35 m/km on the right side. On the left side, the range where the short-interval roughness profile was contaminated up to 14.1 m preceding the stop and up to 48.7 m past the stop for the 12 passes.

Table 3.10 summarizes the observations illustrated for Profiler 2 for passes with stops by each profiler. The passes with stops by each profiler included instigation of the stop from two speeds, at two different target deceleration levels, and short-duration and long-duration stops. However, the severity of the localized roughness and the range contaminated by the stops did not relate systematically to those details. As such, the table lists ranges observed for each profiler.

Table 3.10 Contamination of profile around stops

Profiler	Side	Passes	Peak Localized Roughness (m/km)	Contaminated Area (m)	
				Upstream	Downstream
Profiler 1	Left	14	9-20	-13.5	23.5
	Right	14	6-10	-13.3	41.9
Profiler 2	Left	12	48-99	-14.1	48.7
	Right	12	0-35	-10.4	37.4
Profiler 3	Left	13	0-3	-10.0	29.2
	Right	13	0.5-3	-18.1	28.2
Profiler 4	Left	13	103-651	-23.9	52.1
	Right	13	64-584	-14.1	47.7
Profiler 5	Left	13	425-2698	-46.3	75.6
	Right	13	163-4050	-47.3	74.6
Profiler 6	Right	12	30-159	-22.6	46.6

The severity of localized roughness was the second lowest for Profiler 1, because of the “sample and hold” procedure of suppressing elevation changes applied at low speed. However, the error level is still sufficiently high to render the IRI over a 160.9-m-long road segment unusable. As such, the “sample and hold” algorithm is not recommend. The contaminated range was consistent with the other profilers. Profiler 2 exhibited the third lowest levels of localized roughness. It was also noted for Profiler 2 the peak levels on the right side was much less than the peak levels on the left side. Overall, the contaminated range for this group of profilers covered a range starting 47.3 m before the stop and ending 75.6 m past the stop.

The “stop-and-go” feature used by Profiler 3 greatly reduced the error at stops relative to the other five profilers. This feature uses a proprietary algorithm, and the details of its methodology are not known. However, Table 3.10 and Figure 3.24 show that reduction in roughness measurement errors is possible while maintaining many of the desired features within the measured profile. Chapter 5 offers algorithms for general use that suppress errors at stops.

The error in IRI adjacent to the stop appeared differently in the short-interval roughness profiles from Profiler 3 because of the “stop-and-go” feature, and the severity of localized roughness was the lowest. Figure 3.27 compares a short-interval roughness profile from a pass by Profiler 3 with a stop from 72 km/hr to a pass at a constant speed of 72 km/hr. The pass with the stop included braking with an average deceleration of 0.16 g, a stop at a distance of 242.0 m, and duration of 2.65 seconds. Among the 13 passes by Profiler 3, this was the case with the greatest level of artificial roughness near the stop.

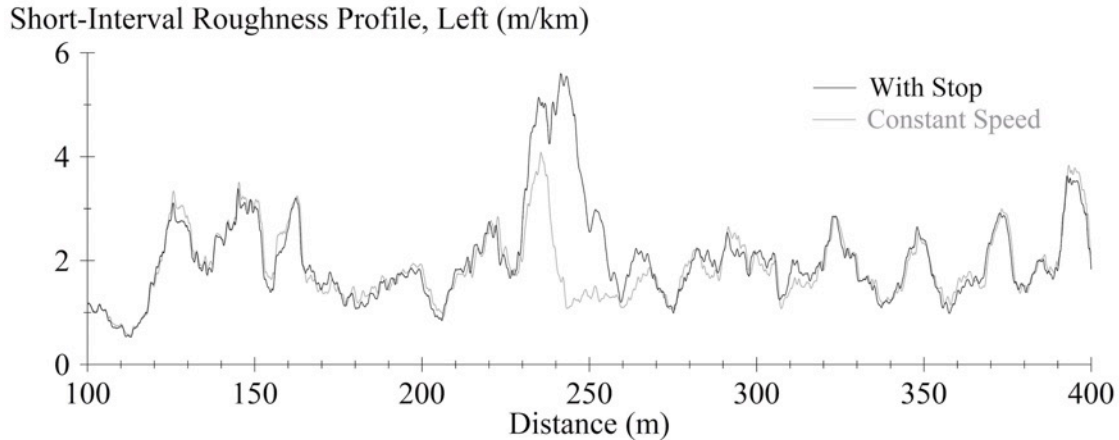


Figure 3.27 Short-interval roughness profiles, Profiler 3, with and without a stop

For inertial profilers that are in current use, it is necessary to mark an area of profile in the vicinity of a stop as invalid. The boundaries of the marked area depend on the high-pass filtering applied by each profiler and the details of any provisions they apply for suppressing errors at stops. The range for each profiler design must be determined experimentally using methods similar to those demonstrated in this research. As shown in Figures 3.20 through 3.24, this range would be quite long for engineering purposes that require valid elevation profile for wavelengths up to 91.44 m. A smaller area for exclusion can be identified for valid measurement of IRI, as shown in Table 3.10. Note that, unlike the braking case, the contaminated range for IRI is not sensitive to the vehicle type for stops. This means that the ranges listed in Table 3.10 are valid for each profiler, so long as no change is made to the profile calculation algorithm.

3.3.8 Operation from a Dead Stop

In these tests, the profiler operators were asked to initiate profile data collection while the profiler was stationary, and then accelerate to 72 km/hr, and maintain this speed until the end of the section. These runs were intended to examine the combined effect of insufficient speed, acceleration, and settling of filter transients.

The software in many of the profilers did not allow data to be recorded until a specific speed was achieved or a specific distance was traveled after data collection was initiated. In some cases, collection from a dead stop was possible using procedures within the data collection software that were contrary to the recommended mode of operation.

Some of the profilers began recording data from a location at or just downstream of the stop, but the profile measurement and computation procedures were running in the background during the approach. Those runs produced results similar to the outcome of the stop-and-go runs, where a large transient appeared in the raw profiles for some distance after the stop, which was caused by the interaction of the high-pass filters with the artificial disturbance measured at the stop.

Profiler 4 was the only unit that behaved differently from a dead stop than it would have while collecting data through a stop. This profiler provided data from a pass where profile was recorded from an instant just after a dead stop that appears to exclude the influence of profile computation during the stop. Figure 3.28 shows raw profiles from Profiler 4 for the following three passes: (1) at constant speed of 72 km/hr, (2) with a stop at a distance of 213.1 m, and (3) beginning from a dead stop at 221.5 m. The passes with stops included similar speed profiles during acceleration to 72 km/hr after the stop. The figure shows that the absence of the step change in elevation at the stop in the profile recorded from a location past the stop greatly reduces the transient superimposed on the profile by the high-pass filter.

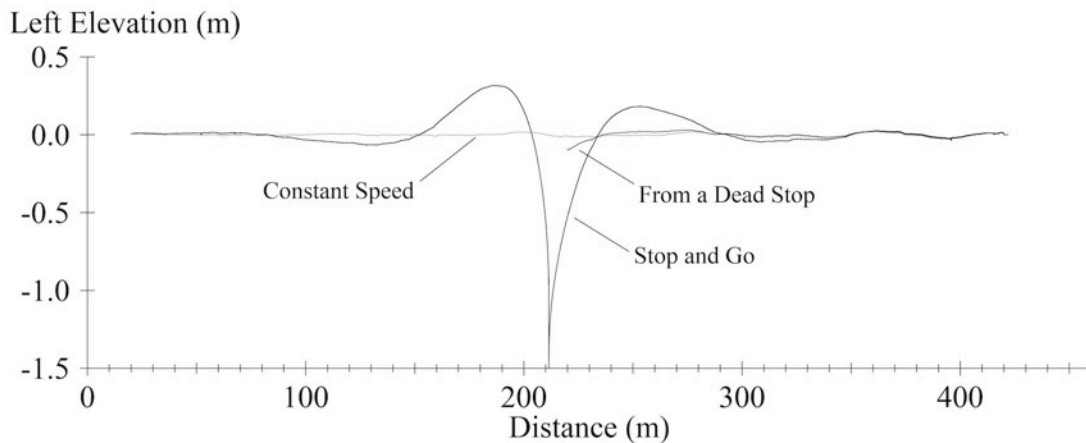


Figure 3.28 Elevation profile measured at constant speed, from a dead stop, and through a stop

Figure 3.29 shows the short-interval roughness profiles for the same three passes collected by Profiler 4. The vertical scale of the plot is truncated to help illustrate the range where agreement exists between passes. The trace for the stop-and-go run rises to a peak of 203.6 m/km at 214.8 m. The trace from the run from a dead stop does not include spurious localized roughness. However, it does not agree as well with the pass at constant speed over the first 30 m after the stop as it does in the area beyond, in part due to insufficient lead-in and in

part due to incompatibility in longitudinal distance measurement. The raw profiles provided by Profiler 3 included similar artificial disturbances in long-wavelength content for a distance after the dead stop as those measured through a stop.

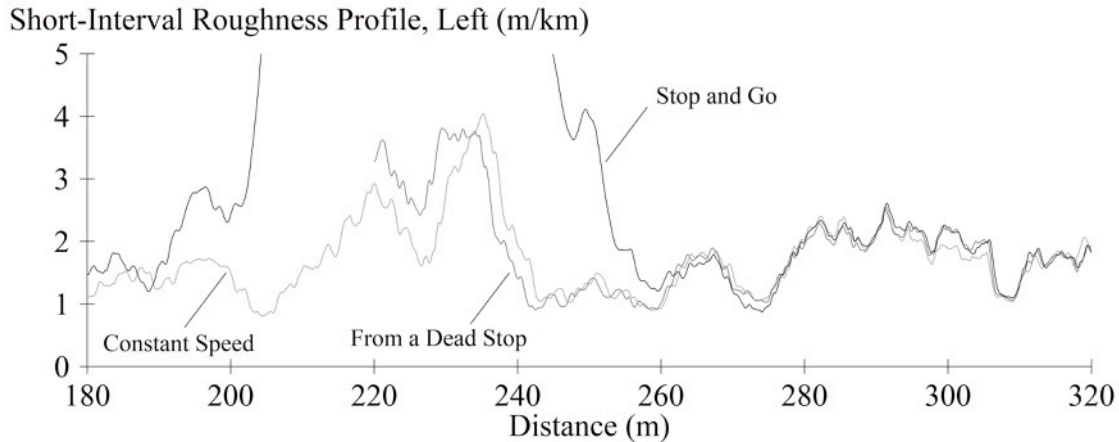


Figure 3.29 Roughness profile measured at constant speed from a dead stop, and through a stop

3.3.9 Longitudinal Distance Measurement

All six of the participating profilers measured longitudinal distance by observing rotation of a host-vehicle wheel. This approach requires calibration by traveling over a pavement section with landmarks that are a known distance apart. However, a typical inertial profiler only applies one calibration factor, which corresponds to a specific travel speed, tire inflation pressure, and tire temperature.

In addition to the thermal state of the tire, the amount of relative distortion in longitudinal distance measurement during the experiment depended on two competing effects:

1. The rolling radius of a free-rolling tire increases with rotational speed. Without a change in calibration, longitudinal distance measured by observing wheel rotation registers a smaller apparent distance at higher speed for the same amount of travel.
2. The tire operates with longitudinal slip that increases with longitudinal acceleration. During braking or coasting, the resulting reduction in tire rotation relative to the free-rolling condition causes it to register a smaller distance for the same amount of travel. Forward acceleration causes a bias in longitudinal distance measurement with the opposite polarity.

The reduction in speed during coasting affected longitudinal distance measurement. Typically, the longitudinal distribution of roughness in runs with coasting matched those at a constant 72 km/hr speed over the first half of the section, but compressed the profile slightly in the second half of the section with misalignment of up to 2 m by the section end. The effect of braking on longitudinal distance measurement is most visible in Figure 3.15. In the figure, the profiles are aligned before the start of braking, but offset longitudinally after braking ended. A reduced estimate of travel distance of about 0.8 m accumulated during the time while the brakes were applied. This phenomenon appeared in passes with braking from all six profilers. The magnitude of the error in distance measurement increased with duration and severity of braking.

Stop-and-go operation affected longitudinal distance measurement by all six profilers. Comparison of profiles measured with a stop to those measured at constant speed showed that a negative bias in longitudinal distance measurement accumulated during braking, and a positive bias accumulated during acceleration after the stop. In most cases the two effects nearly cancelled each other, and the largest distortion in longitudinal distance was confined to the area around the stop.

Chapter 4

System Description

This chapter describes a custom measurement system that was designed and built for this research. The system was designed to enable an experimental demonstration of profile measurement errors that occur at low speed, during braking, and at stops; and an investigation of the efficacy of methods proposed in this research to eliminate those errors. The measurement system was designed to support the research in three ways.

First, the system included, at its core, the sensors that appear in a typical inertial profiler. Profiles produced using only the those sensors and the standard processing algorithms provided a basis for comparison to profiles produced using additional sensors and the methods proposed in this research.

Second, the system stored output signals from each sensor for post-processing, which is not typical for inertial profilers. Detailed sensor signals were needed to assess sources of measurement error systematically. This opportunity did not exist for the profilers evaluated in Chapter 3, because only the profiles were available. Storage of sensor signals was also needed to support the development and evaluation of novel processing algorithms proposed in this research for reducing measurement errors, particularly those that could not be applied in real time.

Third, the system included additional sensors that provided three-dimensional measurement of profiler host-vehicle kinematics. The sensors included body-fixed measurement of acceleration and rotation rate in three dimensions, and GPS measurement of height, vertical velocity, pitch attitude, and roll attitude. These sensors provided the means to resolve the component of profiler reference point acceleration into a truly vertical direction, which was needed to eliminate the primary source of measurement error that occurs at low speed, during braking, and at stops.

The system description includes: an overview of the system, a description of its physical layout, a list of the sensors and their specifications, and a short explanation of the way signals are recorded and synchronized. The chapter provides an evaluation of system performance using the nominal sensors that appear on a typical profiler.

4.1 System Overview

This section provides an overview of the measurement system, and explains the rationale behind specific design specifications described in section 4.2 through 4.4.

4.1.1 Nominal Inertial Profiler

A nominal set of inertial profiler sensors are installed on each side of the vehicle. Each set of sensors includes servo-type accelerometers, ranging lasers, and a rotational encoder. The accelerometers and height sensors are aligned laterally with the host-vehicle wheels on each side. These are design elements that appear on commercial inertial profilers, such as those evaluated in Chapter 3.

This research is concerned with measurement errors related to operation at low travel speed, during braking, and at stops. As such, the nominal system is designed to reduce other common sources of measurement error that might confound the results.

For example, the accelerometers and lasers are mounted rigidly to the host vehicle to avoid excessive vibration. A rigid plate mounted directly to the frame at the rear of the host vehicle provides a system backbone, and rigid sensor pods are attached to it on each side.

The nominal profiler uses aviation-grade accelerometers, which were selected for their accuracy, precision, and low noise floor. The nominal profiler on each side also includes a line laser for measurement of the range to ground. Line lasers detect the road surface using a wide footprint, which helps distinguish changes in elevation of the road surface that occur over a wide area from road surface texture, narrow longitudinal cracks and joints, and other narrow gaps in the road surface [75].

A typical production profiler measures travel distance using a rotational encoder mounted to one wheel. The nominal profiler designed for this research includes rotational encoders mounted to the rear wheels on each side. This provides a specific longitudinal distance measurement to the profiler on each side without the bias associated with driving on a curve.

4.1.2 Three-Dimensional Kinematics

This research proposes using profiler vertical acceleration in a direction aligned with gravity in place of body-fixed vertical acceleration as a way to reduce errors in profile

measurement that occur in typical inertial profilers. To do that, the system combines body-fixed measurements of acceleration and rotation.

Resolving readings from the profiler accelerometers into an axis system fixed in the Earth requires measurement of horizontal acceleration. Servo-type accelerometers fixed in each sensor pod provide body-fixed longitudinal acceleration of the left and right side profilers. An inertial navigation system (INS) fixed to a central pod between the two profilers provides body-fixed lateral acceleration.

The system obtains body-fixed yaw rate using the INS, and it obtains pitch and roll rotation rate using fiber-optic gyroscopes mounted to the center pod. The fiber-optic gyroscopes are needed have better accuracy and time stability than the microelectromechanical angular rate sensors in the INS.

The system also includes measurement of pitch and roll attitude of the host vehicle by a GPS-based system. This system measures pitch and roll by comparing the height of a GPS antenna placed at the rear of the vehicle on the left side to the height of antennas placed forward and rightward of it, respectively. These antennas were placed as far apart as possible to reduce the influence of errors in height on the derived attitude angles.

The GPS-based system is included to provide valid absolute measurements of orientation as a check on the drift that occurs when integrating measured rotation rate. In particular, this research proposes the use of the gyroscopes for measuring high-frequency content, and the GPS-based attitude measurements for low-frequency content. The GPS-based attitude measurements also provide a way to initialize the estimates of pitch and roll that are produced by integrating measurements of rotation rate.

4.1.3 Longitudinal Distance Measurement

Typical inertial profilers measure longitudinal travel distance using a rotational encoder mounted to a host-vehicle wheel. This method of distance measurement is prone to bias caused by changes in tire rotation speed, tire temperature, and tire inflation pressure [14]. Further, the calibration factor that relates travel distance to wheel rotation during constant-speed operation is not valid when application of the brakes or the throttle cause a change in longitudinal slip, as described in Chapter 3. An optical fifth wheel is installed in the center pod to provide a measurement of longitudinal distance that is not prone to these error sources.

As a check on the encoder-based and optical distance measurements, travel distance was also monitored using wheel speeds from Controller Area Network (CAN) bus messages and derived from latitude and longitude measured by a differential GPS system.

4.1.4 Diagnostics

The system includes several elements intended to help explain observations from the subsystems described above, and to help ensure that critical sensors are providing valid readings. This includes: (1) a video-based lane tracking system, (2) a forward-looking camera, (3) a downward-looking camera, (4) a laser for range to the road from the left front corner of the vehicle, and (5) comprehensive outputs from the inertial navigation system (e.g., angular rates, velocity, heading, etc.).

The system also includes point lasers in parallel with each line laser. The point lasers have a very small footprint relative to the line lasers, and are more prone to high-frequency noise on pavements with coarse surface texture. However, point lasers of this type have a longer history in road profiling applications and are less prone to errors caused by variations in surface reflectivity. As such, the point lasers are included for redundancy.

4.1.5 Signal Timing

The accuracy of profiles produced by the processing algorithms proposed in this research depends on accurate signal timing. This is true of the nominal inertial profiler sensors, because the accelerometer signals and height-sensor signals are combined to cancel the influence of host-vehicle vibration. This is equally critical in the augmented sensor configuration proposed in this research, because a Kalman filter combines outputs from the accelerometers, rate gyroscopes, and GPS to estimate the signals needed to obtain valid profile. Section 4.4 describes the provisions applied by the measurement system to ensure accurate signal timing.

4.2 Physical Layout

Figures 4.1 and 4.2 show the system in the side and rear view, respectively. The system host vehicle is a 2008 GMC Savanna Cargo Van, VIN number 1GTGG25C481234303. The host vehicle has a wheelbase of 343 cm, a track width (front and rear) of 172 cm, an overall length of 569 cm, and a height of 207 cm. With the instrumentation installed, the vehicle's rear overhang

is increased by 24.1 cm and the overall height of the system is 254 cm. The interior rearward of the front seats was stripped to accommodate the data acquisition system (DAS), the power supply, tools, and racks for storage of the rear sensors and mounting racks during transport. When the vehicle is fully instrumented, but unoccupied, it weighs 31.49 kN.



Figure 4.1 Measurement system, side view



Figure 4.2 Measurement system, rear view

Figures 4.3 and 4.4 provide schematics of the system. Figure 4.3 shows the top view of the hardware mounted at the lower rear of the vehicle. At the lower rear, three sensor pods are attached to a silver mounting plate, which serves as their “backbone.” This assembly remains intact when the system is disassembled for storage. The silver plate attached to a black mounting plate, which is in turn attached directly to the host-vehicle frame rails. The rear bumper is removed. Figure 4.4 shows the front point laser, the windshield cameras, the rear wheel encoders, and the upper rack for mounting GPS antennas. Appendix B provides several photographs of the hardware.

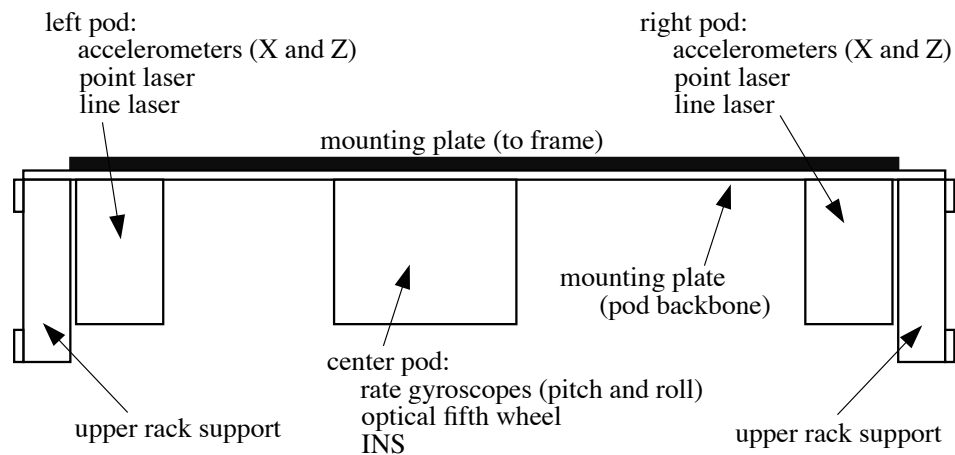


Figure 4.3 Lower sensor rack, top view

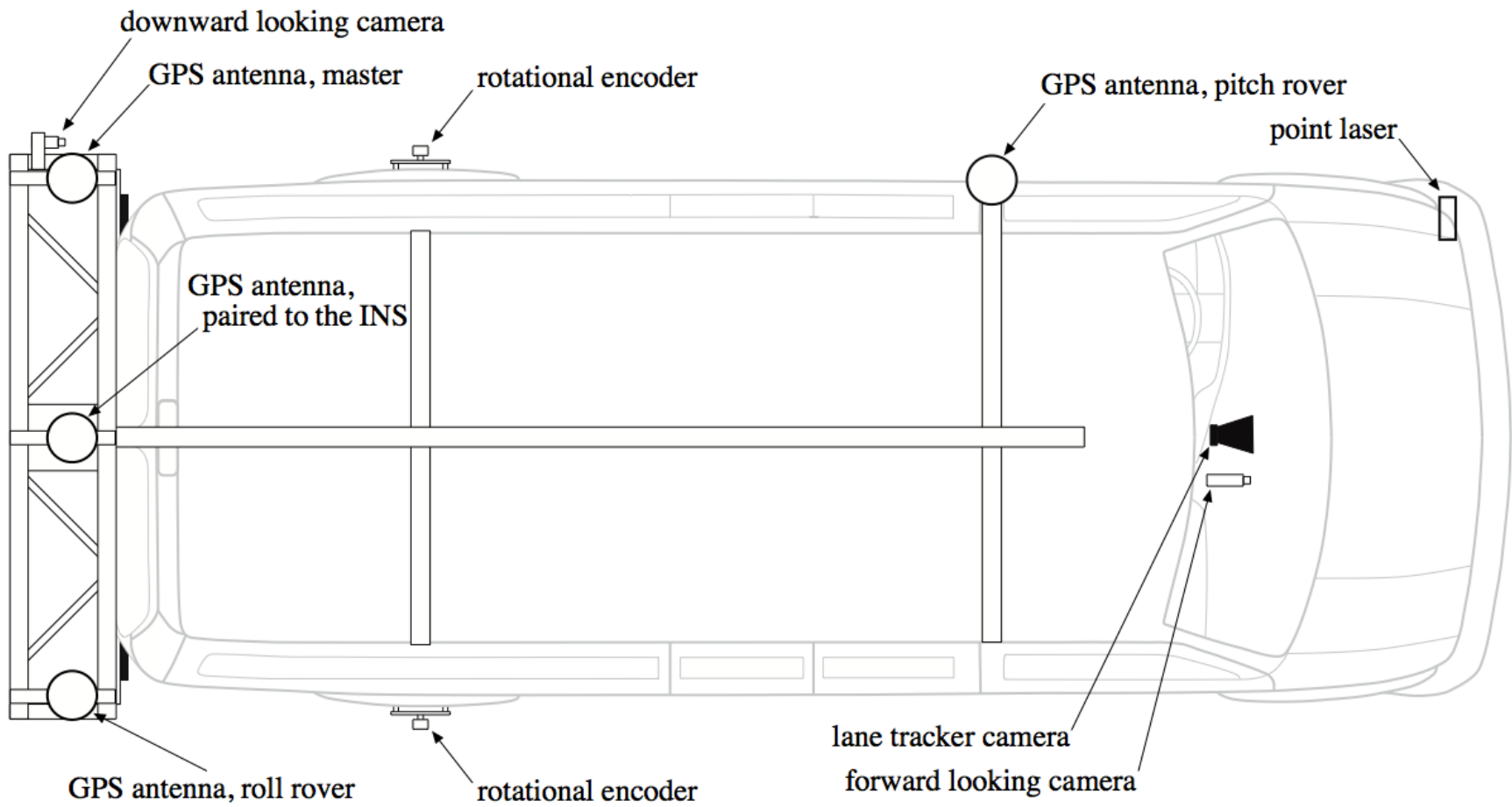


Figure 4.4 System schematic, top view

4.2.1 Outer Pods

Each of the left and right sensor pods carries a point laser, a line laser, a vertically oriented servo-type accelerometer, and a longitudinally oriented servo-type accelerometer. The pods are symmetric about the longitudinal centerline of the vehicle, and the sensors are mounted so that the left and right side profilers are 172.1 cm apart, which aligns them with the center of contact of the rear tires. Figure 4.5 shows the layout of the right pod in the rear and side view. The side view is shown without the right enclosure plate.

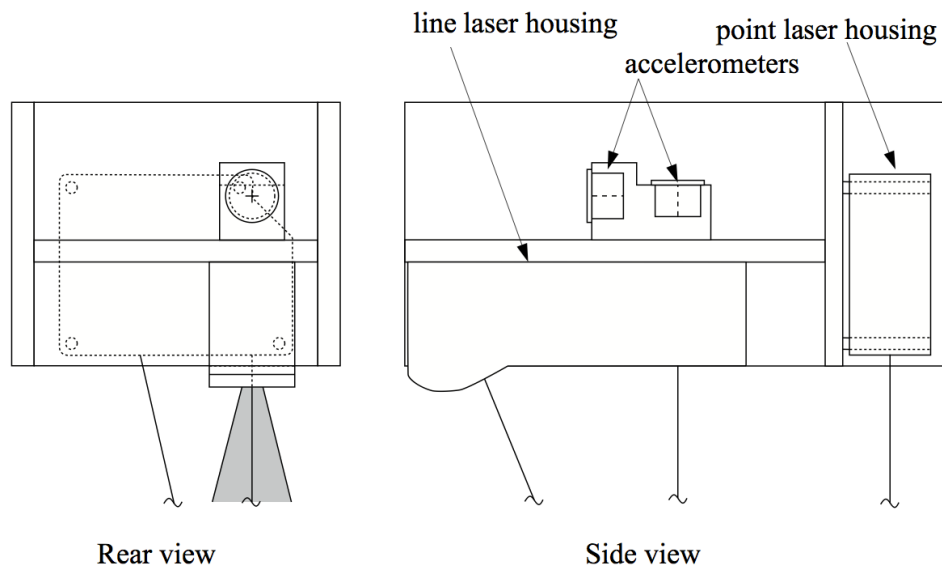


Figure 4.5 Right sensor pod

The line lasers project light over a transversely oriented line more than 100 mm wide, with the detector rearward of the projected light source. Each line laser is mounted so that the center of the light that it projects is aligned with the sensitive axis of its companion accelerometer. The point lasers project light onto the ground over a diameter of 0.3 mm. The point lasers are aligned transversely with the line laser and accelerometers. Their footprint is 10.5 cm forward of the line lasers, and they are mounted with the detectors inboard of the light source. When the vehicle is at rest, the line lasers have an approximate range to ground of 28.2 cm and a triangulation angle of 22 degrees. The point lasers have an approximate range to ground of 28.9 cm and a triangulation angle of 13 degrees.

The longitudinal accelerometers are installed just rearward of the vertical accelerometers within the same mounting blocks.

4.2.2 Center Pod

The center pod carries two rate gyroscopes, an INS, and an optical fifth wheel. Figure 4.6 shows the layout of the center pod in the rear and side view. The side view is shown without the right enclosure plate.

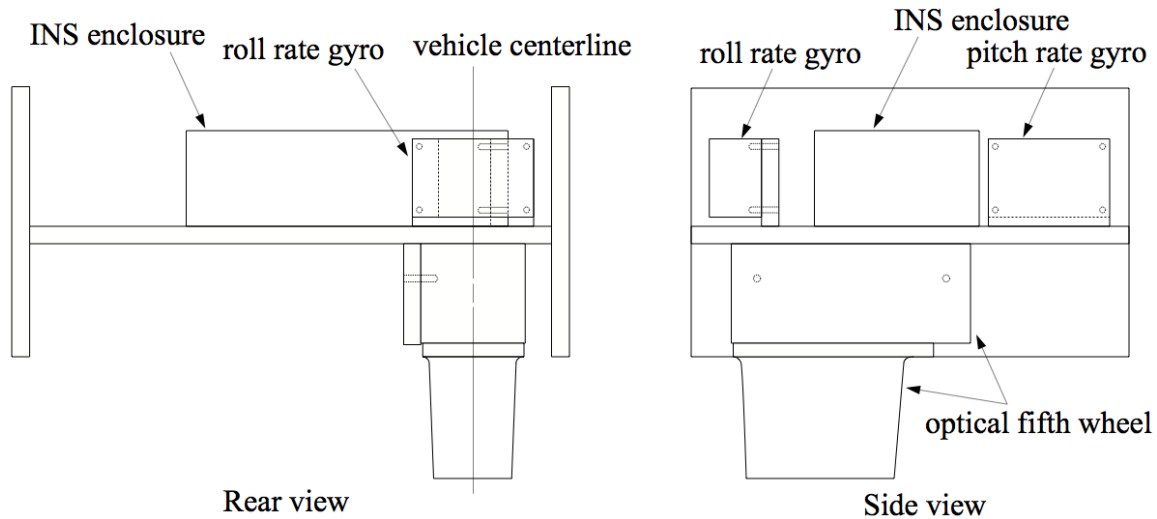


Figure 4.6 Center sensor pod

The rate gyroscopes are mounted along the host-vehicle longitudinal axis of symmetry. One of the gyroscopes is oriented for measurement of profiler pitch rotation rate, and the other is oriented for measurement of profile roll rotation rate. The integrated signals provide relative pitch and roll rotation. An optical fifth wheel is mounted to the underside of the center pod for measurement of longitudinal distance. The center pod also houses the main enclosure for the INS, which contains three accelerometers and three angular rate sensors.

4.2.3 Upper Instrumentation Rack

The upper instrumentation rack carries three GPS antennas for measurement of host-vehicle sprung-mass pitch and roll. (See Figure 4.4.) The master antenna is mounted at the left rear corner. A rover antenna is mounted forward of it for measurement of pitch; and another rover antenna is mounted beside it for measurement of roll. When the vehicle is at rest, the three antennae form a plane that is about 246.4 cm above the ground. The pitch antennae are 335.3 cm apart, and the roll antennae are 200 cm apart.

The upper instrumentation rack also houses a GPS antenna at the center rear, which is used by the INS to eliminate drift in its calculation of position and velocity.

4.2.4 Other Sensors

As shown in Figure 4.4, the system includes several additional sensors:

- Rotational encoders are mounted to each of the vehicle rear wheels.
- A point laser measures range to ground at the front left corner of the vehicle chassis.
- A forward-looking camera is mounted inside the windshield.
- A downward-looking camera is mounted to the left side of the upper instrumentation rack. The field of view includes the rear quarter of the vehicle's left side, the pavement beside it, and a portion of the roadside.
- An optical lane tracker system is mounted inside the windshield.

Although it is not shown in the diagrams, the system also records wheel speeds and other pertinent quantities (transmission status, cruise control, brake light switch, throttle position, etc.) from CAN bus messages.

4.3 Sensors

Table 4.1 identifies each sensor by model number and serial number. The list that follows includes pertinent specifications of each sensor as they were used in this measurement system. The GPS-based attitude measurements were provided by a Novatel Align system, including a RavenX modem for receiving Radio Technical Commission for Maritime (RTCM) correction data from Networked Transport of RTCM via Internet Protocol servers. The INS combines measurements of acceleration, angular rate, and GPS position using Kalman filtering to estimate motion outputs. The specifications below are those listed for the RT3050 once the filter has converged. The actual outputs provide estimates of the probable error level with each set of readings.

Table 4.1 System sensors

Sensor Position	Make and Model Number	Serial Number
Left point laser	LMI Selcom SLS5200/300-RO	1002
Right point laser	LMI Selcom SLS5200/300-RO	2362
Front point laser	LMI Selcom SLS5000-200/300-RO	N2297
Left line laser	LMI Selcom Gocator 2342A-3B-12	00022133
Right line laser	LMI Selcom Gocator 2342A-3B-12	00022135
Left vertical accel.	Honeywell Q-Flex QA1400-AA03-0	459
Left longitudinal accel.	Honeywell Q-Flex QA1400-AA03-0	451
Right vertical accel.	Honeywell Q-Flex QA1400-AA03-0	438
Right longitudinal accel.	Honeywell Q-Flex QA1400-AA03-0	460
Left encoder	BEI XHS25-75-R2-SS-2048	QQ110792
Right encoder	BEI XHS25-75-R2-SS-2048	QQ110791
Optical fifth wheel	Datron DLS-2	06.303
Pitch rate gyro.	KVH DSP-3000 Fiber optic gyro 02-1222-01	RD 16610
Roll rate gyro.	KVH DSP-3000 Fiber optic gyro 02-1222-01	RD 20917
INS	Oxford Technical Solutions RT3050	073
GPS antenna, INS	Novatel GPS-600-SB 01017062	NTM03230018
GPS antenna, master	Novatel GPS-702-GG 01017577	NAE12100014
GPS antenna, pitch rover	Novatel GPS-702-GG 01017577	NAE12100009
GPS antenna, roll rover	Novatel GPS-702-GG 01017577	NAE12100016
GPS receiver, master	Novatel Flex6-G2L-R0G-55R	NKC12240013
GPS receiver, pitch	Novatel Flex6-G2L-B0G-55R	NKC12240021
GPS receiver, roll	Novatel Flex6-G2L-R0G-55R	NKC12240014
Lane tracker	MobilEye C2-270	
Front camera	B&H EVEMC700	
Rear camera	B&H EVEMC700	

Vertical accelerometers

Range: 4 g (+/- 2 g)

Resolution: 0.001076 g left, 0.001095 g right

Bandwidth: to 2,000 Hz

Sample rate: 16,000 Hz

Longitudinal accelerometers

Range: 2 g (+/- 1 g)

Resolution: 0.000543 g left, 0.000544 g right

Bandwidth: to 2,000 Hz

Sample rate: 16,000 Hz

Point lasers

Range: 200 mm (+/- 100 mm)

Resolution: 0.1 mm left, 0.1 mm right, 0.125 mm front

Bandwidth: to 2,000 Hz

Sample rate: 16,000 Hz

Line lasers

Range: 200 mm (+/- 100 mm)

Vertical Resolution: 0.004 mm

Horizontal Resolution: ~400 readings over a 100-mm width at stand-off

Sample rate: ~3,240 Hz

Encoders

Resolution: 2048 cycles per revolution quadrature (8192 counts per revolution, which is ~0.3 mm per count)

Sample rate: recorded at 250 Hz

Optical fifth wheel

Velocity resolution: 0.027129 m/s

Velocity bandwidth: to 2000 Hz

Position resolution: 2 mm

Position sample rate: recorded at 16,000 Hz

Rate gyros

Range: full scale +/- 375 deg/s

Resolution: 0.000001 deg/s

Bandwidth: to 100 Hz

Sample rate: 100 Hz

GPS position (when real-time kinematic (RTK) integer fix is possible)

Sample rate: 20 Hz

Accuracy: 1 cm + 1 ppm of distance to base station

GPS velocity

Sample rate: 20 Hz

Accuracy: 0.03 m/s RMS

GPS heading and pitch

Sample rate: 20 Hz

Accuracy: 0.06 deg

GPS roll

Sample rate: 20 Hz

Accuracy: 0.1 deg

MobilEye lateral lane position

Sample rate: asynchronous

Resolution: 0.004 m

Downward and forward cameras

Sample rate: 30 images per second

Resolution: 720x480

INS outputs

Update rate: 100 Hz

Position Accuracy: 50 cm probable circular error

Velocity Accuracy: 0.8 km/hr RMS

Acceleration bias: 0.001 g at one st. dev.

Roll/pitch: 0.04 deg at one st. dev.

Angular rate: 0.01 deg/s at one st. dev.

4.4 Signal Flow

The measurement system includes a diverse set of sensors and cameras, with diverse outputs and timing. Some sensors provide serial outputs, some provide Ethernet outputs, some provide analog outputs, and others output counter values and digital signals.

Data logging is performed by an embedded system including: a host central processing unit (CPU), a secondary CPU, a counter/timer card, an A/D card with high-speed digital inputs, a dual channel CAN bus interface, and a video frame grabber. The A/D card is connected to a custom 8 channel analog signal conditioning chassis.

Synchronization of data from various sources is done in both distance and time. Temporal synchronization is done using constant monitoring of a common time signal by most sensors, and

monitoring of a common pulse by others. The system records a reference time from a CPU clock with every video image, and every sample from the accelerometers, point lasers, rate gyroscopes, INS, lane tracker, and GPS receivers. The A/D card also outputs a pulse every 4 seconds. The pulse appears in the outputs from each line laser and the high-speed outputs from the accelerometers and point lasers. This provides a way to reconcile the internal clocks from each line laser with the common clock used by most of the rest of the system. For redundancy, a synchronization output from each frame recorded by the line laser is monitored synchronously with the 16,000 Hz outputs from the accelerometers and point lasers.

For spatial synchronization, the system records counts from the optical fifth wheel and both rotational encoders every 4 milliseconds using the CPU clock; as described above these counts are also synchronized in time with GPS position. The system also routes rotational encoder counts to each liner laser. The vehicle odometer, while low in resolution, is logged over the CAN interface.

4.5 Nominal System Performance

This section characterizes the performance of the nominal inertial profiling system mounted on the left side of the host vehicle. This system includes measurement of vertical acceleration by a servo-type accelerometer, measurement of range to ground by a line laser, and measurement of longitudinal distance by a rotational encoder mounted to the left rear wheel. System performance is characterized using stationary testing, profile measurement repeatability, and agreement to a reference profile measurement.

4.5.1 Stationary Testing

Stationary testing was performed at the start of each test day to verify basic system health and vertical calibration, as described in AASHTO R 57-14 [92]. In a stationary test, profile data are collected with the engine on and the vehicle parked on a flat, level platform. Longitudinal motion is simulated using an artificial distance encoder signal, which progresses at a constant rate. The results described here correspond to a simulated travel speed of 72 km/hr. In all stationary tests, a clipboard was placed under each laser sensor to reduce the effect of surface texture on measurements of range to ground.

Stationary tests provide an efficient way to identify excessive noise, sensor malfunctions, poor sensor calibration, and signal processing errors in the field. Since the elevation of the road surface beneath the profiler remains constant throughout stationary tests, a perfect system would measure a flat profile and register no roughness. Two types of stationary tests were performed: quiescent tests and bounce tests.

Quiescent tests are typically performed with the engine on and no additional motion imposed on the vehicle chassis. The primary purpose of the quiescent test is to characterize the level of sensor noise that appears as artificial roughness in the measured profile. AASHTO R57-14 deems an IRI of 0.047 m/km or less acceptable for a quiescent test [92].

In most cases, quiescent tests on the nominal inertial profiling system produced profiles with IRI values below 0.01 m/km. These profiles included evidence of sensor noise and imperfect cancelation of profiler motion caused by engine vibration. Roughness caused by engine vibration appeared at a simulated wavelength of 1.47 m, which corresponds to an engine speed of 820 rpm (13.7 Hz). In specialized quiescent tests with the profiler removed from its mounts and supported by a rack (and the engine on), the roughness reduced to 0.004 m/km. With the engine off and the profiler mounted to the vehicle, quiescent tests produced profiles with IRI values near 0.005 m/km.

During a bounce test, the operator moves the profiler vertically by exercising the host-vehicle suspensions in jounce and rebound. A standard bounce test includes several seconds of quiescent operation followed by several seconds of induced vertical motion. Ideally, the cyclic changes in profiler reference height detected by the accelerometer would be perfectly canceled by equal changes in relative range to ground measured by the height sensor. AASHTO R57-14 deems an IRI of 0.126 m/km an acceptable level for a bounce test [92].

Figure 4.7 shows a short-interval roughness profile produced by a bounce test using the nominal inertial profiling system. In this case, the induced motion took place over an interval of 6.5 seconds, which corresponds to a distance of approximately 130 m at the simulated test speed. During the middle two thirds of the induced motion, the profiler moved downward 5.6 cm and upward 3.0 cm from its static position at a frequency very close to 2 Hz.

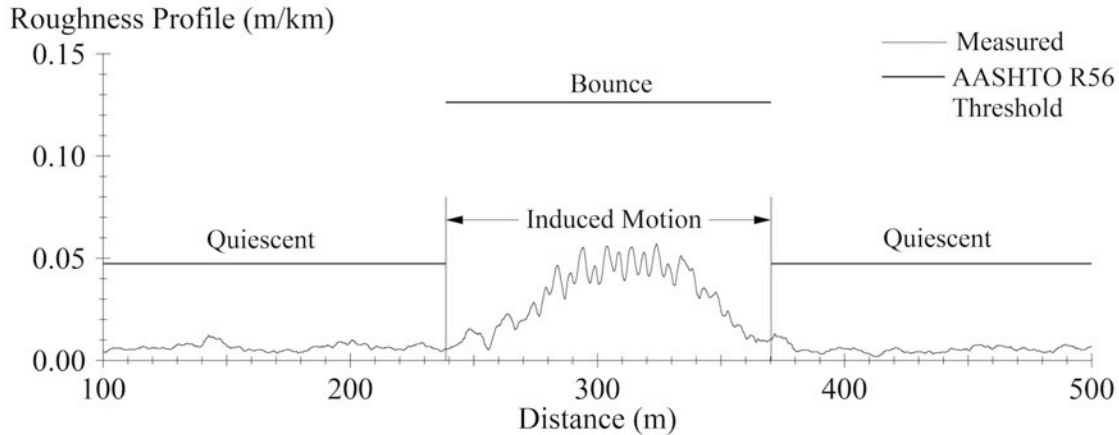


Figure 4.7 Short-interval roughness profile produced by a bounce test

Artificial roughness appeared in the measured profile with amplitude of 0.1 mm and a wavelength of 10 m due to imperfect cancelation of the vehicle motion between the height-sensor signal and the floating-reference-height signal. As shown in Figure 4.7, the average IRI was 0.05 m/km when the induced motion was at its most severe, which is well below the threshold value of 0.126 m/km. The low roughness value over this interval is strong evidence that the sensors are functioning, are properly calibrated, and are stored with consistent signal timing. During the quiescent portions of the test, the IRI was 0.006 m/km. The low quiescent roughness value demonstrates a low level of system noise.

4.5.2 Agreement to the Reference

Several test runs were performed over the same test section at various host-vehicle travel speeds to examine the influence of speed on profile measurement repeatability and agreement to the reference profile measurement. These data were collected on the tangent section at MnROAD. (See Chapter 3.) The runs included 28 passes: 3 passes at each speed in the range from 24 to 80 km/hr in 8 km/hr increments, 2 passes at 16 km/hr, and 2 passes at 97 km/hr.

Cross correlation analysis using profile traces filtered by the IRI algorithm produced an average agreement score of 0.914 when the profiles were compared to the reference measurement. The comparisons were made over a 160.9-m-long segment of the left wheel path. The IRI of the reference profile over this range was 1.82 m/km. The overall range of agreement scores for the 28 passes was 0.823 to 0.990. However, the individual agreement scores did not

correlate to travel speed. Rather, agreement to the reference profile measurement was strongly influenced by errors in lateral tracking.

Unfortunately, none of the constant-speed runs tracked perfectly over the trace followed by the reference profiler. Figure 4.8 shows the lateral position of the left side profiler footprint relative to the reference trace for two of the runs. Absolute position of the left profiler footprint was derived using absolute position of the master GPS antenna, GPS-based measurements of the pitch and roll attitude of the measurement platform, and the lever arm between the master GPS antenna and the left profiler footprint. These readings were transformed to a local coordinate system within the test section established using static GPS measurements at the end points. (See Section 3.2.2.) The profiler traveled at 32 km/hr and 80 km/hr in the passes shown in Figure 4.8. Each pass followed a similar trajectory with an average of 14 cm left of the reference track. The agreement score for each profile was 0.949.

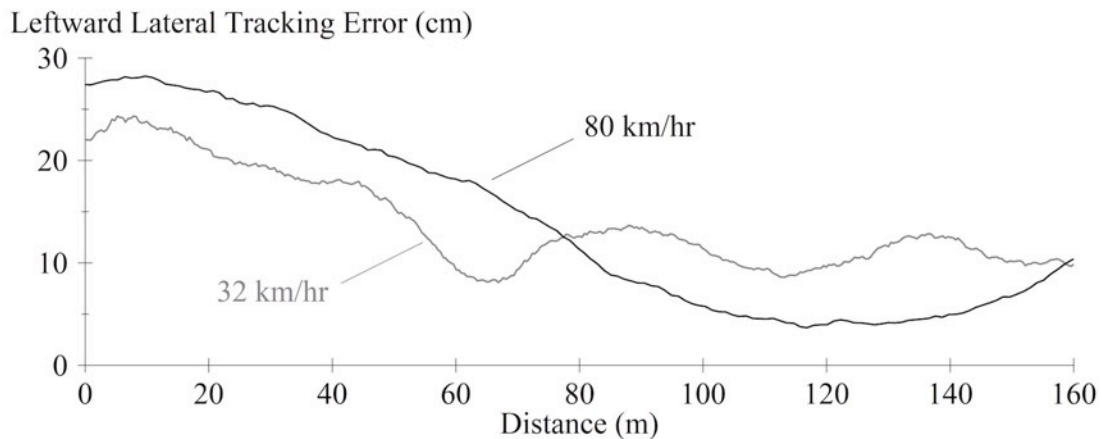


Figure 4.8 Leftward tracking error

Figure 4.9 shows the profile agreement score versus leftward tracking bias for the 28 test runs. The figure demonstrates a strong association between leftward tracking bias and agreement score for this test section. The agreement score is above 0.98 for the three runs with an average leftward tracking error below 6.5 cm. A value of 0.98 has been proposed as the threshold for “reference quality” agreement in past studies [75,86,93].

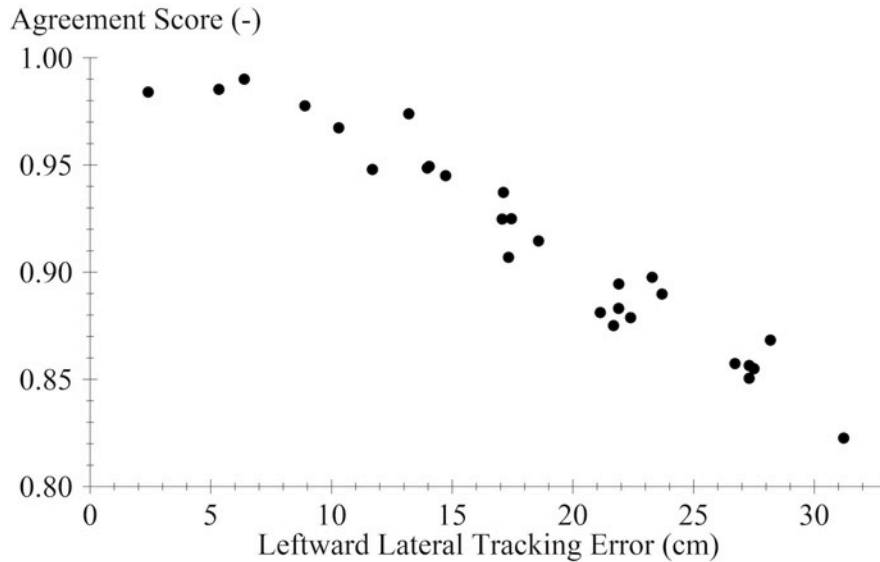


Figure 4.9 Agreement score versus lateral tracking error

4.5.3 Repeatability

For the 28 passes examined in Figure 4.9, cross correlation analysis using profile traces filtered by the IRI algorithm produced an average repeatability score of 0.944 for the 378 permutations of two profiles from the group, with a range from 0.808 to 0.998.

Like agreement to the reference measurement, lateral tracking strongly influenced the repeatability scores. Figure 4.10 shows the repeatability scores versus average lateral separation. The average lateral separation is the average absolute difference in lateral position between the paths followed by the two runs over the length of the test segment. The 14 pairs of passes with an average lateral separation of 3 cm or less produced repeatability scores above 0.98 with one exception (0.976). For the passes shown in Figure 4.8, the average lateral separation was 5.2 cm, and their agreement score was 0.993.

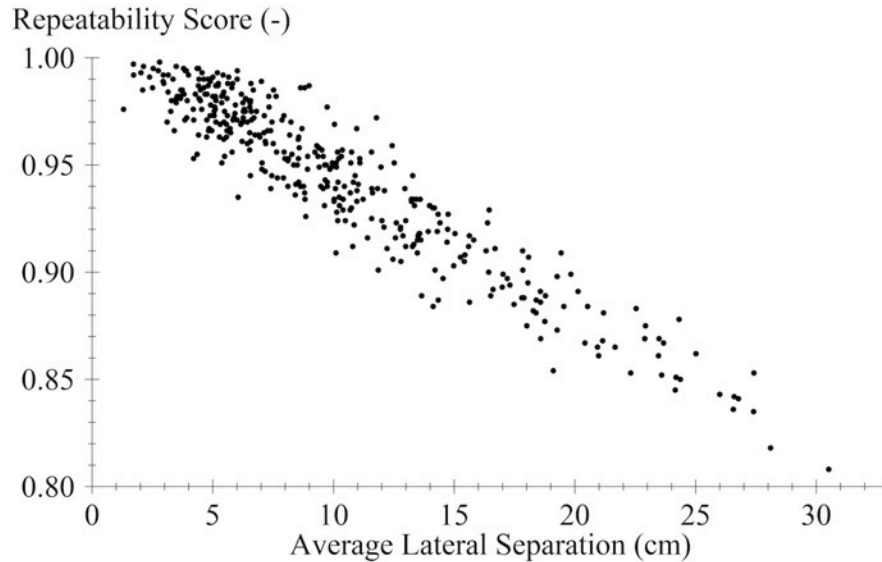


Figure 4.10 Repeatability score versus average lateral separation

The results in Figures 4.9 and 4.10 imply that production measurement of profile in two wheel paths, which is common in practice, provide only a sampling of the true roughness of a pavement section. Using a lane keeping assist system on inertial profilers is likely to improve the interpretation of changes in a pavement's roughness over time by reducing the confounding effects of inconsistent lateral tracking. Measurement of the road surface in three dimensions coupled with detection of lane edges would offer further improvement.

Measurements collected to establish the accuracy and repeatability of profilers should, at minimum, include a record of lateral position versus distance along the test section. To establish the maximum capability of the profiler sensors and processing software, the use of automated steering control is recommended. For profilers that are steered manually, clear guide marks should be provided.

Chapter 5

Error Suppression Algorithms

This chapter presents algorithms for suppressing artificial localized roughness at locations where an inertial profiler host vehicle brakes, stops, or operates at low speed. The proposed error suppression algorithms operate using only the nominal profiler sensors: an accelerometer, a height sensor, and a distance encoder. That is, the proposed algorithms are designed to reduce measurement errors as much as possible on typical commercial profilers without incorporating additional sensors. Chapter 6 addresses the use of additional sensors.

Double integration of profiler accelerometer signals with slowly varying bias causes drift in the calculated vertical position of the profiler reference point. During low-speed operation and during stops, the calculated elevation change is concentrated over a small longitudinal distance and registers as roughness. The algorithms presented attempt to limit the magnitude of this change while removing as little of the profile content in the waveband of interest as possible. In particular, the algorithms reduce artificial localized roughness at stops without adversely affecting measurement of profile at host-vehicle travel speeds above 16 km/hr.

The chapter introduces a basic temporal profile calculation algorithm and a basic spatial profile calculation algorithm, which use methods that are common in commercial inertial profilers. The proposed error suppression algorithms include additions or modifications to the basic algorithms. The performance of the basic algorithms serves as a baseline for comparison to the error suppression algorithms.

The chapter reviews the engineering requirements that influenced the design of the proposed error suppression algorithms. The chapter also describes the test conditions used to challenge each algorithm. The chapter proposes and evaluates four error suppression algorithms for use with temporal profile calculation architecture and two error suppression algorithms for use with spatial profile calculation architecture. The performance of each algorithm is characterized for test runs at low speed, during braking, and with stops. Performance is characterized by comparing profile (via cross correlation) and roughness to that of a reference run.

5.1 Profile Calculation Algorithms

This chapter examines both temporal and spatial profile calculation algorithms, because both types are used in practice. Temporal algorithms calculate profile in the time domain, and then resample the profile to a constant distance interval afterward using the distance encoder signal. As such, temporal algorithms double integrate the accelerometer signal to obtain the floating-reference-height signal and combine it with the height-sensor signal in the time domain. Spatial algorithms resample the accelerometer and height-sensor signals to a constant distance interval before calculating profile. When a spatial algorithm is used, temporal signals only exist in analog form in the time domain, and the distance encoder triggers digital sampling at each distance increment. That process is simulated here on stored temporal signals using algorithms that could function in real time.

The chapter presents basic temporal and spatial profile calculation algorithms and variations on them intended to suppress artificial localized roughness during host-vehicle stops. The basic algorithms include high-pass filtering on the profile to remove the low-frequency content. This is done in common practice because the low-frequency content is often contaminated by low signal strength in the accelerometer or slowly fluctuating accelerometer misalignment from a truly vertical orientation.

Variations on these algorithms used for error suppression include:

Mean Removal: This procedure removes the bias from the accelerometer signal prior to each stage of integration.

High-Pass Filtering, Pre-Integration: This procedure applies high-pass filtering to the individual sensor signals in addition to applying high-pass filtering to the computed profile. In particular, application of high-pass filtering to the accelerometer signal before each stage of the integration reduces drift.

Other variations on the basic temporal profile calculation algorithm specifically apply provisions for suppressing integrator drift in areas where the host-vehicle speed passes below 16 km/hr:

Local Suppression: This procedure augments the pre-integration high-pass filtering. It uses discrete-time proportional-integral (PI) control to suppress bias in the integrated accelerometer signal at low speed.

Adaptive High-Pass Filtering: This procedure modifies the pre-integration high-pass filtering algorithm by adapting the high-pass filter cut-off frequency as a function of

host-vehicle speed. In particular, this algorithm maintains a constant cut-off wavelength in areas of high-speed operation, and transitions to a set temporal cut-off frequency as speed diminishes.

The basic spatial profile calculation algorithm offers fewer options for suppressing integrator drift, because of the long time interval associated with consecutive distance samples digitized at low host-vehicle travel speed and at a stop. In addition to high-pass filtering, variations on the basic spatial algorithm apply the following provisions in areas where the speed passes below 16 km/hr:

Timer Distortion: This procedure artificially limits the integration time interval associated with consecutive spatial profile samples in areas of low-speed operation.

Height-Sensor Reflection: This procedure works in conjunction with timer distortion. Height-sensor reflection enforces cancelation of fluctuations in the height-sensor signal in areas where timer distortion has suppressed content within the floating-reference-height signal.

These algorithms function in typical fashion in areas where the host-vehicle speed is above 16 km/hr. However, each suppression algorithm introduces error into the profile in areas where the host-vehicle speed is below 16 km/hr.

The chapter compares the performance of each modification to the basic profile calculation algorithms in light of the following design objectives:

1. Reduction in the magnitude of artificial roughness caused by braking and stops: This is quantified using the peak value of the short-interval roughness profile in the area where the host vehicle stopped or released the brakes. An artificially high peak value in the short-interval roughness profile is undesirable for two reasons. First, the corresponding error in the average roughness of the overall road segment affects statistics used for pavement management and assessment of pavement network health. Second, the high peak value causes a false positive for an area of localized roughness that needs attention.
2. Valid measurement of profile and roughness at speeds above 16 km/hr: This is quantified by comparing the average values of segment-wide roughness from runs collected at various host-vehicle travel speeds and cross correlation to profile measured under ideal conditions. A minimum threshold value for cross correlation of

0.92 is adopted from AASHTO R56-14 [87]. This depends on maintaining content within the profile in the waveband of interest for the measurement of IRI. In terms of wavelength, this is 0.6-42.9 m. (See Chapter 2.)

3. Standardized high-pass filtering: Whenever it is possible, these algorithms adhere to the high-pass filtering requirement in AASHTO M 328-14 of 3 dB reduction in gain for the wavelength range of 91.44 m and above [40]. Retaining the waveband of interest for general roughness measurement (0.14-65.6 m) is also preferred.
4. Minimization of signal storage: The design of these algorithms prioritizes real-time analysis of sensor signals, particularly in the time domain. This minimizes the burden of storing all of the signals needed for profile computation until the end of a measurement run. To support real-time operation, these algorithms apply infinite impulse response (IIR) high-pass filters. These algorithms apply equivalent reverse-running filters to cancel the phase shift imposed in the real-time filtering stages. The reverse-running filters are applied as late in the process as possible to avoid increasing the storage burden.

Section 5.2 describes the test conditions used to evaluate the performance of each algorithm. The sections that follow describe each algorithm and their performance in light of the design objects listed above. The description of the basic temporal profile calculation algorithm includes an illustrative example of drift in the floating-reference-height signal from a run that included a stop.

5.2 Test Conditions

The error suppression algorithms examined in this chapter are evaluated using test runs collected on the tangent section at MnROAD. (Section 3.1.1 describes the test section.) The test runs include seven staged stop-and-go runs, a near stop with movement at low speed for a short time, seven runs with braking (but no stop), and two passes at low speed. These runs were selected based on observations from Chapter 3 to challenge the performance of the proposed algorithms as much as possible.

During each stop-and-go run, the host vehicle entered the test section with cruise control set at approximately 72 km/hr, decelerated to a stop near a designated landmark, remained still

for a short time interval, then accelerated to a target speed of 58 km/hr. Figure 5.1 shows the temporal and spatial speed profile from one of these runs. In this run the average deceleration of the host vehicle over the speed range from 70.5 km/hr to 0.5 km/hr was 0.20 g. The profiler stopped 216.5 m from the test section starting location and remained stopped for 10.7 seconds. Table 5.1 describes each of the seven stop-and-go runs by average deceleration, stop duration, and stop location. The table also provides a designation used to identify each run in tabulated results throughout the rest of this document.

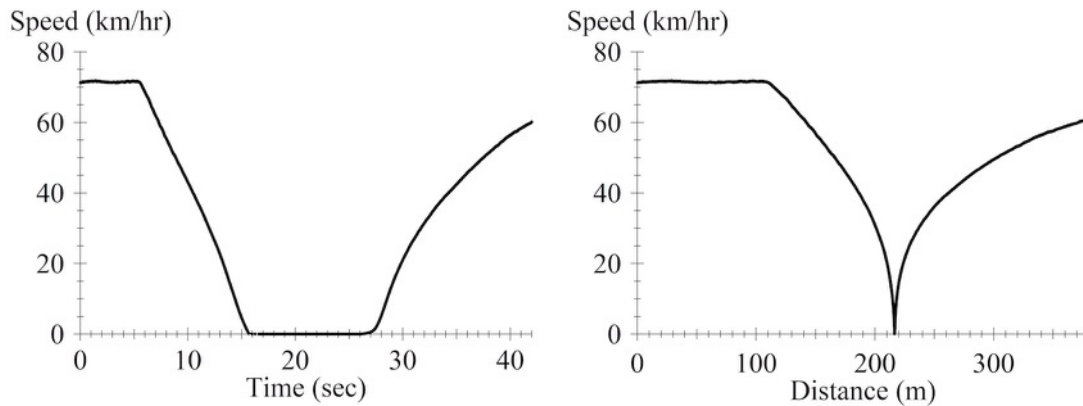


Figure 5.1 Stop-and-go run speed profiles

Table 5.1 Stop-and-go run characteristics and designations

Designation	Average Decel. (g)	Stop Duration (sec)	Stop Location (m)
S&G, 1.1-sec stop, 0.17 g	0.171	1.07	215.1
S&G, 1.1-sec stop, 0.20 g	0.203	1.12	216.1
S&G, 2.1-sec stop, 0.33 g	0.329	2.10	216.6
S&G, 5.8-sec stop, 0.17 g	0.167	5.77	214.6
S&G, 5.7-sec stop, 0.20 g	0.202	5.69	215.4
S&G, 5.8-sec stop, 0.20 g	0.201	5.78	216.5
S&G, 10.7-sec stop, 0.20 g	0.200	10.70	216.5

In the pass with a near stop, the host vehicle entered the test section with cruise control set at approximately 71.6 km/hr, reduced its speed to 11.4 km/hr with an average deceleration of 0.196 g, coasted for 2.19 seconds, and then accelerated to 58 km/hr. The coast occurred while the profiler passed over a range from 215.1 m to 220.9 m from the test section start.

During each “braking run” (i.e., run with braking, but no stop), the host vehicle entered the test section traveling at a constant speed, applied the brakes to slow to a lower target speed, and continued to the end of the test section at the new target speed. Figure 5.2 shows the

temporal and spatial speed profile from one of these runs. In this run, the driver applied the brakes while the vehicle traveled over a range from 176.4 m to 218.6 m from the test section starting location. Over this interval, 4.2 seconds elapsed and the host vehicle decelerated from 49 km/hr to 23 km/hr. This corresponds to an average deceleration of 0.18 g. Table 5.2 describes each of the seven braking runs and the near stop by average deceleration, initial speed, final speed, and the location where the brakes were released. The table also provides a designation used to identify each run in tabulated results throughout the rest of this chapter.

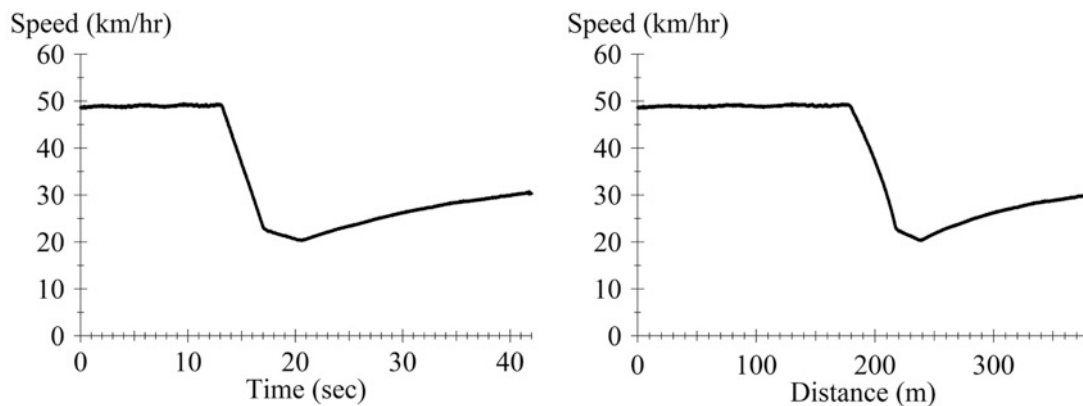


Figure 5.2 Braking run speed profiles

Table 5.2 Braking run characteristics and designations

Designation	Average Decel. (g)	Speed Range During Braking (km/hr)	Location, End of Braking (m)
Brk, 71-30 km/hr, 0.19 g	0.195	71.4-29.9	213.0
Brk, 72-29 km/hr, 0.39 g	0.390	71.8-29.1	201.2
Brk, 49-22 km/hr, 0.16 g	0.163	49.1-22.1	220.2
Brk, 49-23 km/hr, 0.18 g	0.178	49.3-23.2	221.4
Brk, 49-20 km/hr, 0.25 g	0.248	49.1-19.6	217.6
Brk, 49-23 km/hr, 0.18 g	0.178	49.2-22.7	218.6
Brk, 49-34 km/hr, 0.84 g	0.842	48.8-34.1	197.6
NS, 72-11 km/hr, 0.20 g	0.196	44.5-7.1	215.1

The test conditions also include three passes at (relatively) constant speed. In one pass, profile data were collected with cruise control set to 72 km/hr. Since this pass was conducted under favorable test conditions, the roughness values it produced serve as reference values. In another, the host vehicle operated at a speed near 16 km/hr over the entire test section. This pass is included to confirm that the proposed error suppression algorithms and sensor augmentation do not affect the validity of profile measured at a travel speed of 16 km/hr or above. In the third

pass, the host vehicle traveled over the test section at speeds in a range from 4 to 5 km/hr. This pass is included to demonstrate the performance at very low speed.

For the stop-and-go, near stop, and braking runs, this chapter quantifies the artificial roughness caused by measurement error using the peak value of the short-interval roughness profile in the range from 180 m to 228 m from the test section start. This is the area where the vehicle came to a stop in the stop-and-go runs. (See Table 5.1.) It is also the area where the brakes were released in the runs with braking, but no stop. (See Table 5.2.) Testing of production profilers, as described in Chapter 3, showed that this is the area where artificial roughness was expected to be the most severe.

Figure 5.3 shows the short-interval roughness profile from a measurement run performed at a constant speed of 72 km/hr. In the range near the stop location for stop-and-go runs and the coast for the near stop, the peak value of this short-interval roughness profile is 2.397 m/km. This is considered a reference roughness value, since the run was performed under ideal conditions. The average roughness measured at 72 km/hr for the segment shown in Figure 5.3 is 1.578 m/km. This is the reference value for average IRI over the test section.

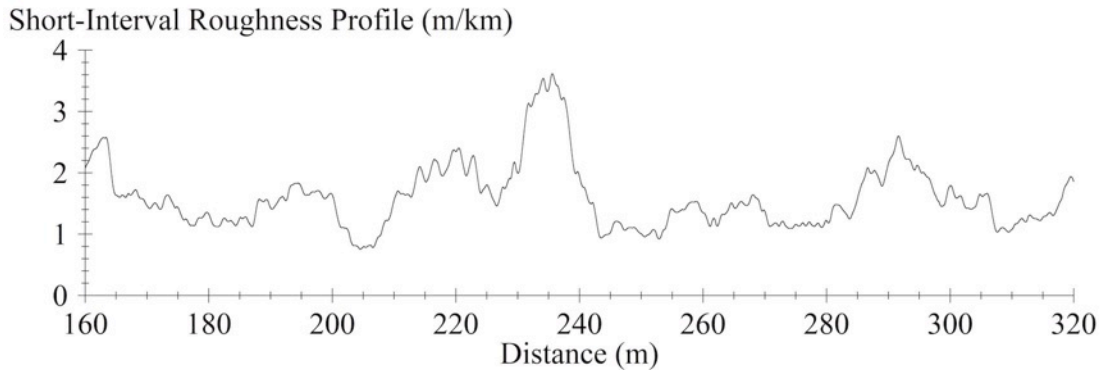


Figure 5.3 Short-interval roughness profile measured under favorable conditions

5.3 Basic Temporal Algorithm

The basic temporal algorithm represents a baseline case. The algorithm includes common practices among commercial profilers with temporal data collection architecture, with no added provisions for error suppression. Figure 5.4 describes the basic temporal profile calculation algorithm. The digitized accelerometer signal, $a_{zp}(t_k)$, is integrated twice. This produces the floating-reference-height signal, which is a time history of vertical position of the profiler

reference point, $r_{zp}(t_k)$. The height-sensor signal, $h(t_k)$, provides the relative height of the profiler reference point above the road. Subtraction of it from the vertical position of the profiler reference point produces the time history of relative road elevation beneath the profiler. This is the temporal profile, $r_{zr}(t_k)$. Note that the second character of the subscript on position and motion variables indicates whether a quantity represents the profiler reference point (p) or the road surface (r). The index, k , on time (t) indicates progression at a constant time interval, Δt .

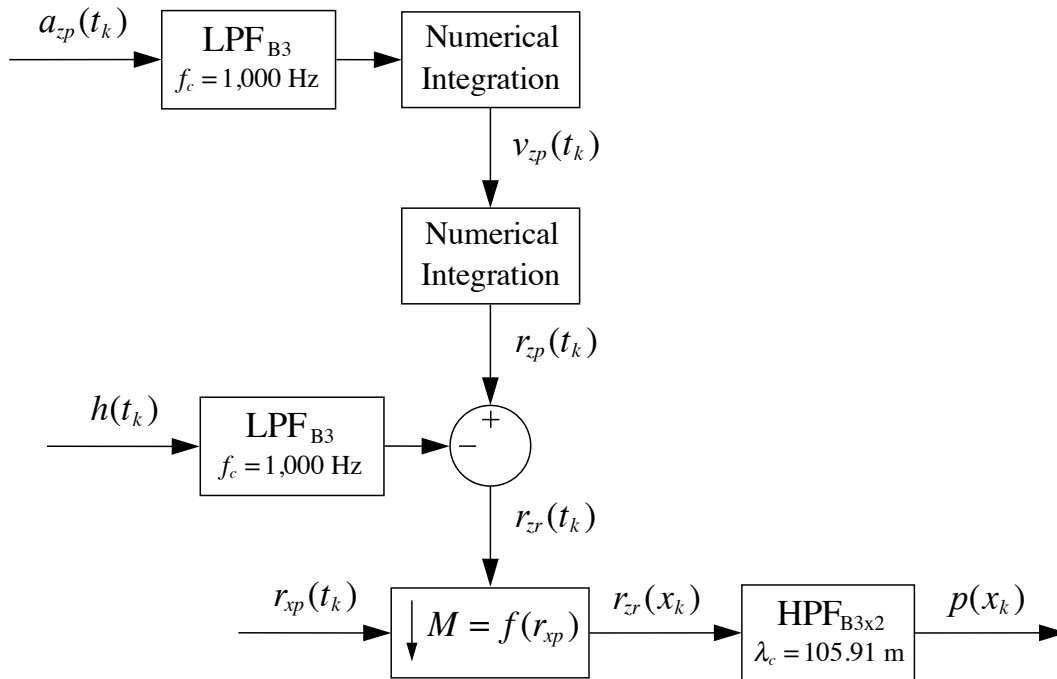


Figure 5.4 Basic temporal profile calculation algorithm

All of the profile computation algorithms discussed in this chapter use the following procedures for anti-aliasing, numerical integration, and conversion from the time domain to the distance domain:

- The accelerometer and height-sensor signals are low-pass filtered to avoid aliasing. The filter is a third-order Butterworth type with a cut-off frequency of 1,000 Hz. (See LPF_{B3} in Appendix A.) At this cut-off frequency, the gain of the filter is very close to unity (>0.9999) in the wavelength range of interest for the IRI and general roughness measurement at practical levels of host-vehicle travel speed.
- Digital integration is performed using the trapezoidal rule.

- The temporal profile, $r_{zr}(t_k)$, is decimated to obtain spatial profile, $r_{zr}(x_k)$, as a function of distance at a constant interval Δx . Temporal data were digitized at a sampling rate of 16,000 Hz, and the profile was decimated to a constant distance interval of 5.08 mm. The decimation factor, M , varies with host-vehicle speed, v_{xp} . In this implementation, the decimation factor depends directly on the progression of pulses from the distance encoder at the left rear wheel. The block diagram represents this signal as host-vehicle longitudinal travel distance, $r_{xp}(t_k)$.

In the basic temporal algorithm, a high-pass filter removes very long wavelength content from the spatial profile. This is done to eliminate content outside of the waveband of interest, which is often contaminated by low signal strength in the accelerometer or slowly fluctuating accelerometer alignment. High-pass filtering of the spatial profile was performed using a set of Butterworth filters. Butterworth filters are IIR type. As such, they impose a non-linear phase shift on the profile. To avoid this, equivalent third-order filters were applied in the forward and reverse directions to cancel the phase shift. (See HPF_{B3x2} in Appendix A.)

The cut-off wavelength setting, λ_c , for the filter (in each direction) was set to 105.91 m. This results in a reduction of 3 dB at a wavelength of 91.44 m for the forward and backward passes combined. The gain of this filter is 0.996 at the upper limit of the wavelength range of interest for the IRI (42.9 m) and 0.947 at the upper limit of the wavelength range of interest for general roughness measurement (65.6 m).

The basic temporal algorithm contains no provisions for avoiding drift in the integrated accelerometer signal. As such, a very small bias in the accelerometer signal during the stop translates to a large error in the computed vertical position of the profiler reference point. For example, Figure 5.5 shows a portion of the accelerometer signal for a run with a 10.7-second-long stop. The trace shows a reduction in the severity of acceleration as the speed diminishes. The profiler oscillates vertically at about 2 Hz for a short time after coming to a stop because of pitch motion of the host-vehicle sprung mass. The accelerometer also detects motion at about 13.7 Hz (~820 rpm) caused by engine vibration.

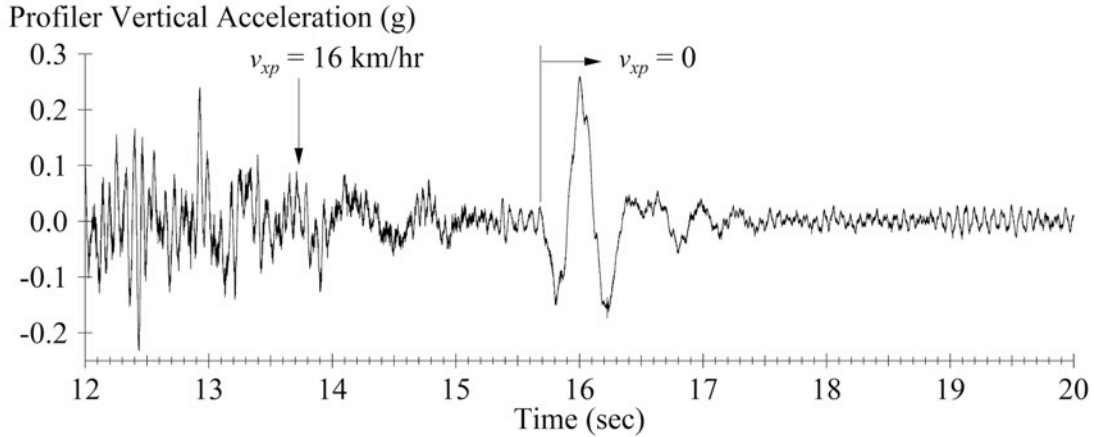


Figure 5.5 Accelerometer signal, 10.7-second-long stop

A small bias exists in the accelerometer signal over the duration of the stop. This is caused by a combination of misalignment of the sensitive axis from true vertical, local variations in the acceleration due to gravity from the assumed nominal value of 9.80665 m/s^2 , fluctuations caused by temperature variations, etc. For this run, the vehicle is stopped for 10.7 seconds, and the average value of the accelerometer signal is 0.00115 g over this interval. This translates to a 0.644 m increase in elevation after double integration.

The profile also includes the cumulative effect of drift before the stop. Figure 5.6 shows a portion of the integrated accelerometer signal. At the beginning of the stop, the computed velocity of the profiler reference point is 0.675 m/s . When it is combined with the bias in acceleration, this initial velocity translates to a change in vertical position of the profiler reference point of 7.860 m while the vehicle is stopped. Most of this change is artificial, and it is not cancelled by a commensurate change in the height-sensor signal. Since the profiler was not progressing forward over this interval, the elevation change is concentrated at the location of the stop in the spatial profile.

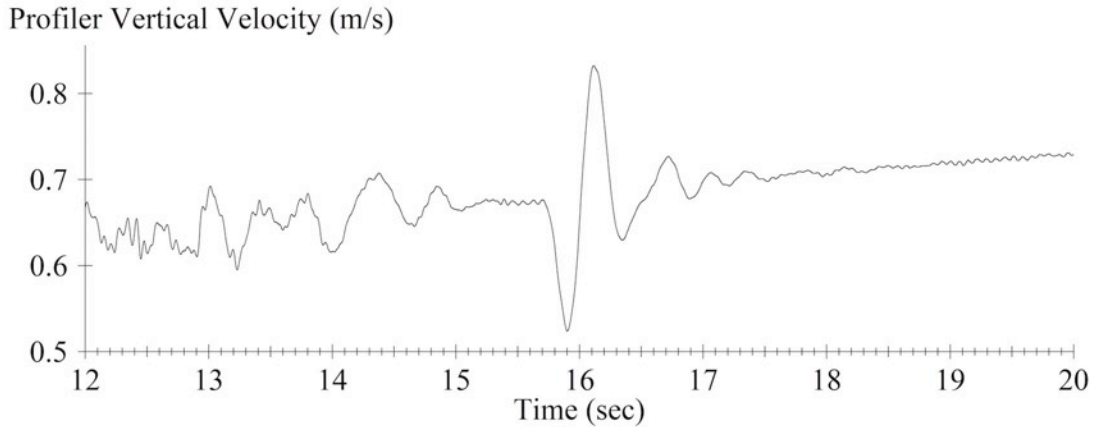


Figure 5.6 Integrated accelerometer signal, 10.7-second-long stop

Figure 5.7 shows the spatial profile after high-pass filtering. The total magnitude of the change in elevation is greater than 7.860 m, because of the additional effects of drift during very low-speed operation near the stop. The concentrated elevation change registers as severe localized roughness in the short-interval roughness profile, as shown in Figure 5.8. The short-interval roughness profile rises to a peak value of 3299.8 m/km. This implies a contribution to the average IRI value for a 160.9-m long segment of 156.2 m/km.

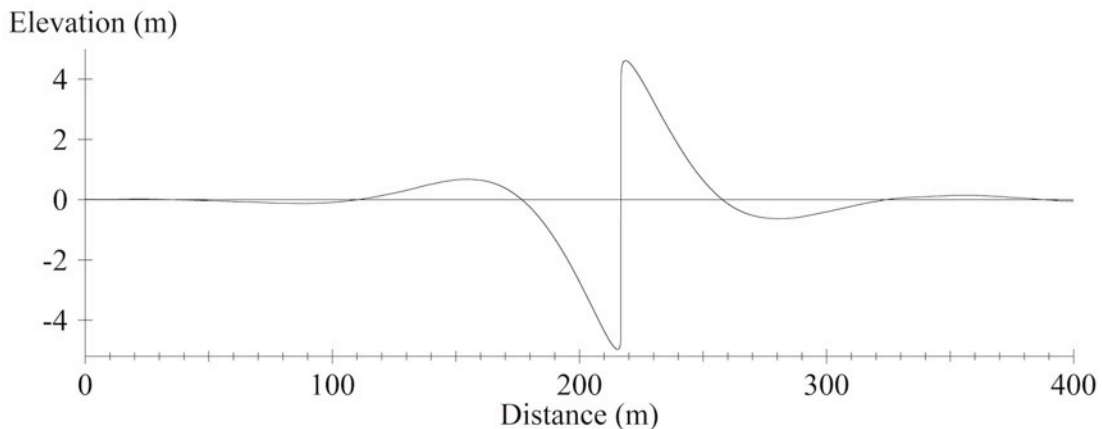


Figure 5.7 High-pass filtered profile, 10.7-second-long stop

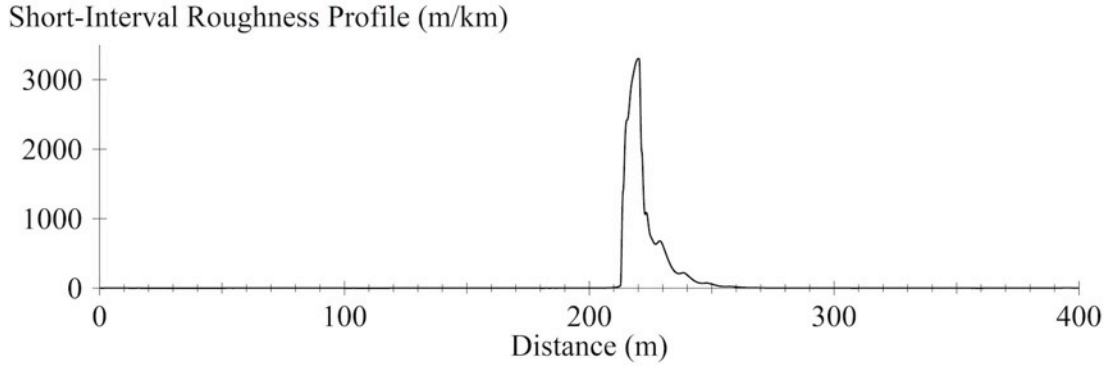


Figure 5.8 Short-interval roughness profile, 10.7-second-long stop

Table 5.3 lists the peak roughness, the percentage error in average roughness, and cross correlation to the reference profile for each test run processed using the basic temporal algorithm. Peak roughness is the highest value in the short-interval roughness profile in the range from 180 to 228 m from the test section start. This is the area where the host vehicle came to a stop in the stop-and-go runs or released the brakes in the braking runs without a stop.

Table 5.3 Results for the basic temporal algorithm

Run Designation	Peak Roughness (m/km)	Average Roughness Error (Percent)	Cross Correlation
S&G, 1.1-sec stop, 0.17 g	413.4	1,736.8	< 0.2
S&G, 1.1-sec stop, 0.20 g	855.0	3,588.0	< 0.2
S&G, 2.1-sec stop, 0.33 g	216.1	862.6	< 0.2
S&G, 5.8-sec stop, 0.17 g	1156.6	4,678.9	< 0.2
S&G, 5.7-sec stop, 0.20 g	949.0	3,784.1	< 0.2
S&G, 5.8-sec stop, 0.20 g	1053.2	4,222.7	< 0.2
S&G, 10.7-sec stop, 0.20 g	3299.8	13,139.7	< 0.2
NS, 72-11 km/hr, 0.20 g	28.4	195.3	< 0.2
Brk, 71-30 km/hr, 0.19 g	3.4	10.5	0.836
Brk, 72-29 km/hr, 0.39 g	2.4	1.7	0.841
Brk, 49-22 km/hr, 0.16 g	4.9	17.7	0.650
Brk, 49-23 km/hr, 0.18 g	4.7	15.3	0.668
Brk, 49-23 km/hr, 0.18 g	6.2	27.9	0.605
Brk, 49-20 km/hr, 0.25 g	2.2	0.0	0.944
Brk, 49-34 km/hr, 0.84 g	2.6	9.3	0.889
16 km/hr	2.3	9.2	0.863
5 km/hr	54.2	1622.7	< 0.2

Reference peak roughness value: 2.4 m/km. Adequate cross correlation > 0.92.

The test runs with a stop or a near stop produced profile with very high peak roughness. This caused a large error in the average roughness for the test section and very low cross

correlation. The high peak roughness was caused by a large artificial change in the floating reference height, which was concentrated over a short distance. This is the phenomenon illustrated in Figure 5.5 through 5.8.

The test runs with braking also produced erroneously high peak roughness and a commensurate error in the average roughness. Cross correlation for the majority of braking runs is well below the threshold value of 0.92. Integrator drift caused artificially high roughness throughout the test section for the lower-speed runs. In particular, the integrated signal grew very large in magnitude relative to the terms that are added at each time step. This reduced the effective numerical precision of the calculation. Performing the calculations with higher precision arithmetic would mitigate this error for these test runs. High-precision arithmetic was not incorporated into the algorithm, because it would not eliminate this phenomenon during very long production runs.

The basic temporal algorithm performed inadequately for runs with low speed, with braking, and with stops. The performance of the basic temporal algorithm serves as a baseline for demonstrating improvement offered by the other temporal algorithms, because it includes no explicit procedures for error suppression. The temporal error suppression algorithms described in Sections 5.4 through 5.7 are designed to improve the performance of the temporal algorithm.

5.4 Temporal Mean Removal

This algorithm removes the mean from $a_{zp}(t_k)$ and $v_{zp}(t_k)$ before integration. This is done to reduce the drift that accumulates at each stage of integration. In turn, this reduces the magnitude of the artificial elevation change at stops. For example, removal of the mean from the accelerometer signal in the run with the 10.7-second-long stop reduced the mean value during the stop to -0.000454 g. Subsequent removal of the mean from the integrated accelerometer signal produced a value of 0.0922 m/s for velocity of the profiler reference point at the beginning of the stop. Together, these conditions produced a calculated change in vertical position of the profiler reference point of 0.722 m. As a result, mean removal reduced the peak value of the short-interval roughness profile for the 10.7-second-long stop to 317.5 m/km. However, this value remains very high, and implies a contribution to the average IRI value for a 160.9-m-long segment of 15.0 m/km.

Table 5.4 provides roughness and cross correlation results for profiles processed using mean removal. Mean removal offered some improvement in cross correlation over the basic temporal algorithm for the braking test runs, and eliminated the issues with numerical integration for the test run at 5 km/hr. However, test runs with stops register very large errors in peak roughness and very low cross correlation.

Table 5.4 Results for temporal mean removal

Run Designation	Peak Roughness (m/km)	Average Roughness Error (Percent)	Cross Correlation
S&G, 1.1-sec stop, 0.17 g	103.5	417.2	< 0.2
S&G, 1.1-sec stop, 0.20 g	98.8	398.5	< 0.2
S&G, 2.1-sec stop, 0.33 g	58.2	220.9	< 0.2
S&G, 5.8-sec stop, 0.17 g	251.7	998.2	< 0.2
S&G, 5.7-sec stop, 0.20 g	223.4	871.2	< 0.2
S&G, 5.8-sec stop, 0.20 g	232.6	920.1	< 0.2
S&G, 10.7-sec stop, 0.20 g	317.5	1258.2	< 0.2
NS, 72-11 km/hr, 0.20 g	8.9	47.5	0.332
Brk, 71-30 km/hr, 0.19 g	2.5	2.4	0.954
Brk, 72-29 km/hr, 0.39 g	2.2	0.5	0.848
Brk, 49-22 km/hr, 0.16 g	2.3	-0.9	0.930
Brk, 49-23 km/hr, 0.18 g	2.4	-0.8	0.941
Brk, 49-23 km/hr, 0.18 g	2.9	1.1	0.953
Brk, 49-20 km/hr, 0.25 g	2.2	-0.1	0.942
Brk, 49-34 km/hr, 0.84 g	2.5	9.4	0.891
16 km/hr	2.3	-0.7	0.985
5 km/hr	2.4	-4.5	0.903

Reference peak roughness value: 2.4 m/km. Adequate cross correlation > 0.92.

Temporal mean removal is an undesirable method for suppressing integrator drift, because it requires storage of the accelerometer, height sensor, and encoder signals in the time domain until the end of the profile measurement run. (For algorithms that do not convert signals to spatial coordinates in real time, the encoder signal is most likely replaced by distance or speed as a function of time.) Further, removal of the global mean from each signal does not guarantee a reduction in accelerometer bias during each stop, so drift in the floating-reference-height signal is still possible. This is particularly true in profile measurements for pavement network monitoring. In that application the profile measurement runs often go on for more than an hour and cover tens of kilometers of roadway. In such cases, mechanisms that determine the level of accelerometer bias often change between stops, such as temperature, road grade, and cross slope.

An alternative form of mean removal was considered that set the accelerometer signal to zero during stops. This was not viable for two reasons. First, this introduces a concentrated change in curvature into the profile at the beginning and end of the stop. Second, the content that captures true vertical vibration of the profiler reference point during the stop is needed to cancel the equal and opposite fluctuations in distance to the road surface measured by the height sensor.

5.5 Temporal High-Pass Filtering, Pre-Integration

This proposed algorithm applies high-pass filtering to the accelerometer signal before integration to suppress drift in the floating reference height. In particular, by reducing the mean value of each signal before integration, the concentrated elevation change that appears in areas with braking and stops is reduced.

Figure 5.9 shows a block diagram of the time-domain portion of the basic temporal algorithm with temporal high-pass filtering added. Accelerometer and height-sensor signals are high-pass filtered in the time domain. Once the temporal profile is computed, the cascaded version of the third-order Butterworth high-pass filter is applied in reverse order and in the reverse direction ($\text{HPF}_{\text{B3S2R}}$, $\text{HPF}_{\text{B3S1R}}$). The reverse passes cancel the phase shift imposed by the forward passes. Appendix A describes each filter stage in detail. To support the reverse filtering stage, the temporal high-pass filtering algorithm requires storage of the pre-filtered temporal profile, $r_{zr}(t_k)$, and the encoder signal, $r_{xp}(t_k)$, in the time domain until the end of the profile measurement run.

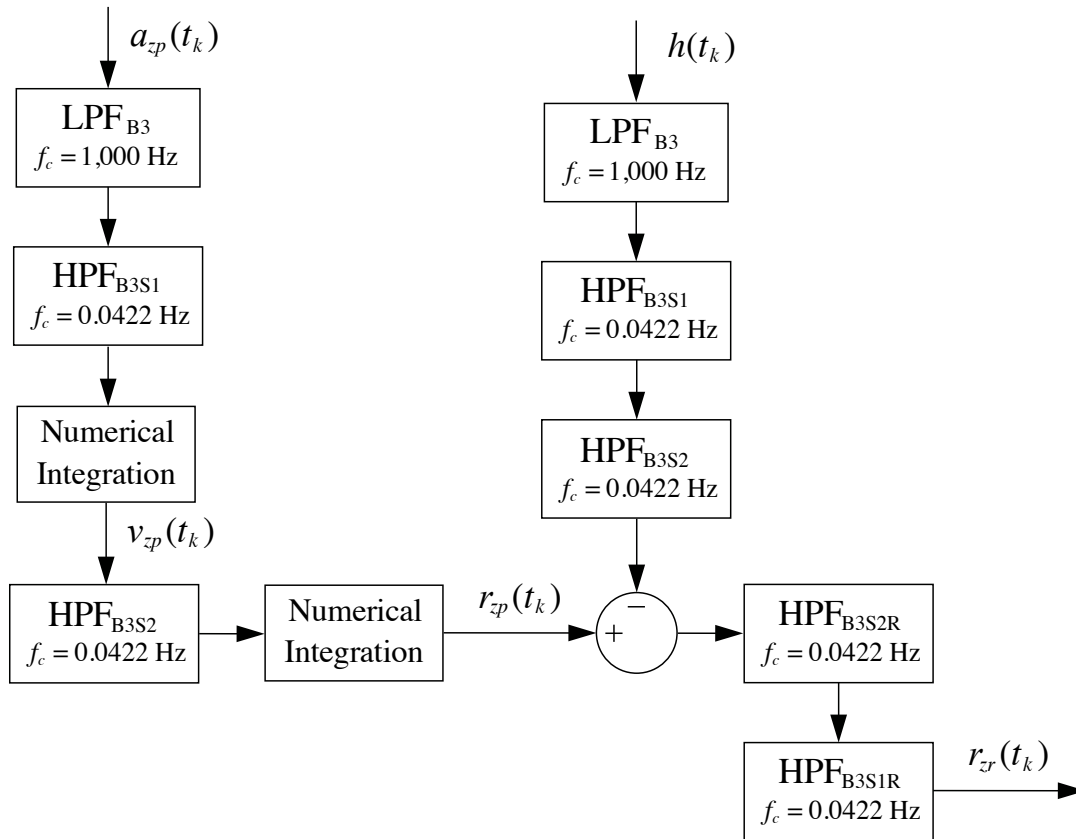


Figure 5.9 Temporal profile calculation algorithm with high-pass filtering

The high-pass filtering in the temporal portion of this algorithm is applied in lieu of spatial high-pass filtering. That is, no additional filtering is performed after decimation to spatial profile. The cut-off frequency values for the individual high-pass filtering stages shown in Figure 5.9 were adjusted to place the cut-off frequency of the collective set at 0.0489 Hz. This corresponds to a cut-off wavelength of 91.44 m at a host-vehicle speed of 16 km/hr.

Temporal high-pass filtering suppressed integrator drift more effectively than mean removal. For example, the change in profiler reference point height during the 10.7-second-long stop was reduced to 0.213 m. This reduced the peak value of the short-interval roughness profile to 29.0 m/km.

Table 5.5 provides roughness and cross correlation results for profiles processed using temporal high-pass filtering. Temporal high-pass filtering consistently lowered the errors in peak roughness values relative to the basic temporal algorithm and relative to mean removal for the stop-and-go runs and the near stop. However, in the runs with a stop, cross correlation values were very low, and the artificial roughness values exceed the typical range for very rough

localized road features. With one exception, use of temporal high-pass filtering reduced peak roughness values relative to the basic temporal algorithm.

Table 5.5 Results for temporal high-pass filtering

Run Designation	Peak Roughness (m/km)	Average Roughness Error (Percent)	Cross Correlation
S&G, 1.1-sec stop, 0.17 g	32.7	117.1	< 0.2
S&G, 1.1-sec stop, 0.20 g	31.2	107.2	< 0.2
S&G, 2.1-sec stop, 0.33 g	12.3	36.8	0.256
S&G, 5.8-sec stop, 0.17 g	42.6	151.5	< 0.2
S&G, 5.7-sec stop, 0.20 g	24.0	78.7	< 0.2
S&G, 5.8-sec stop, 0.20 g	30.9	106.5	< 0.2
S&G, 10.7-sec stop, 0.20 g	29.0	99.5	< 0.2
NS, 72-11 km/hr, 0.20 g	5.0	17.7	0.578
Brk, 71-30 km/hr, 0.19 g	2.5	2.3	0.954
Brk, 72-29 km/hr, 0.39 g	2.2	1.2	0.848
Brk, 49-22 km/hr, 0.16 g	2.3	-1.0	0.929
Brk, 49-23 km/hr, 0.18 g	2.3	-0.8	0.941
Brk, 49-23 km/hr, 0.18 g	2.7	0.6	0.963
Brk, 49-20 km/hr, 0.25 g	2.3	0.1	0.948
Brk, 49-34 km/hr, 0.84 g	2.5	8.6	0.898
16 km/hr	2.3	-0.7	0.985
5 km/hr	2.3	-4.2	0.940

Reference peak roughness value: 2.4 m/km. Adequate cross correlation > 0.92.

Temporal high-pass filtering increased cross correlation for all braking test runs relative to the basic temporal algorithm (see Table 5.3), and adequate cross correlation is achieved for five of the seven runs as shown in Table 5.5. Cross correlation was improved relative to the basic temporal algorithm (see Table 5.3) for the low-speed runs, and was well within the adequate range as shown in Table 5.5. However, the use of a constant cut-off frequency of 0.0489 Hz caused a reduction in the IRI value for the test run at 5 km/hr. This is because 0.0489 Hz corresponds to a cut-off wavelength of 28.4 m at 5 km/hr, and some of the wavelength range of interest for the IRI is removed. This demonstrates the trade-off imposed by using temporal high-pass filtering with a constant cut-off frequency: Removal of low-frequency content reduces artificial localized roughness during braking and at stops by suppressing integrator drift, but removes some of the content of interest at very low speed.

5.6 Local Suppression

The “local suppression” algorithm applies digital control to eliminate bias in the integrated accelerometer signal when the host vehicle is traveling at low speed. This algorithm is applied in conjunction with temporal high-pass filtering. At higher host-vehicle speeds, the algorithm applies temporal high-pass filtering as shown in Figure 5.9. When the travel speed passes below 16 km/hr, the portion of the algorithm where the accelerometer signal is integrated switches to the procedure shown in Figure 5.10.

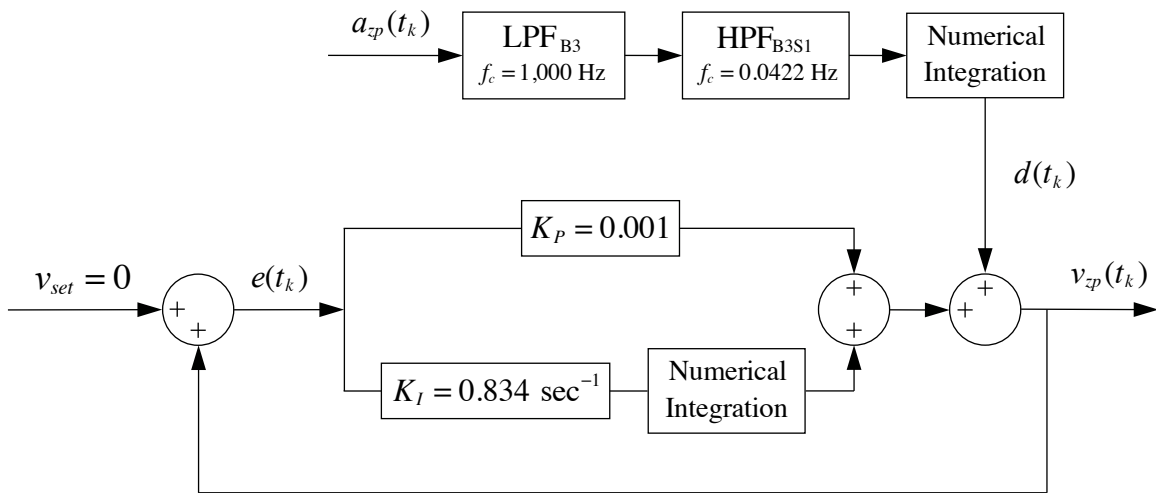


Figure 5.10 Local suppression algorithm applied at low speed

The concept of the local suppression algorithm is to artificially suppress the absolute value of the integrated accelerometer signal, $v_{zp}(t_k)$, when the travel speed is low. In turn, this suppresses the computed change in height of the profiler reference point after the next stage of integration. A controller is used in place of directly setting the integrated accelerometer signal to zero in regions with low travel speed, because preliminary analysis showed that doing so introduced a sudden change in slope into the computed profile. As an alternative, the suppression algorithm proposed here attempts to mitigate the slope break by introducing a gradual reduction in the magnitude of $v_{zp}(t_k)$ in regions of low travel speed. This is done using a simple PI controller with a slow time constant. The controller is designed to retain content at frequencies above 2 Hz with minimal phase shift. The procedure retains high-frequency content, because it is needed to cancel relative motion between the profiler reference point and the road surface detected by the height sensor.

In the procedure illustrated in Figure 5.10, a discrete-time PI controller operates on vertical velocity (i.e., integrated vertical acceleration) with a set point of zero. The integrated accelerometer signal serves as a disturbance, $d(t_k)$. The controller rejects the initial offset at the instant of the switch and low-frequency content from the disturbance.

The controller time constant (τ) for a step response is:

$$\tau = \frac{K_p + 1}{K_I} \quad (5.1)$$

The frequency response for the output relative to the disturbance is:

$$\frac{v_{zp}(\omega)}{d(\omega)} = \frac{1}{K_I} \left[\frac{j\omega - \tau\omega^2}{1 + \tau^2\omega^2} \right] \quad (5.2)$$

Where ω is angular frequency. The controller settings ($K_p = 0.001$, $K_I = 0.834 \text{ sec}^{-1}$) produce a time constant of 1.2 seconds. At 2 Hz, this frequency response function has a gain of 0.996 and a phase shift of 1.9 degrees. At 14 Hz, the gain is 0.999 and the phase shift is 0.3 degrees. For very high-frequency content, the gain approaches 0.999 and the phase shift diminishes to zero.

The criterion for activating local suppression depends on host-vehicle speed. Direct numerical differentiation of the wheel encoder signal at a sampling rate of 16,000 Hz produces a very noisy estimate of speed. As such, the decision to switch at any instant is based on the accumulated progression of encoder pulses over the preceding 0.05 seconds.

Table 5.6 provides roughness and cross correlation results for test runs with stops, with a near stop, and at low speed using local suppression together with temporal high-pass filtering. In every case, the error in peak roughness was reduced by a factor of at least 10 relative to the basic temporal algorithm. With one exception, adding local suppression reduced the error in peak roughness values relative to temporal high-pass filtering alone for the runs with a stop. In many cases, the peak roughness values were reduced to less than half. However, the peak roughness values for the runs with stops remain several times larger than the reference value in many of the test runs. As a result, large errors remain in the average roughness values; and cross correlation is well below 0.92 in all of the runs. Note that local suppression was not activated in the other runs with braking, so those results are unchanged relative to temporal high-pass filtering.

Table 5.6 Results for local suppression combined with temporal high-pass filtering

Run Designation	Peak Roughness (m/km)	Average Roughness Error (Percent)	Cross Correlation
S&G, 1.1-sec stop, 0.17 g	8.0	20.9	0.374
S&G, 1.1-sec stop, 0.20 g	14.0	42.3	0.219
S&G, 2.1-sec stop, 0.33 g	15.3	46.0	< 0.2
S&G, 5.8-sec stop, 0.17 g	6.7	18.3	0.443
S&G, 5.7-sec stop, 0.20 g	7.7	14.9	0.379
S&G, 5.8-sec stop, 0.20 g	5.7	12.1	0.530
S&G, 10.7-sec stop, 0.20 g	7.0	16.4	0.460
NS, 72-11 km/hr, 0.20 g	3.4	10.5	0.702
16 km/hr	2.0	-0.7	0.985
5 km/hr	2.4	-14.4	0.588

Reference peak roughness value: 2.4 m/km. Adequate cross correlation > 0.92.

At 16 km/hr, the switch to local suppression was not activated. As such, the profile and the resulting roughness was the same as in the temporal high-pass filtering algorithm. In the run at 5 km/hr, removal of content from the integrated accelerometer signal caused a reduction in the measured roughness. The cut-off frequency for disturbance response in the local suppression procedure is 0.13 Hz. At frequencies near this value and below, the floating-reference-height signal derived from the accelerometer contributes much more heavily to the profile than the height sensor. Attenuating it removed some of the measured roughness.

Local suppression offers an improvement over temporal high-pass filtering alone and a major improvement over the basic temporal algorithm. However, profile content measured a low speed is lost, and the overall performance is not adequate.

5.7 Adaptive High-Pass Filtering

The performance of the temporal high-pass filtering algorithm with a fixed cut-off frequency is limited, because the effective cut-off wavelength increases in proportion to speed. The cut-off frequency was set to 0.0489 Hz to enforce a cut-off wavelength of 91.44 m at a host-vehicle speed of 16 km/hr. At higher travel speeds, where the effective cut-off wavelength is greater than 91.44 m, additional drift in the integrated accelerometer signal accumulates that is not needed to retain content of interest. This mechanism is illustrated conceptually in Figures 5.5 and 5.6.

A modified high-pass filter is proposed with a cut-off frequency that adapts to host-vehicle speed to address this shortcoming of the temporal high-pass filtering algorithm. To do this, the adaptive high-pass filtering algorithm imposes an upper limit on the cut-off wavelength at progressively higher travel speeds and an upper limit on cut-off frequency at progressively lower travel speeds.

The adaptive high-pass filtering algorithm includes the same components as the temporal high-pass filtering algorithm, with the exception that the high-pass filter cut-off frequency (f_c) is adjusted at each time step as follows:

$$f_c(t_k) = \frac{f_{ls} + (v_{xp}(t_k) / \lambda_c) e^{\alpha(v_{xp}(t_k) - v_0)}}{1 + e^{\alpha(v_{xp}(t_k) - v_0)}} \quad (5.3)$$

Where $v_{xp}(t_k)$ is the current value of host-vehicle speed in m/s, f_{ls} is the desired cut-off frequency for low-speed operation in Hz, and λ_c is the desired cut-off wavelength for high-speed operation in m. Parameters v_0 and α determine the speed range where the cut-off transitions from the high-speed wavelength setting to the low-speed frequency setting and the steepness of the transition. Like the local suppression algorithm, real-time estimates of speed are averaged over 0.05 seconds.

In this implementation, f_{ls} is 0.45 Hz, λ_c is 105.91 m, v_0 is 2.778 m/s, and α is 2.5 (for speed expressed in m/s). Figure 5.11 shows the cut-off frequency and the effective cut-off wavelength as a function of speed using these settings. The plots produced by this function include three features that affect the performance of the algorithm.

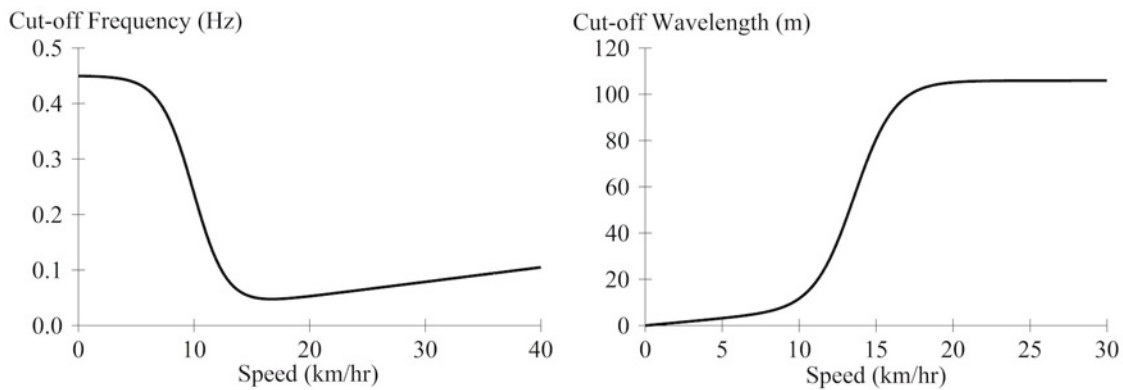


Figure 5.11 Adaptive high-pass filter cut-off frequency and wavelength

First, the function limits the cut-off wavelength explicitly at high speed. This avoids rapid changes in the cut-off wavelength as host-vehicle speed changes during braking, which would introduce artificial curvature into the floating-reference-height signal. Similarly, the gradual transition between the high-speed and low-speed limits for speeds below 16 km/hr helps mitigate this problem.

Second, the function maintains the wavelength range of interest for host-vehicle speeds of 16 km/hr and above. At 16 km/hr, the cut-off frequency is 0.0481 Hz, which is an effective cut-off wavelength of 93.04 m. For the combined filtering applied by this algorithm, this is a gain of 0.991 at the upper limit of the wavelength range of interest for the IRI (42.9 m) and 0.891 at the upper limit of the wavelength range of interest for general roughness measurement (65.6 m).

Third, the function limits temporal frequency rather than spatial frequency at low speeds to avoid an infinite cut-off wavelength as speed approaches zero. This helps reduce drift in the double-integrated accelerometer signal. However, the filtering removes a progressively larger portion of the wavelength range of interest as speed diminishes.

This algorithm requires storage of the computed profile and the encoder signal (or an equivalent) until the end of the measurement run. To avoid this, a version of the algorithm is proposed in which the backward filtering pass is performed after decimation to spatial profile. As such, the algorithm performs all temporal calculations in real-time. Figure 5.12 presents the details of the adaptive high-pass filtering algorithm with the spatial backward pass.

In this implementation the speed signal, $v_{xp}(t_k)$, is derived in real-time in the temporal portion of the algorithm using the progression of encoder pulses over the preceding 0.05 seconds. Like the temporal profile, the temporal speed record is decimated and converted to the distance domain. To accommodate the backward filtering pass, the spatial record of speed must be stored until the end of the measurement run.

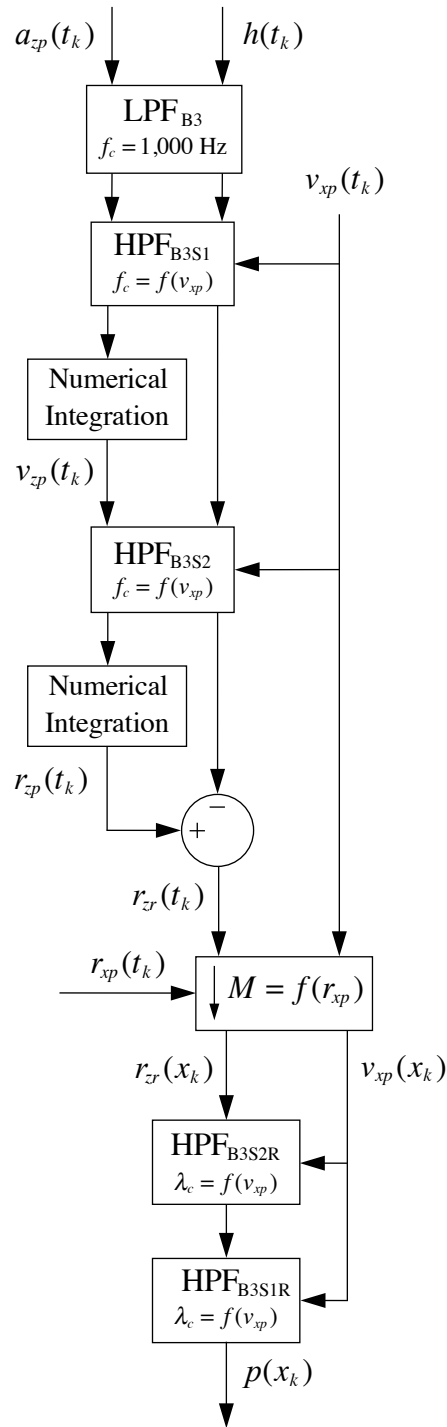


Figure 5.12 Adaptive high-pass filtering algorithm, spatial backward pass

Tables 5.7 and 5.8 list the peak roughness, the percentage error in average roughness, and cross correlation to the reference profile for each test run processed using the two adaptive filtering algorithms. Both adaptive algorithms demonstrated a major improvement over the basic temporal algorithm. (See Table 5.3.) Relative to their non-adaptive counterpart (i.e., the temporal

high-pass filtering algorithm), both adaptive high-pass filtering algorithms reduced the errors in peak roughness level in all of the runs with a stop and the near stop. In all of the runs with a stop, the artificial localized roughness was less severe using the real-time adaptive high-pass filtering algorithm than the temporal high-pass filtering algorithm, both with and without with local suppression. (See Tables 5.6 and 5.5, respectively.) Neither of the adaptive algorithms offered consistently better results than the other for the test runs with braking and stops.

Both algorithms removed valid content in the wavelength range of interest from the profile measured at 5 km/hr, and reduced the measured roughness by half. This is reflected in the low cross correlation levels.

Table 5.7 Results for adaptive high-pass filtering

Run Designation	Peak Roughness (m/km)	Average Roughness Error (Percent)	Cross Correlation
S&G, 1.1-sec stop, 0.17 g	5.3	10.3	0.742
S&G, 1.1-sec stop, 0.20 g	3.7	3.1	0.831
S&G, 2.1-sec stop, 0.33 g	7.1	18.9	0.565
S&G, 5.8-sec stop, 0.17 g	11.9	38.7	0.302
S&G, 5.7-sec stop, 0.20 g	4.5	5.8	0.764
S&G, 5.8-sec stop, 0.20 g	4.7	10.1	0.716
S&G, 10.7-sec stop, 0.20 g	4.6	9.0	0.727
NS, 72-11 km/hr, 0.20 g	2.4	1.3	0.852
Brk, 71-30 km/hr, 0.19 g	2.5	2.6	0.951
Brk, 72-29 km/hr, 0.39 g	2.2	1.7	0.844
Brk, 49-22 km/hr, 0.16 g	2.3	-0.8	0.931
Brk, 49-23 km/hr, 0.18 g	2.4	-0.7	0.943
Brk, 49-23 km/hr, 0.18 g	2.7	0.8	0.958
Brk, 49-20 km/hr, 0.25 g	2.3	0.3	0.950
Brk, 49-34 km/hr, 0.84 g	2.6	8.5	0.859
16 km/hr	2.3	-0.8	0.985
5 km/hr	1.2	-52.0	0.321

Reference roughness value: 2.4 m/km. Adequate cross correlation > 0.92.

Table 5.8 Results for adaptive high-pass filtering with a backward pass

Run Designation	Peak Roughness (m/km)	Average Roughness Error (Percent)	Cross Correlation
S&G, 1.1-sec stop, 0.17 g	2.8	1.6	0.880
S&G, 1.1-sec stop, 0.20 g	4.2	4.7	0.815
S&G, 2.1-sec stop, 0.33 g	5.8	17.5	0.581
S&G, 5.8-sec stop, 0.17 g	6.6	20.1	0.576
S&G, 5.7-sec stop, 0.20 g	2.8	0.3	0.854
S&G, 5.8-sec stop, 0.20 g	5.4	12.1	0.655
S&G, 10.7-sec stop, 0.20 g	4.6	9.3	0.724
NS, 72-11 km/hr, 0.20 g	3.9	4.9	0.793
Brk, 71-30 km/hr, 0.19 g	2.5	2.7	0.950
Brk, 72-29 km/hr, 0.39 g	2.2	1.6	0.846
Brk, 49-22 km/hr, 0.16 g	2.4	-0.8	0.932
Brk, 49-23 km/hr, 0.18 g	2.4	-0.7	0.943
Brk, 49-23 km/hr, 0.18 g	2.8	1.0	0.955
Brk, 49-20 km/hr, 0.25 g	2.5	1.1	0.952
Brk, 49-34 km/hr, 0.84 g	3.2	10.5	0.841
16 km/hr	2.3	-0.8	0.985
5 km/hr	1.2	-51.9	0.322

Reference peak roughness value: 2.4 m/km. Adequate cross correlation > 0.92.

The adaptive high-pass filtering algorithms offered the greatest reduction in artificial localized roughness for runs with braking and stops. However, a high percentage error in peak roughness remains for most of the runs with stops, and cross correlation levels are below the threshold value of 0.92 for all of the runs with stops, two of the runs with braking, and the run at 5 km/hr. The adaptive high-pass filtering algorithm with the spatial backward pass is recommended for use on profilers with temporal architecture, but only as a means of avoiding large error in roughness measurement when it is not practical to use additional sensors.

5.8 Basic Spatial Algorithm

The basic spatial algorithm represents a baseline case. The algorithm includes common practices among commercial profilers with spatial data collection architecture, with no added provisions for error suppression. Figure 5.13 describes the basic spatial profile calculation algorithm.

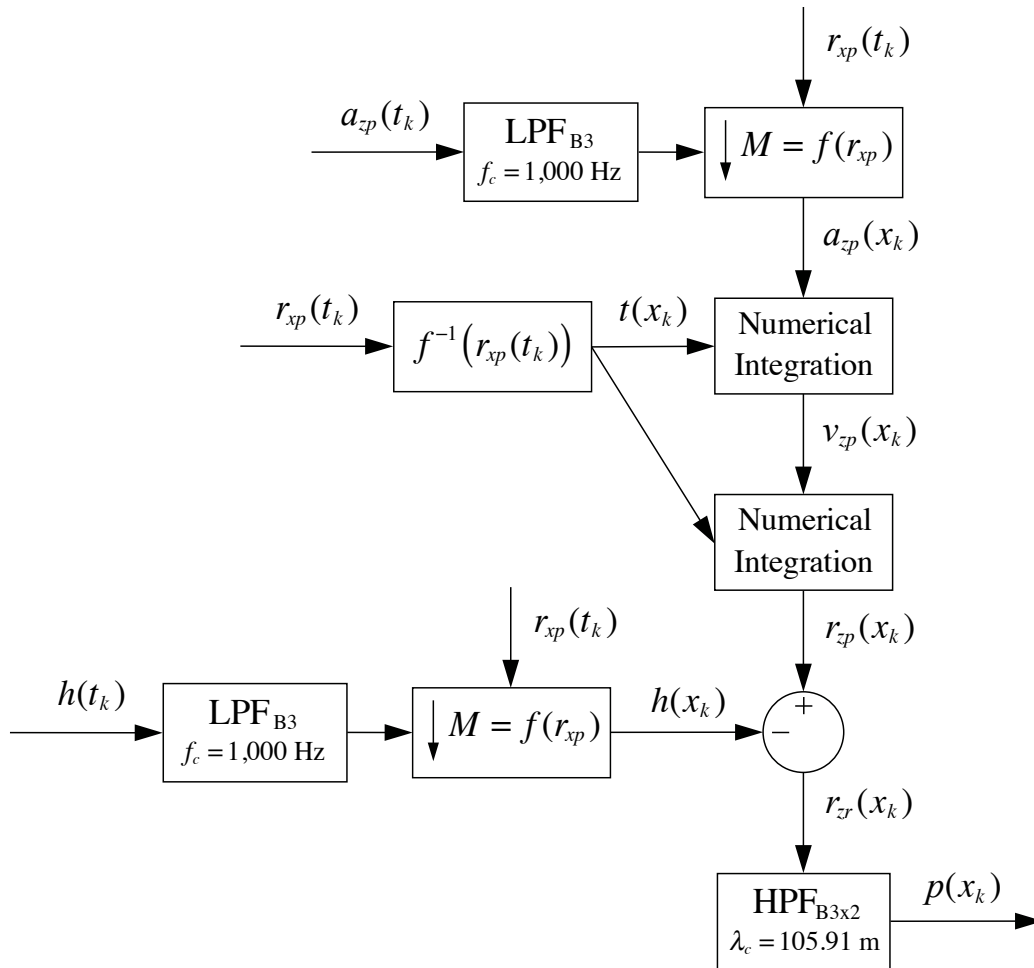


Figure 5.13 Basic spatial profile calculation algorithm

This algorithm includes the same processing steps as the basic temporal algorithm with one exception. The algorithm converts the accelerometer and height-sensor signals to spatial coordinates before combining them to calculate the profile. As a result, numerical integration of the accelerometer signal is performed in the distance domain. A high-pass filter removes very long-wavelength content from the spatial profile. As described in Appendix A (see HPF_{B3x2}), equivalent third-order IIR filters are applied in the forward and reverse directions to cancel the phase shift.

The basic spatial calculation algorithm shown in Figure 5.13 typically operates in real time. Real-time operation was simulated using the stored time-domain signals. The simulated algorithm “captures” accelerometer and height-sensor readings from the time-domain signals each time it is triggered by a distance encoder pulse. To accommodate changes in host-vehicle speed, the algorithm must calculate a time step for integration corresponding to each distance

increment. To support integration in the distance domain, the simulated algorithm stores the time associated with each distance sample. In turn, the numerical integration algorithm computes the elapsed time between spatial samples (Δt):

$$\Delta t(x_k) = t(x_k) - t(x_{k-1}) \quad (5.4)$$

$$v_{zp}(x_k) = v_{zp}(x_{k-1}) + \Delta t(x_k)(a_{zp}(x_k) + a_{zp}(x_{k-1})) \quad (5.5)$$

$$r_{zp}(x_k) = r_{zp}(x_{k-1}) + \Delta t(x_k)(v_{zp}(x_k) + v_{zp}(x_{k-1})) \quad (5.6)$$

Like the basic temporal algorithm, this algorithm often produces a large artificial change in elevation at the location where the host vehicle stops. For example, in the run with the 10.7-second-long stop, the time difference between the readings surrounding the stop was 10.7643 seconds. The accelerometer reading at the spatial sample preceding the stop was -0.01865 g and the trailing reading was 0.00910 g. This resulted in a change of the integrated accelerometer signal to -0.50744 m/s from a leading value of -0.00319 m/s. After the second stage of integration, these readings translated to a computed change in vertical position of the profiler reference point of 2.748 m downward. This is not balanced by the height-sensor reading, which indicated an upward change of 15 mm. The peak value of the short-interval roughness profile at the stop for this run was 2,141.5 m/km.

Table 5.9 lists the peak roughness, the percentage error in average roughness, and cross correlation to the reference profile for each test run processed using the basic spatial algorithm. All test runs with a stop or a near stop produce profiles with very high errors in peak localized roughness. This caused a large error in the average roughness for the test section and very low cross correlation.

Cross correlation for the majority of braking test runs is well below the threshold value of 0.92. In the test run at 5 km/hr, excessive drift in the floating-reference-height signal caused issues with numerical precision during integration. Overall, the basic temporal calculation algorithm demonstrated inadequate performance at stops, during braking, and at 5 km/hr.

Table 5.9 Results for the basic spatial algorithm

Run Designation	Peak Roughness (m/km)	Average Roughness Error (Percent)	Cross Correlation
S&G, 1.1-sec stop, 0.17 g	442.4	1859.7	< 0.2
S&G, 1.1-sec stop, 0.20 g	799.9	3374.5	< 0.2
S&G, 2.1-sec stop, 0.33 g	213.6	852.5	< 0.2
S&G, 5.8-sec stop, 0.17 g	898.9	3668.3	< 0.2
S&G, 5.7-sec stop, 0.20 g	447.3	1807.1	< 0.2
S&G, 5.8-sec stop, 0.20 g	880.0	3544.9	< 0.2
S&G, 10.7-sec stop, 0.20 g	2141.0	8607.7	< 0.2
NS, 72-11 km/hr, 0.20 g	27.8	190.8	< 0.2
Brk, 71-30 km/hr, 0.19 g	3.4	10.8	0.848
Brk, 72-29 km/hr, 0.39 g	2.4	1.9	0.838
Brk, 49-22 km/hr, 0.16 g	4.8	15.8	0.671
Brk, 49-23 km/hr, 0.18 g	4.8	16.7	0.684
Brk, 49-23 km/hr, 0.18 g	6.1	27.2	0.621
Brk, 49-20 km/hr, 0.25 g	2.2	0.1	0.942
Brk, 49-34 km/hr, 0.84 g	2.8	10.3	0.879
16 km/hr	2.4	0.2	0.985
5 km/hr	23.0	928.5	< 0.2

Reference peak roughness value: 2.4 m/km. Adequate cross correlation > 0.92.

The performance of the basic spatial algorithm serves as a baseline for demonstrating improvement offered by the other spatial algorithms, because it includes no explicit procedures for error suppression. The spatial error suppression algorithms described in Sections 5.9 and 5.10 are designed to improve the performance of the spatial algorithm.

5.9 Spatial High-Pass Filtering, Pre-Integration

This proposed algorithm is a variation on the basic spatial algorithm in which high-pass filtering is applied to the accelerometer signal before each stage of integration. Application of high-pass filtering to the accelerometer signal before each stage of integration suppresses drift in the integrated accelerometer signal. This algorithm applies forward-running filtering stages to the height-sensor and accelerometer signals after conversion to spatial coordinates, but before combining them into profile. The backward-running filtering stages are applied to the profile. (Appendix A describes each filtering stage.) The backward-running filters are applied to cancel the phase shift imposed by the filters that are applied to the sensor signals. Figure 5.14 provides the details of this algorithm.

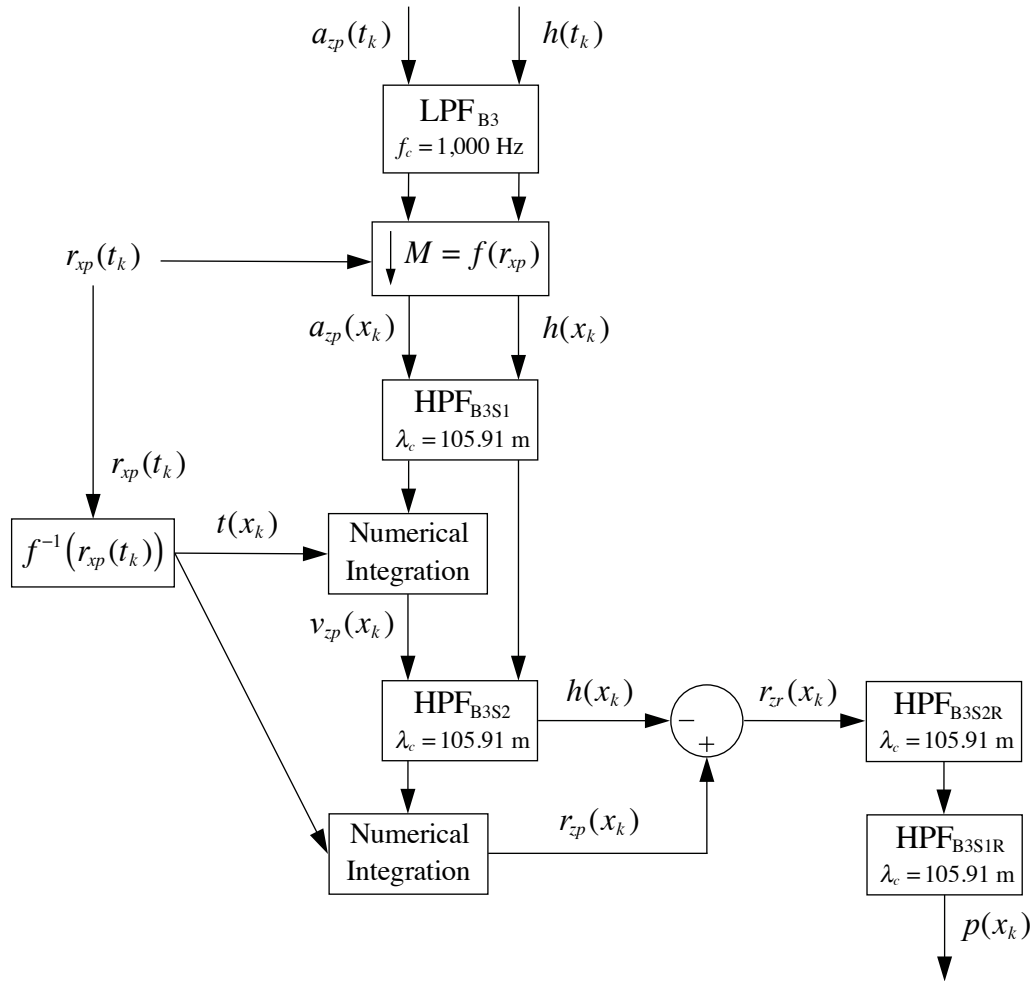


Figure 5.14 Spatial high-pass filtering, pre-integration

In the spatial algorithms, the magnitude of the computed change in vertical position of the reference point during a stop no longer depends on the prevailing level of bias in the accelerometer signal. Instead, it depends on the values from the accelerometer signal at the specific temporal samples when each spatial sample was established. All of the information about vehicle vibration between the distance samples is lost in the conversion to spatial coordinates. Together, the temporal gap in the spatial accelerometer signal and the large numerical value of time step used in the integration reduce the effectiveness of high-pass filtering.

Table 5.10 provides roughness and cross correlation results for profiles processed using the spatial algorithm with pre-integration high-pass filtering. High-pass filtering before integration consistently reduced the peak roughness values in runs with a stop. However, the level of reduction is somewhat arbitrary, since the artificial change in elevation at the location

where the host vehicle stops depends primarily on the average of two accelerometer samples surrounding the stop. The influence of these accelerometer readings grows very large, because they are multiplied by a large time step at each stage of integration.

Table 5.10 Results for the spatial algorithm with pre-integration high-pass filtering

Run Designation	Peak Roughness (m/km)	Average Roughness Error (Percent)	Cross Correlation
S&G, 1.1-sec stop, 0.17 g	24.6	96.8	< 0.2
S&G, 1.1-sec stop, 0.20 g	75.9	295.1	< 0.2
S&G, 2.1-sec stop, 0.33 g	58.3	231.3	< 0.2
S&G, 5.8-sec stop, 0.17 g	253.1	1022.7	< 0.2
S&G, 5.7-sec stop, 0.20 g	432.9	1788.8	< 0.2
S&G, 5.8-sec stop, 0.20 g	155.9	616.4	< 0.2
S&G, 10.7-sec stop, 0.20 g	1186.7	4946.6	< 0.2
NS, 72-11 km/hr, 0.20 g	2.7	8.1	0.713
Brk, 71-30 km/hr, 0.19 g	2.6	3.3	0.891
Brk, 72-29 km/hr, 0.39 g	2.3	1.4	0.789
Brk, 49-22 km/hr, 0.16 g	2.3	0.5	0.871
Brk, 49-23 km/hr, 0.18 g	2.4	0.5	0.889
Brk, 49-23 km/hr, 0.18 g	2.8	1.8	0.900
Brk, 49-20 km/hr, 0.25 g	2.4	1.7	0.902
Brk, 49-34 km/hr, 0.84 g	3.6	13.2	0.781
16 km/hr	2.4	-1.0	0.927
5 km/hr	2.8	14.5	0.746

Reference peak roughness value: 2.4 m/km. Adequate cross correlation > 0.92.

Spatial high-pass filtering reduced errors in peak roughness in the most severe cases among the braking runs, but increased peak roughness in others. This algorithm failed to produce cross correlation above the 0.92 threshold value in any of the test runs.

Tables 5.9 and 5.10 demonstrate that spatial high-pass filtering of the accelerometer signal, applied before or after integration, does not offer adequate performance. Large errors in roughness and very low cross correlation are shown for runs with a stop. Additional provisions are needed to address the artificial roughness at the stop caused by the large integration time step.

5.10 Timer Distortion and Height-Sensor Reflection

Walker and Becker [15] recommended timer distortion during low-speed profiler operation as a means to minimize “wide swings” that appear in computed profile during stop-

and-go operation. Timer distortion artificially adjusts the elapsed time between spatial samples in areas where the host vehicle travels at low speed. This approach offers a way to address the main weakness in the spatial high-pass filtering algorithm, because it reduces the potentially large changes in elevation that occur over distance increments that are associated with a large time step. This section describes the application of a version of Walker's approach to the spatial high-pass filtering algorithm shown in Figure 5.14.

This procedure replaces time interval associated with consecutive samples used for numerical integration (as shown in Equations (5.5) and (5.6)) with an adjusted value based on travel speed. At high host-vehicle speed, no adjustment is applied, and this procedure is equivalent to the pre-integration spatial high-pass filtering algorithm. At low speed, this algorithm imposes an artificial limit on the time step associated with each distance increment. This suppresses the magnitude of the changes in floating reference height after double integration.

The time interval used for numerical integration is unaffected at high speed and limited to a maximum value of Δt_0 at low speed:

$$\Delta t_0 = \frac{\Delta x}{v_0} \quad (5.7)$$

Where Δx is the distance increment of the spatial profile and v_0 is a low-speed threshold. The adjusted time interval (Δt_{Adj}) is calculated based on the actual time interval (Δt) and the limit value as follows:

$$\Delta t_{Adj} = \Delta t_0 \left(1 + \left(\frac{\Delta t}{\Delta t_0} \right) - \left(1 + \left(\frac{\Delta t}{\Delta t_0} \right)^\beta \right)^{1/\beta} \right) \quad (5.8)$$

This function returns an adjusted value of time step close to the actual value at high host-vehicle speed (i.e., low Δt). At very low speed, when the actual time interval is much larger, this function returns the limit value. The coefficient β determines the sharpness of the transition between the unaltered and limited ranges.

This implementation uses a value for β of 25 and Δt_0 of 0.0014205 seconds. The time interval threshold corresponds to a distance interval of 0.00508 m and a speed of 3.576 m/s. Figure 5.15 shows the ratio of adjusted to actual values of time interval as a function of speed.

Note that the ratio shown in Figure 5.15 approaches 1 as speed increases. At speeds of 16 km/hr and above, the actual and adjusted time interval values agree to within 0.004 percent.

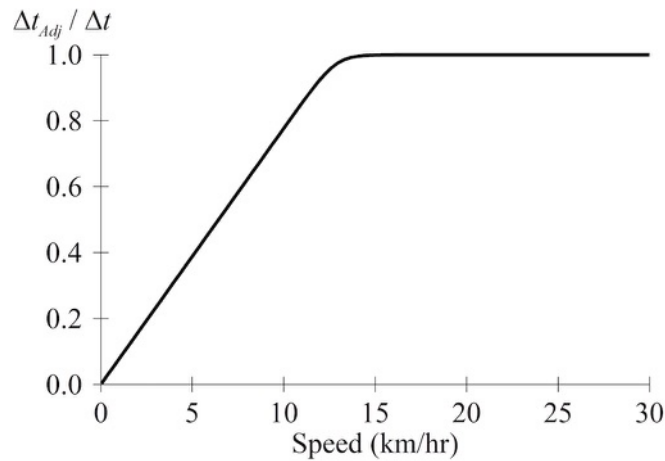


Figure 5.15 Timer adjustment versus speed

Table 5.11 provides roughness and cross correlation results for test runs with braking and stops using the spatial algorithm with high-pass filtering and timer distortion. (The adjusted time interval is virtually equal to the actual time interval in the braking runs, and their results are the same as in Table 5.10.) Timer distortion greatly reduces the peak roughness values for the runs with stops by removing the large artificial change in height of the profiler reference point. For example, in the run with the 10.7-second-long stop, the time difference between the readings surrounding the stop was adjusted from 10.7643 to 0.0014205 seconds. This, and the change to the integrated accelerometer signal leading to the stop, reduced the magnitude of the step change in height of the profiler reference point from 2.748 m to 0.009 mm.

Table 5.11 Results for stops and the near stop, timer distortion

Run Designation	Peak Roughness (m/km)	Average Roughness Error (Percent)	Cross Correlation
S&G, 1.1-sec stop, 0.17 g	8.7	31.4	0.327
S&G, 1.1-sec stop, 0.20 g	12.9	45.8	0.230
S&G, 2.1-sec stop, 0.33 g	18.0	66.3	< 0.2
S&G, 5.8-sec stop, 0.17 g	9.7	36.5	0.263
S&G, 5.7-sec stop, 0.20 g	13.0	46.6	< 0.2
S&G, 5.8-sec stop, 0.20 g	13.8	54.0	0.208
S&G, 10.7-sec stop, 0.20 g	13.7	52.4	0.236
NS, 72-11 km/hr, 0.20 g	3.5	10.9	0.609

Reference peak roughness value: 2.4 m/km. Adequate cross correlation > 0.92.

Timer distortion greatly reduced peak roughness on runs with a stop relative to the spatial algorithms without timer distortion. However, the peak roughness values remain more than three times the reference values in all of those runs, and the cross correlation values were all well below the threshold value of 0.92. Further provisions are needed to suppress artificial localized roughness at stops.

The remaining artificial localized roughness in the runs with a stop is caused by a step change between the height-sensor readings surrounding the stop. Figure 5.16 shows the floating-reference-height signal and height-sensor signal for the run with a 10.7-second-long stop. The stop occurred 216.5 m from the start of the test section. Timer distortion removed the large change in the floating-reference-height signal at the stop, and attenuated the fluctuations in the signal in the region near the stop (214.5 m to 219 m).

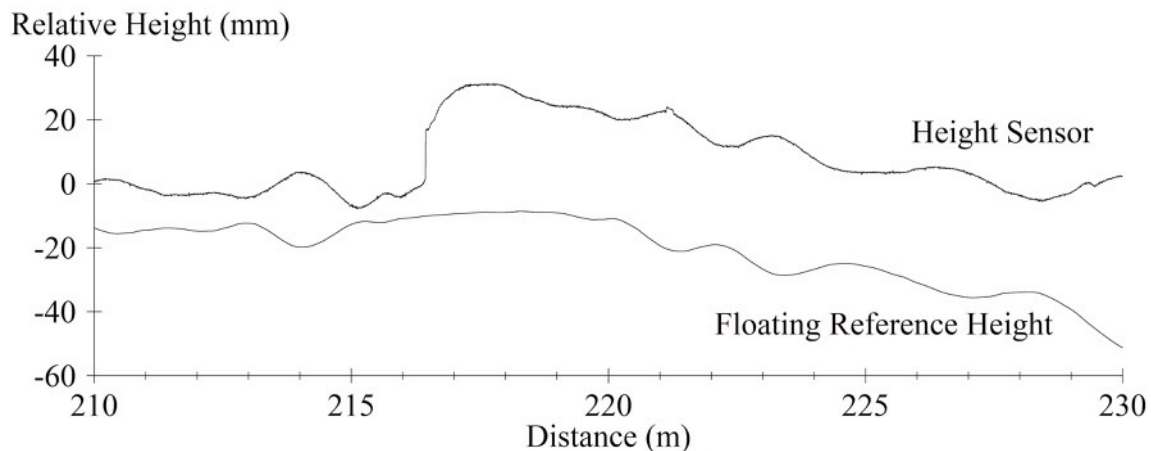


Figure 5.16 Height-sensor and floating-reference-height signals, timer distortion

As shown in Figure 5.16, the height sensor detected a 15-mm change in road height relative to the profiler during the stop. This indicates a net downward motion of the profiler over the 10.7 seconds that elapsed between distance samples, due primarily to settling of pitch motion caused by deceleration leading to the stop. The floating-reference-height signal, which was attenuated at the stop by timer distortion, does not properly detect this aspect of vehicle motion or the dynamics detected by the height sensor in the area surrounding the stop. Similarly, timer distortion caused the peak roughness to increase in the run with a near stop due to a lack of cancellation of content from the height sensor.

Walker and Becker [15] passed the computed profile through a “slew” to mitigate the cancellation error caused by attenuating the floating-reference-height signal. The slew limited the rate of change in elevation of the profile near the stop. The method applied here superimposes fluctuations onto the floating-reference-height signal that are equal and opposite to those of the height-sensor signal in the attenuated area.

This procedure is based on the assumption that the floating-reference-height signal is not valid in the area near the stop, and that removing the roughness from the profile in this area is preferable to introducing artificial roughness. In this procedure, Equation (5.9) replaces the second stage of integration of the accelerometer signal:

$$r_{zp}(x_k) = r_{zp}(x_{k-1}) + \Delta t_{Adj}(x_k)(v_{zp}(x_k) + v_{zp}(x_{k-1})) - \left(1 - \left(\frac{\Delta t_{Adj}(x_k)}{\Delta t(x_k)}\right)^2\right)(h(x_k) - h(x_{k-1})) \quad (5.9)$$

The second term after the equal sign represents integration using the adjusted time interval. Since this algorithm also applies the adjusted time interval in the first stage of integration, fluctuations in the floating-reference-height signal are reduced in proportion to the square of $\Delta t_{Adj}/\Delta t$. The third term after the equal sign imposes the opposite of changes that appear in the height-sensor signal. This term is scaled in proportion to attenuation imposed on the accelerometer signal.

Figure 5.17 shows the height-sensor signal and the adjusted floating-reference-height signal produced by this process for the run with the 10.7-second-long stop. In the region near the stop (214.5 m to 219 m) the adjusted time interval is below the actual time interval, and the floating-reference-height signal includes reflected content from the height sensor. In this region

the content cancels and the profile is essentially flat. However, a rapid change in slope appears in the profile at the end of the affected region, which registers as roughness.

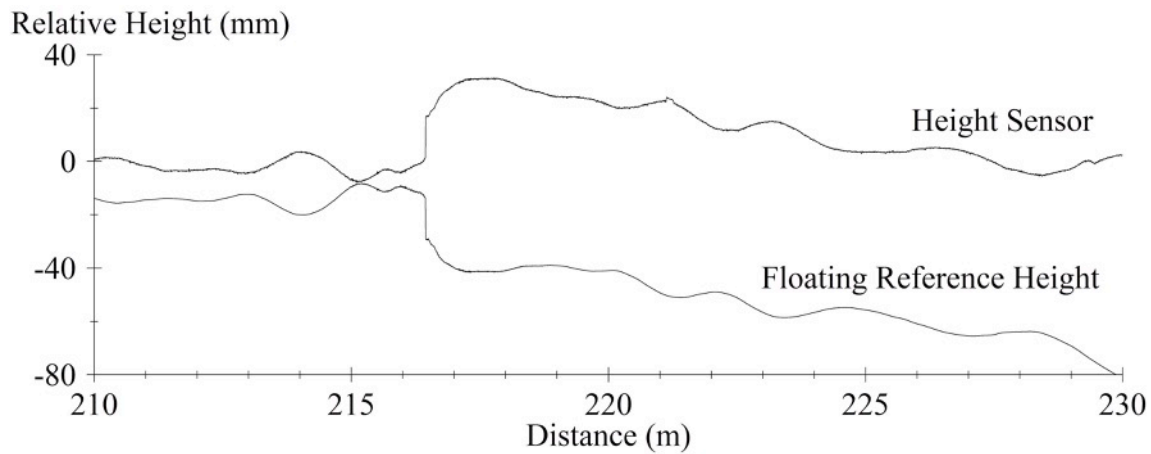


Figure 5.17 Height-sensor and floating-reference-height signals, timer distortion and height-sensor reflection

Table 5.12 lists roughness and cross correlation results for test runs at low speed, with stops, and with a near stop using the spatial algorithm with high-pass filtering, timer distortion, and height-sensor reflection. Together, these provisions reduced the peak roughness values to a small fraction of those produced by the basic spatial algorithm. Cross correlation values are greatly improved, yet well below the 0.92 threshold value.

Table 5.12 Results for stops and the near stop, timer distortion and height-sensor reflection

Run Designation	Peak Roughness (m/km)	Average Roughness Error (Percent)	Cross Correlation
S&G, 1.1-sec stop, 0.17 g	4.2	7.4	0.693
S&G, 1.1-sec stop, 0.20 g	4.3	7.5	0.702
S&G, 2.1-sec stop, 0.33 g	4.6	11.7	0.587
S&G, 5.8-sec stop, 0.17 g	4.4	12.3	0.616
S&G, 5.7-sec stop, 0.20 g	3.9	6.2	0.696
S&G, 5.8-sec stop, 0.20 g	4.8	13.8	0.652
S&G, 10.7-sec stop, 0.20 g	4.7	11.8	0.678
NS, 72-11 km/hr, 0.20 g	2.3	3.4	0.756
16 km/hr	2.4	-1.0	0.927
5 km/hr	0.3	-86.6	< 0.2

Reference peak roughness value: 2.4 m/km. Adequate cross correlation > 0.92.

The provisions used to suppress errors at the stop removed more than 85 percent of the valid roughness in the test run at 5 km/hr. Note that adjustment of the speed threshold to capture

more valid profile content for constant-speed runs at low speed reduced error suppression at stops.

Overall, spatial high-pass filtering combined with timer distortion and height-sensor reflection greatly reduced the artificial localized roughness registered at stops. However, this reduction was achieved at the cost of valid profile measurement at very low speed. In particular, the profile measured at 5 km/hr was completely invalid. Further, runs with a stop correlated poorly to the reference runs, because of missing profile content in the vicinity of the stop.

5.11 Summary

This chapter presented algorithms for suppressing artificial localized roughness at locations where an inertial profiler host vehicle brakes, stops, or operates at low speed. The chapter examined each algorithm using only the sensors that appear in a typical commercial profiler.

As a baseline, the chapter presented results for basic profile calculation algorithms that use methods found in common practice. This included a basic temporal algorithm and a basic spatial algorithm. Both of the basic algorithms demonstrated errors in profile and roughness measurement at low speed, during braking, and at stops. This included very large errors in roughness for runs with a stop, including extremely high values of peak roughness in the location of the stop.

Application of high-pass filters to the accelerometer signal before each stage of integration (i.e., “temporal high-pass filtering, pre-integration”) demonstrated adequate performance for runs at low speed and a majority of runs with braking. This algorithm greatly reduced the error in roughness measurement for runs with stops, but large errors in roughness remained. The stages of this algorithm that occur before decimation to the distance domain do not run in real time, and storage of the temporal profile and distance encoder output in the time domain are required.

Modification of the temporal high-pass filter to use an adaptive cut-off frequency reduced errors in roughness measurement at stops further. However, the performance for runs with stops was not adequate, and the improvement came at the cost of errors in measurement of profile at very low speed. This filter enforces a limit of cut-off wavelength at high speed and a limit of cut-

off frequency at low speed. This adaptation allows for application of the filter in the time and distance domain. Application of a backward-running filter after digitizing the profile to a constant distance interval cancelled the phase shift associated with the forward-running (temporal) filter applied to the sensor signals. Applying the backward pass in the distance domain avoids the burden of storing any time-domain signals.

Pre-integration high-pass filtering was not as effective in the spatial profile calculation algorithm. Digitizing the accelerometer signal to a constant distance step before filtering and integration removes an opportunity for effective removal of drift in the integrated signals. Further, it causes the integrator to use a very large time step for the distance interval that includes the stop.

A specialized version of an algorithm recommended by Walker and Becker [15] is proposed here that includes pre-integration high-pass filtering, temporal distortion at very low speed, and height-sensor reflection at very low speed. Together, these provisions remove profile content at very low speed without introducing a large step change in elevation or slope, and rapid changes in curvature are minimized. As a result, errors in roughness measured at stops are greatly reduced. However, the performance for runs with stops was not adequate, and the improvement came at the cost of errors in measurement of profile at very low speed.

These algorithms establish performance limits that can be attained without adding sensors to the nominal commercial profiler design. The adaptive pre-integration high-pass filtering algorithm is recommended for profilers with temporal profile calculation architecture. The pre-integration high-pass filtering algorithm with temporal distortion and height-sensor reflection is recommended for profilers with spatial profile calculation architecture. Neither algorithm offers adequate performance during braking or at stops, nor are they capable of roughness measurement at speeds below 16 km/hr. However, they both reduce errors in roughness measurement from a factor of 10 and above to 20 percent and below.

These algorithms are only recommended for error mitigation when the resources are not available for adding sensors. Chapter 6 demonstrates a profiler design that achieves adequate performance using additional sensors.

Chapter 6

Sensor Augmentation

This chapter describes the use of additional sensors to improve inertial profiler performance at very low speed, during braking, and in stop-and-go operation. Like a strap-down inertial navigation system, the augmented profiler uses measurements from body-fixed accelerometers and rate gyroscopes in three dimensions to calculate position of the profiler reference point. In this application, only the change in vertical position of the profiler reference point is of interest. However, measurements are needed in three dimensions to resolve body-fixed acceleration into a truly vertical direction (i.e., aligned with gravity).

A multi-rate extended Kalman filter with a Rauch-Tung-Striebel (RTS) smoother eliminates drift in the integrated acceleration and rate signals using GPS measurements of host-vehicle height, vertical velocity, pitch, and roll. In the Kalman filter, the core of the process includes kinematic resolution of acceleration into the vertical direction, as well as integration of acceleration and rate of rotation to obtain position and orientation. Measurements of acceleration and rate of rotation drive the system, and determine its high-frequency output. The GPS sensors provide an absolute reference, and establish the low-frequency output of the system and impose a limit on integrator drift.

This application required a multi-rate implementation, because the frequency range of interest exceeded the waveband of the outputs from the GPS. Further, the inertial sensors provided inputs at 16,000 Hz, whereas the GPS provided observations at 20 Hz. Additionally, this application required a Kalman smoother to help eliminate drift in the floating-reference-height signal that occurred during braking, particularly near stops.

The Kalman smoother produced better reproduction of the reference profile measurement during braking and at stops than the error suppression algorithms proposed in Chapter 5. Unlike the error suppression algorithms, the smoother demonstrated improvement in profile measurement at low speed. Adaptation of the Kalman filtering stage to use the height sensor in place of the GPS outputs at speeds below 0.16 km/hr further reduced profile measurement error

at stops. Additional implementations of the Kalman smoother that do not depend on GPS measurements are demonstrated for cases in which GPS readings are unavailable.

The chapter presents a review of Kalman filtering, the RTS smoother, and relevant kinematics of rotating and accelerating reference frames. The chapter also presents the system equations used in this application of the Kalman filter and smoother, and estimates of system and measurement noise. Five implementations of the Kalman filter and smoother are demonstrated. The performance of each is presented for test runs at low speed, with braking, and with stops. Results are quantified using cross correlation to profile measured in a reference test run and comparison of IRI values.

6.1 The Kalman Filter

The Kalman filter is an optimal state estimation algorithm, which was originally proposed for prediction of random signals and separation of random signals from noise [94-96]. The algorithm combines discrete-time models of system and sensor dynamics with statistical descriptions of system noise and measurement errors to estimate the system state [97]. In this manner, the Kalman filter infers values of state variables that are not measured directly or are measured imperfectly. State estimates are optimal in that the Kalman filter minimizes the estimated error covariance, so long as the system is linear with additive Gaussian noise in both the system dynamics and the measurement [98,99]. The Kalman filter is recursive, in that it updates estimates of the state using a weighted average of the previous state estimate and new values based on the latest measurement data [100]. The relative efficiency of the recursive approach has led to broad application in numerous fields, including as terrestrial navigation [98,101].

Welch and Bishop [98] provide an introductory description of the Kalman filter and the extended Kalman filter. Portions of those descriptions are summarized here with changes in notation.

6.1.1 Linear Kalman Filter

The Kalman filter estimates the state recursively for a linear stochastic system in state space form:

$$\begin{aligned}x_k &= A_{k-1}x_{k-1} + B_{k-1}u_{k-1} + w_{k-1} \\y_k &= H_k x_k + v_k\end{aligned}\tag{6.1}$$

Where the subscript k represents the time step. If the system has ns state variables, is monitored by nm measurements, and is driven by ni inputs, then: $x_k \in \mathfrak{R}^{ns \times 1}$ is the state, $u_{k-1} \in \mathfrak{R}^{ni \times 1}$ is the input, and $y_k \in \mathfrak{R}^{nm \times 1}$ is the output (i.e., measurements). The system equation includes a state transition matrix $A_{k-1} \in \mathfrak{R}^{ns \times ns}$ and an input matrix $B_{k-1} \in \mathfrak{R}^{ns \times ni}$. The measurement equation includes an observation matrix $H_k \in \mathfrak{R}^{ns \times nm}$, which relates the state to the available measurements.

The system includes independent zero-mean, Gaussian process noise $w_{k-1} \in \mathfrak{R}^{ns \times 1}$ and independent zero-mean, Gaussian measurement noise $v_k \in \mathfrak{R}^{nm \times 1}$:

$$p(w) \sim \mathcal{N}(0, \sigma_w^2)\tag{6.2}$$

$$p(v) \sim \mathcal{N}(0, \sigma_v^2)\tag{6.3}$$

The Kalman filtering equations do not include the noise signals directly. Rather, they incorporate noise using the process noise covariance matrix $Q_{k-1} \in \mathfrak{R}^{ns \times ns}$ and the measurement noise covariance matrix $R_k \in \mathfrak{R}^{nm \times nm}$:

$$\begin{aligned}Q_{k-1} &= \mathcal{E}\{w_{k-1}w_{k-1}^T\} \\R_k &= \mathcal{E}\{v_k v_k^T\}\end{aligned}\tag{6.4}$$

At each time step the Kalman filter performs a *time update* and a *measurement update*. The time update makes the best possible estimate of the state at time step k , given the sequence of inputs and measurements up to time step $k-1$ and the known system dynamics:

$$\begin{aligned}\hat{x}_{k|k-1} &= A_{k-1}\hat{x}_{k-1|k-1} + B_{k-1}u_{k-1} \\P_{k|k-1} &= A_{k-1}P_{k-1|k-1}A_{k-1}^T + Q_{k-1}\end{aligned}\tag{6.5}$$

Where $\hat{x}_{k|k-1}$ is the *a priori* (i.e., predicted) estimate of x_k and $P_{k|k-1} \in \mathfrak{R}^{ns \times ns}$ is the *a priori* estimate of the error covariance at time step k :

$$P_{k|k-1} = \varepsilon\{(x_k - \hat{x}_{k|k-1})(x_k - \hat{x}_{k|k-1})^T\} \quad (6.6)$$

The measurement update refines the estimates of the state and the error covariance at time step k using the measurements at time step k and the predictions produced in the time update:

$$\begin{aligned} K_k &= P_{k|k-1} H_k^T (H_k P_{k|k-1} H_k^T + R_k)^{-1} \\ \hat{x}_{k|k} &= \hat{x}_{k|k-1} + K_k (y_k - H_k \hat{x}_{k|k-1}) \\ P_{k|k} &= (I - K_k H_k) P_{k|k-1} \end{aligned} \quad (6.7)$$

Where $\hat{x}_{k|k}$ and $P_{k|k}$ are the *a posteriori* (i.e., corrected) estimates of x_k and P_k , respectively. The matrix $K_k \in \mathfrak{R}^{ns \times nm}$ is the Kalman gain, and is often referred to as the blending factor. The Kalman gain determines the relative influence of measurements and system dynamics in the refined state estimate. The Kalman gain is optimal, because it minimizes the mean square state estimation error by minimizing the trace of the error covariance matrix.

The filter typically runs from $k=1$ to N , where N is the number of time steps. At the first time step, initial estimates of the state vector \hat{x}_{00} and error covariance matrix P_{00} take the place of the previous measurement update. Note that, for the linear Kalman filter, the subscripts on A , B , w , H , v , Q , and R only appear to accommodate time-variant systems.

6.1.2 Extended Kalman Filter

The extended Kalman filter estimates the state for a non-linear discrete time process:

$$\begin{aligned} x_k &= f(x_{k-1}, u_{k-1}, w_{k-1}) \\ y_k &= h(x_k, v_k) \end{aligned} \quad (6.8)$$

Where f is a set of nn non-linear functions in the state equation, and h is a set of nm non-linear functions in the measurement equation. Like the linear Kalman filter, the extended Kalman filter includes a time update and a measurement update.

The time update estimates the state using non-linear system equations:

$$\hat{x}_{k|k-1} = f(\hat{x}_{k-1|k-1}, u_{k-1}, 0) \quad (6.9)$$

However, the estimate of the state error covariance depends on linearized versions of the state transition matrix A and process noise matrix W :

$$P_{k|k-1} = A_{k-1}P_{k|k-1}A_{k-1}^T + W_{k-1}Q_{k-1}W_{k-1}^T \quad (6.10)$$

Where $A_{k-1} \in \mathfrak{R}^{ns \times ns}$ is a Jacobian matrix of partial derivatives of f with respect to the system state:

$$A_{k-1}[i, j] = \frac{\partial f[i]}{\partial x[j]}(\hat{x}_{k-1|k-1}, u_{k-1}, 0) \quad (6.11)$$

Note that a one-to-one mapping may not exist between process noise terms and state variables. As such, the process noise covariance matrix, $Q_{k-1} \in \mathfrak{R}^{nm \times nm}$, corresponds to nm noise terms, and $W_{k-1} \in \mathfrak{R}^{ns \times nm}$ is a Jacobian matrix of partial derivatives of f with respect to process noise:

$$W_{k-1}[i, j] = \frac{\partial f[i]}{\partial w[j]}(\hat{x}_{k-1|k-1}, u_{k-1}, w_{k-1}) \quad (6.12)$$

The measurement update incorporates the non-linear measurement equation, but the Kalman matrix and state error covariance updates depend on linearization of the measurement equation:

$$\begin{aligned} K_k &= P_{k|k-1}H_k^T (H_k P_{k|k-1}H_k^T + V_k R_k V_k^T)^{-1} \\ \hat{x}_{k|k} &= \hat{x}_{k|k-1} + K_k (y_k - h(\hat{x}_{k|k-1}, 0)) \\ P_{k|k} &= (I - K_k H_k) P_{k|k-1} \end{aligned} \quad (6.13)$$

Where:

$$H_k[i, j] = \frac{\partial h[i]}{\partial x[j]}(\hat{x}_{k|k-1}, 0) \quad (6.14)$$

$$V_k[i, j] = \frac{\partial h[i]}{\partial v[j]}(\hat{x}_{k|k-1}, v_k) \quad (6.15)$$

Each element in the matrices A , W , H and V are linearized using the first term in the Taylor expansion. Since they are evaluated using the most recent input and the most recent available estimates of the state, they change with time. With this formulation, the filter is

linearized about the estimated system trajectory [101]. This has three consequences relative to the standard Kalman filter. First, the covariance estimates change with changes in system dynamics, even with constant estimates of system and measurement noise. As such, the Kalman gain and state error covariance matrix must be evaluated at every time step [99]. Second, convergence of the filter is not guaranteed. Third, the extended Kalman filter is not optimal, because propagating Gaussian random variables through the non-linear equations does not always produce Gaussian outputs. This violates the assumptions in the minimization of state error covariance [98].

6.1.3 Multi-Rate Kalman Filter

The Kalman filtering application described in this chapter applies the process model (i.e., the dynamical equations) at a higher rate than the updates prompted by observations. This is because the sensors detect system inputs (e.g., acceleration, rate of rotation) at a higher rate than measurements used to adjust the state estimates (e.g., GPS position, velocity, and orientation). As such, the measurement update is only applied when an observation is available. At time steps with no corresponding observation, the a posteriori estimates of x_k and P_k are equal to the a priori estimates:

$$\begin{aligned}\hat{x}_{k|k} &= \hat{x}_{k|k-1} \\ P_{k|k} &= P_{k|k-1}\end{aligned}\tag{6.16}$$

Jones [102] and Cipra and Romero [103] established this procedure as optimal for linear systems. Smyth and Wu [104] demonstrated the efficacy of this approach for multi-rate Kalman filters that estimate position based on integrated acceleration.

6.1.4 Kalman Smoother

The Kalman filter estimates current and future values of state variables based only on existing measurements, whereas a smoother applies the available measurements to past values [105]. That is, the smoother improves the state estimates at a given time using measurements that occur afterward [104,106]. The improvement comes at the cost of reduced computational efficiency. Further, the possibility of obtaining state estimates in real time is lost.

The RTS smoother “starts with the filtered estimate at the last point and calculates backward point by point determining the smoothed estimate as a linear combination of the

filtered estimate at that point and the smoothed estimate at the previous point.” [105] This procedure requires the application of a Kalman filter over a specified time interval; followed by a backward pass to improve the state estimates based on statistics influenced by all of the available measurements. Meditch [107] describes this as *fixed-interval smoothing*. (See Brown and Huang [101] or Aslan [108] for straightforward descriptions of the numerical procedure.)

For an interval including N time steps, the smoothing stage runs backward from time step $N-1$ to 1. The smoothed state estimates, $\hat{x}_{k|N}$, are computed recursively as follows:

$$\begin{aligned}\hat{x}_{k|N} &= \hat{x}_{k|k} + L_k(\hat{x}_{k+1|N} - \hat{x}_{k+1|k}) \\ L_k &= P_{k|k} A_k^T P_{k+1|k}^{-1}\end{aligned}\tag{6.17}$$

For a system with non-linear dynamics, A_k is a Jacobian matrix of partial derivatives of the state equations with respect to the system state:

$$A_k[i, j] = \frac{\partial f[i]}{\partial x[j]}(\hat{x}_{k|k}, u_k, 0)\tag{6.18}$$

For the initial step in the backward pass ($k=N-1$), the smoothed versions of the state estimate, $\hat{x}_{N|N}$, and the state error covariance matrix, $P_{N|N}$, are obtained from the final step in the forward pass.

Note that the notation used for estimated state corresponds to the distinction between the outputs of the Kalman filter and the Kalman smoother. In the Kalman filter, $\hat{x}_{k+1|k}$ represents an estimate of the state at time step $k+1$, given the information available up to time step k . In the RTS Kalman smoother, $\hat{x}_{k+1|N}$ represents an estimate of the state at time step $k+1$, given the information available up to time step N (i.e., over the entire testing interval).

The smoother equations above require storage of the inputs; the a priori states and state error covariance matrix; and the a posteriori states and state error covariance matrix. Some of the storage burden is eliminated by redundantly calculating a priori variables using stored values of a posteriori variables and inputs:

$$\hat{x}_{k+1|k} = f(\hat{x}_{k|k}, u_k, 0)\tag{6.19}$$

$$P_{k+1|k} = A_k P_{k|k} A_k^T + W_k Q_k W_k^T\tag{6.20}$$

$$W_k[i, j] = \frac{\partial f[i]}{\partial w[j]}(\hat{x}_{k|k}, u_k, w_k) \quad (6.21)$$

The state error covariance for the smoothed state estimates are calculated as follows:

$$P_{k|N} = P_{k|k} + L_k(P_{k+1|N} - P_{k+1|k})L_k^T \quad (6.22)$$

Calculation of the smoothed state estimates does not require knowledge of $P_{k|N}$.

6.2 Coordinate Reference Frames

Each rate gyroscope and accelerometer provides measurements relative to the inertial reference and resolved along their sensitive axes. This section introduces coordinate reference frames in support of discussions that follow of measurements and system dynamics. The axis systems defined here are dextral and orthogonal.

Inertial Frame (i): A non-rotating, non-accelerating reference frame with respect to distant stars with its origin fixed in the center of the Earth. Its Z-axis is aligned with the Earth's spin axis running northward.

Earth-Fixed Frame (e): A reference frame fixed in the Earth. Its origin and its Z-axis are coincident with the Inertial Frame. The Earth frame X-axis passes through the intersection of the plane of the Greenwich meridian with the equatorial plane.

Navigation Frame (n): A local geographic frame with its origin fixed at a reference point on the vehicle. The Z-axis is aligned with the gravity vector running upward. The X-axis and Y-axis are parallel to the ground plane, running eastward and northward, respectively.

Body Frame (b): A reference frame fixed in the sprung mass of a vehicle with its origin fixed at a reference point on the vehicle. The X-axis is parallel to the vehicle plane of symmetry running forward, and is approximately parallel to the road surface when the vehicle is at rest. The Y-axis is perpendicular to the vehicle plane of symmetry running leftward. The Z-axis runs upward, and is approximately perpendicular to the road surface.

Wander Frame (w): A reference frame whose Z-axis coincides with the navigation frame, and whose origin coincides with the body frame and the navigation frame. The X-axis

and Y-axis are parallel to the ground plane. The X-axis is aligned with the vertical projection of the body X-axis into the ground plane.

The inertial frame and Earth-fixed frame are adopted from terrestrial navigation. The body frame and wander frame correspond to the vehicle and intermediate axis systems as defined in SAE J670 [91], respectively. The navigation frame is similar to the east-north-up navigation frame, except the horizontal plane is normal to gravity, rather than referenced to the Earth ellipsoid. A *reference point* is established for each of the left and right profilers where the sensitive axes of their vertical and longitudinal accelerometers intersect. For each profiler, the reference point is used as an origin for the navigation, wander, and body frames.

Orientation of one coordinate frame relative to another is parameterized in this research using Euler angles for successive body-axis rotations. This is defined by yaw rotation (ψ) about the reference Z-axis, a pitch rotation (θ) about the reoriented Y-axis, and a roll rotation (ϕ) about the reoriented X-axis. A vector in the rotated frame, b , can be resolved to the un-rotated frame, n , as follows:

$$\vec{a}^n = \begin{bmatrix} c_\psi c_\theta & c_\psi s_\theta s_\phi - s_\psi c_\phi & c_\psi s_\theta c_\phi + s_\psi s_\phi \\ s_\psi c_\theta & s_\psi s_\theta s_\phi + c_\psi c_\phi & s_\psi s_\theta c_\phi - c_\psi s_\phi \\ -s_\theta & c_\theta s_\phi & c_\theta c_\phi \end{bmatrix} \vec{a}^b = C^{nb} \vec{a}^b \quad (6.23)$$

Where s and c represent sine and cosine functions, respectively, of the angle that appears in the subscript. C^{nb} is the direction cosine matrix. Resolving a matrix in the reference system to the rotated system requires the transpose of C^{nb} :

$$\vec{a}^b = (C^{nb})^T \vec{a}^n = C^{bn} \vec{a}^n \quad (6.24)$$

Formulation of the kinematic measurement equations and system dynamic equations required elements of the direction cosine matrix and their time derivatives. The time rate of change is caused by an instantaneous rate of rotation of frame b relative to frame n :

$$\vec{\omega}_{b/n}^b = \omega_x \hat{i}^b + \omega_y \hat{j}^b + \omega_z \hat{k}^b \quad (6.25)$$

Where the subscript on the term to the left of the equal sign indicates rotation of the first frame relative to the second, and the vector is resolved into the frame that appears in the superscript.

The rate of change of the direction cosine matrix is given by:

$$\dot{C}^{nb} = C^{nb} \Omega_{b/n}^b = C^{nb} \begin{bmatrix} 0 & -\omega_z^b & \omega_y^b \\ \omega_z^b & 0 & -\omega_x^b \\ -\omega_y^b & \omega_x^b & 0 \end{bmatrix} \quad (6.26)$$

Where $\Omega_{b/n}^b$ is the skew symmetric matrix that corresponds to the angular rate vector $\vec{\omega}_{b/n}^b$ [109]. This allows the expression of the rate of change of a direction cosine matrix element as a function of direction cosine matrix elements and angular rates measured in the rotated frame, and derivation of the rate of change of the pitch and roll angle:

$$\dot{\theta} = c_\phi \omega_y^b - s_\phi \omega_z^b \quad (6.27)$$

$$\dot{\phi} = \omega_x^b + s_\theta (s_\phi \omega_y^b + c_\phi \omega_z^b) / c_\theta \quad (6.28)$$

6.3 System Equations

This section presents the system dynamics used by the Kalman filter. Prior work in sensor fusion for human and vehicle motion tracking guided the formulation of the process model and the sensor error modeling [110,111]. The purpose of the process model is estimation of changes in vertical position of the profiler reference point, r_{zp}^n , using inputs from body-mounted accelerometers and rate gyroscopes.

The state equations follow the same signal flow as a typical strap-down navigation system, as shown in Figure 6.1. Three-dimensional measurements of specific force and rate of rotation by body-fixed sensors provide the means to derive vertical acceleration of the profiler reference point in the navigation frame. In turn, vertical acceleration is integrated twice to obtain relative vertical position. As described below, the measurement model compares independent measurements of height, vertical velocity, pitch inclination, and roll inclination to estimates from the state equations.

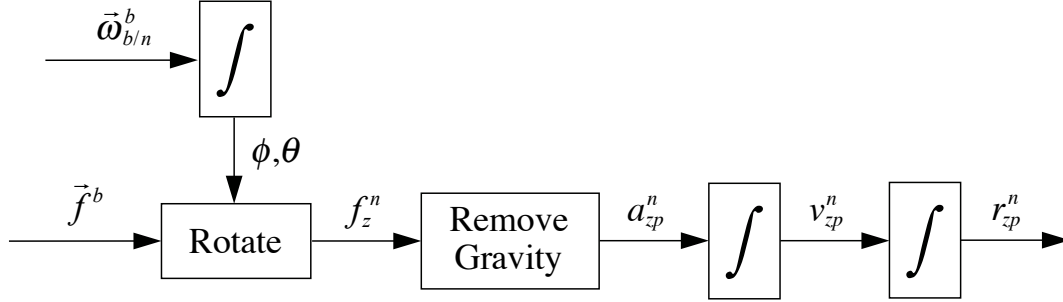


Figure 6.1 Process model signal flow, after Hol [110]

6.3.1 Angular Rate

The angular rate vector, $\vec{\omega}$, of the body frame relative to the inertial frame can be expressed using the following components:

$$\vec{\omega}_{b/li}^b = C^{bn}(\vec{\omega}_{eli}^n + \vec{\omega}_{n/le}^n) + \vec{\omega}_{w/n}^b + \vec{\omega}_{b/w}^b \quad (6.29)$$

The rotation rate of the Earth relative to the inertial frame, $\vec{\omega}_{eli}^n$, has a magnitude of approximately 7.3×10^{-5} rad/s. The rate of rotation of the navigation frame relative to the Earth, which is the magnitude of $\vec{\omega}_{n/le}^n$, depends on the motion of the vehicle reference point with respect to the Earth. This is referred to as the *transport rate* [112]. For surface travel along a meridian at speeds below 160 km/hr, the magnitude of the transport rate is less than 10 percent of the Earth rotation rate. For surface travel at speeds below 160 km/hr along a circle of latitude below 82 degrees, the magnitude of the transport rate is below the Earth rotation rate.

In this formulation, the transport rate and the Earth's rotation rate are considered components of the time-varying bias, and output of the gyroscopes are interpreted as angular rate of the body-fixed frame relative to navigation frame.

The gyroscopes produce a measurement of each component of angular rate, u_ω , along their sensitive axis resolved into the body-fixed frame:

$$u_\omega = \omega_{b/in}^b - \delta_\omega - e_\omega \quad (6.30)$$

Where $\omega_{b/in}^b$ is considered the true angular rate, δ_ω accounts for slowly time-varying bias, and each component of e_ω accounts for additive Gaussian white noise measurement error.

6.3.2 Linear Acceleration

Acceleration of the profiler reference point at the navigation frame origin \vec{a}_p as the Earth rotates relative to the inertial frame can be expressed as the sum of linear acceleration of the navigation frame relative to the Earth $\vec{a}_{n/e}$, Coriolis acceleration, and centrifugal acceleration:

$$\vec{a}_p = \vec{a}_{n/e} + 2\vec{\omega}_{eli} \times \vec{v}_{n/e} + \vec{\omega}_{eli} \times \vec{\omega}_{eli} \times \vec{p}_{n/e} \quad (6.31)$$

At sea level, the centrifugal acceleration due to the Earth's rotation is limited to 0.0035 g. For horizontal or vertical motion at speeds below 160 km/hr, the Coriolis acceleration is limited to 0.00066 g. In this formulation, centrifugal acceleration due to the Earth's rotation is considered a bias in the local gravity vector and Coriolis acceleration is considered a component of the slowly time-varying bias.

The accelerometers produce a measurement of each component of specific force, u_a , along their sensitive axis in the body-fixed frame:

$$u_a = f^b + \delta_a^b + e_a^b \quad (6.32)$$

Where f^b is the true specific force, δ_a^b is slowly time-varying bias, and each component of e_a^b is additive Gaussian white noise.

The specific force includes a contribution due to gravity. Written as a vector resolved into the body-fixed frame, it is:

$$\vec{f}^b = C^{bn} (\vec{a}_{n/e}^n - \vec{g}^n) \quad (6.33)$$

Accelerometer measurements, represented as a vector, are:

$$\vec{u}_a = C^{bn} (\vec{a}_{n/e}^n - \vec{g}^n) + \vec{\delta}_a^b + \vec{e}_a^b \quad (6.34)$$

Rearranging this expression to obtain acceleration as a function of sensor output, gravity, and error terms produces the following:

$$\vec{a}_{n/e}^n = C^{nb} (\vec{u}_a - \vec{\delta}_a^b - \vec{e}_a^b) + \vec{g}^n \quad (6.35)$$

Only the vertical component is required for calculation of profiler reference point height:

$$a_{zp}^n = C_{31}^{nb} u_{ax} + C_{32}^{nb} u_{ay} + C_{33}^{nb} u_{az} + \delta_a + e_a - g \quad (6.36)$$

Only the third row of the direction cosine matrix is required to make this calculation, which only requires knowledge of the pitch and roll angle. In order to minimize the number of states in the system equation, this formulation uses pitch and roll angle directly:

$$a_{zp}^n = -s_\theta u_{ax} + c_\theta s_\phi u_{ay} + c_\theta c_\phi u_{az} + \delta_a + e_a - g \quad (6.37)$$

This expression combines terms for accelerometer noise and time-varying bias from each sensor into a consolidated error model. The consolidated error terms correspond to vertical acceleration in the navigation reference frame. These terms incorporate the influence of input measurement errors, errors in sensor mounting and alignment, numerical approximation errors, local fluctuations in the acceleration due to gravity, etc.

6.3.3 Sensor Drift

Slowly varying bias in the roll rate, pitch rate, and the resultant vertical acceleration are all modeled using random walk with the following discrete representation:

$$\begin{aligned} \delta_{a,k+1} &= \delta_{a,k} + e_{a',k} \\ \delta_{\omega_1,k+1} &= \delta_{\omega_1,k} + e_{\omega_1',k} \\ \delta_{\omega_2,k+1} &= \delta_{\omega_2,k} + e_{\omega_2',k} \end{aligned} \quad (6.38)$$

Since the system dynamics do not require a measure of yaw angle, no random walk is assigned to yaw rate.

6.3.4 GPS Position and Velocity

The system includes height and vertical velocity measured by a GPS using an antenna mounted to the host-vehicle body. Figure 6.2 shows a schematic of the measurement system hardware in the rear view with some roll of the body frame relative to the navigation frame. The figure shows the position of the GPS antenna relative to the profiler reference point $\vec{r}_{gps/p}^b$, which is considered constant in the body-fixed frame.

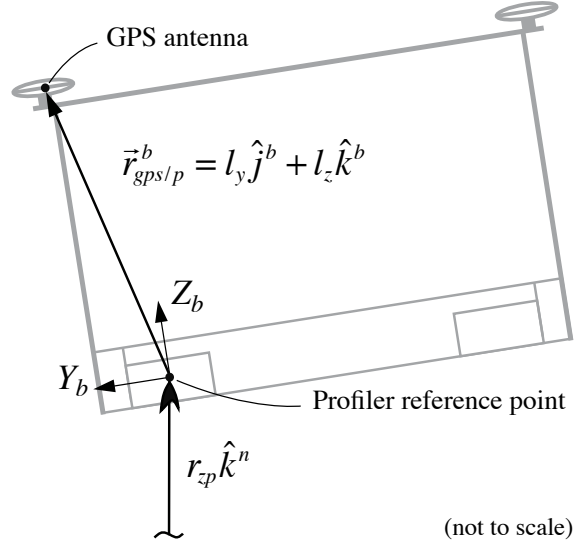


Figure 6.2 GPS antenna offset, rear view

In the navigation frame, the vertical offset of the GPS antenna relative to the profiler reference point is: $\vec{r}_{gps/p}^b = l_y \hat{j}^b + l_z \hat{k}^b$

$$\vec{r}_{gps/p}^b \cdot \hat{k}^n = C_{32}^{nb} l_y + C_{33}^{nb} l_z \quad (6.39)$$

This is a function of elements of the direction cosine matrix that depend on pitch and roll rotation and the locally horizontal offset (l_y) and locally vertical offset (l_z) of the GPS antenna. The vertical velocity of the GPS antenna relative to the profiler reference point is:

$$\vec{v}_{gps/p}^n \cdot \hat{k}^n = \dot{C}_{32}^{nb} l_y + \dot{C}_{33}^{nb} l_z = C_{31}^{nb} (\omega_y l_z - \omega_z l_y) - C_{32}^{nb} \omega_x l_z + C_{33}^{nb} \omega_x l_y \quad (6.40)$$

The model for measured GPS height, y_{rz} , and vertical velocity, y_{vz} , are:

$$y_{rz} = r_{zp}^n + c_\theta (s_\phi l_y + c_\phi l_z) + e_{rz} \quad (6.41)$$

$$y_{vz} = v_{zp}^n + s_\theta (\omega_z l_y - \omega_y l_z) + c_\theta \omega_x (c_\phi l_y - s_\phi l_z) + e_{vz} \quad (6.42)$$

Where r_{zp}^n and v_{zp}^n are height and velocity of the profiler reference point relative to the Earth ellipsoid expressed in the navigation (and wander) frame. Each measurement includes independent Gaussian white noise (e_{rz} and e_{vz}).

6.3.5 GPS Pitch and Roll

Figure 4.4 shows a schematic of the GPS-based attitude measurement system. A master antenna is placed at the rear left corner of the vehicle. A “pitch rover” antenna appears forward of the master antenna, and is aligned with it in the body-fixed longitudinal (X) direction. A “roll rover” antenna appears rightward of the master antenna, and is aligned with it in the body-fixed lateral (Y) direction. The GPS-based attitude measurement system provides inclination of the body-fixed X-axis and Y-axis relative to the horizontal plane. For each axis, inclination is positive when the rover antenna is above the master antenna.

Inclination of the X-axis (θ_{gps}) is equivalent to the Euler pitch angle. Euler rotation in both pitch and roll of the body-fixed axis system relative to the navigation system affect inclination of the Y-axis (ϕ_{gps}). Roll inclination relates to the Euler angles as follows:

$$\theta_{gps} = \theta \quad (6.43)$$

$$\phi_{gps} = \sin^{-1}(c_\theta s_\phi) \quad (6.44)$$

Each measurement includes independent Gaussian white noise (e_θ and e_ϕ):

$$y_\theta = \theta + e_\theta \quad (6.45)$$

$$y_\phi = \sin^{-1}(c_\theta s_\phi) + e_\phi \quad (6.46)$$

6.3.6 Discrete System Equations

The process model includes seven state variables ($r_{zp}^n, v_{zp}^n, \theta, \phi, \delta_a, \delta_{\omega_1}, \delta_{\omega_2}$) and seven system error terms ($e_a, e_{\omega_1}, e_{\omega_2}, e_{\omega_3}, e_{a'}, e_{\omega_1'}, e_{\omega_2'}$). In discrete form, the equations for the process model are:

$$\begin{aligned}
r_{zp,k}^n &= r_{zp,k-1}^n + v_{zp,k-1}^n \Delta t \\
&\quad + (-s_{\theta_{k-1}} u_{ax,k-1} + c_{\theta_{k-1}} s_{\phi_{k-1}} u_{ay,k-1} + c_{\theta_{k-1}} c_{\phi_{k-1}} u_{az,k-1} + \delta_{a,k-1} + e_{a,k-1} - g) \Delta t^2 / 2 \\
v_{zp,k}^n &= v_{zp,k-1}^n + (-s_{\theta_{k-1}} u_{ax,k-1} + c_{\theta_{k-1}} s_{\phi_{k-1}} u_{ay,k-1} + c_{\theta_{k-1}} c_{\phi_{k-1}} u_{az,k-1} + \delta_{a,k-1} + e_{a,k-1} - g) \Delta t \\
\theta_k &= \theta_{k-1} + (c_{\phi_{k-1}} (u_{\omega_2,k-1} + \delta_{\omega_2,k-1} + e_{\omega_2,k-1}) - s_{\phi_{k-1}} (u_{\omega_3,k-1} + e_{\omega_3,k-1})) \Delta t \\
\phi_k &= \phi_{k-1} + (u_{\omega_1,k-1} + \delta_{\omega_1,k-1} + e_{\omega_1,k-1}) \Delta t \\
&\quad + t_{\theta_{k-1}} (s_{\phi_{k-1}} (u_{\omega_2,k-1} + \delta_{\omega_2,k-1} + e_{\omega_2,k-1}) + c_{\phi_{k-1}} (u_{\omega_3,k-1} + e_{\omega_3,k-1})) \Delta t \\
\delta_{a,k} &= \delta_{a,k-1} + e_{a',k-1} \\
\delta_{\omega_1,k} &= \delta_{\omega_1,k-1} + e_{\omega_1',k-1} \\
\delta_{\omega_2,k} &= \delta_{\omega_2,k-1} + e_{\omega_2',k-1}
\end{aligned} \tag{6.47}$$

Where Δt is the interval between time steps, and index for time step (e.g., k or $k-1$) is appended to the subscript of any quantity that varies with time.

The measurement model includes four measurements ($y_{rz}, y_{vz}, y_{\theta}, y_{\phi}$), and four measurement error terms ($e_{rz}, e_{vz}, e_{\theta}, e_{\phi}$). In discrete form, the equations for the measurement model are:

$$\begin{aligned}
y_{rz,k} &= r_{zp,k}^n + c_{\theta_k} (s_{\phi_k} l_y + c_{\phi_k} l_z) + e_{rz,k} \\
y_{vz,k} &= v_{zp,k}^n + s_{\theta_k} (u_{\omega_3,k} l_y - (u_{\omega_2,k} + \delta_{\omega_2,k}) l_z) + c_{\theta_k} (u_{\omega_1,k} + \delta_{\omega_1,k}) (c_{\phi_k} l_y - s_{\phi_k} l_z) + e_{vz,k} \\
y_{\theta,k} &= \theta_k + e_{\theta,k} \\
y_{\phi,k} &= \sin^{-1}(c_{\theta_k} s_{\phi_k}) + e_{\phi,k}
\end{aligned} \tag{6.48}$$

Appendix C provides the linearized matrices used in the extended Kalman filter and smoother.

6.4 Sensor Errors

This section examines noise sources in the rate gyroscopes and GPS outputs using Allan deviation, and describes the approach used to tune the noise estimate for the Kalman filter.

6.4.1 Allan Variance

Allan variance was originally developed to characterize the frequency instability in precision oscillators [113]. The formulas presented here use notation adapted from subsequent applications of Allan variance to sensors from inertial navigation systems, such as fiber-optic

gyroscopes [114-116]. Allan variance is calculated by comparing adjacent cluster averages. As shown, a cluster average is calculated by averaging a set of consecutive sampled values.

$$\bar{\Omega}_k(n\Delta t) = \frac{1}{n} \sum_{j=k}^{k+n-1} \Omega_j \quad (6.49)$$

The corresponding cluster time is $n\Delta t$, where n is the number of samples in the cluster and Δt is the time interval between samples. For a signal with N samples, the overlapping Allan variance is defined for a given cluster time as follows:

$$\sigma_A^2(n\Delta t) = \frac{1}{2(N-2n+1)} \sum_{k=1}^{N-2n+1} (\bar{\Omega}_{k+n} - \bar{\Omega}_k)^2 \quad (6.50)$$

The term “overlapping” applies here to signify that each time the index, k , increments forward, the two new clusters overlap the clusters used in the previous step by $n-1$ samples. Typically, this formula is applied for many possible values of cluster time, and displayed in a plot as Allan deviation (σ_A) versus cluster time. El-Sheimy et al. [116] describe Allan variance as a representation of “the RMS random-drift errors as a function of averaging times.” Indeed, the Allan deviation for a normally distributed signal with zero mean approximates the standard deviation.

Computational effort is greatly reduced by preprocessing the signal using simple (rectangular) integration and substituting differences from the integrated signal for the cluster averages, as follows:

$$\theta_k = \Delta t \sum_{j=1}^k \Omega_j \quad (6.51)$$

$$\sigma_A^2(n\Delta t) = \frac{1}{2(N-2n+1)} \frac{1}{(n\Delta t)^2} \sum_{k=1}^{N-2n+1} (\theta_{k+2n-1} - 2\theta_{k+n-1} + \theta_{k-1})^2 \quad (6.52)$$

6.4.2 Rate Gyroscopes

Three tests were performed with a rate gyroscope still (in the Earth-fixed frame) to characterize its noise and bias using Allan deviation. In two of the tests, the sensitive axis was parallel to a circle of latitude (i.e., pointing east-west). As such, the sensor was subjected to a zero rate input. In the third, the axis was aligned with a meridian (i.e., pointing north-south), and

could detect the rotation of the Earth. Each test proceeded for at least 17.5 hours, and data were obtained at 100 Hz. Figure 6.3 shows the Allan deviation for a zero-input test performed over 21.5 hours.

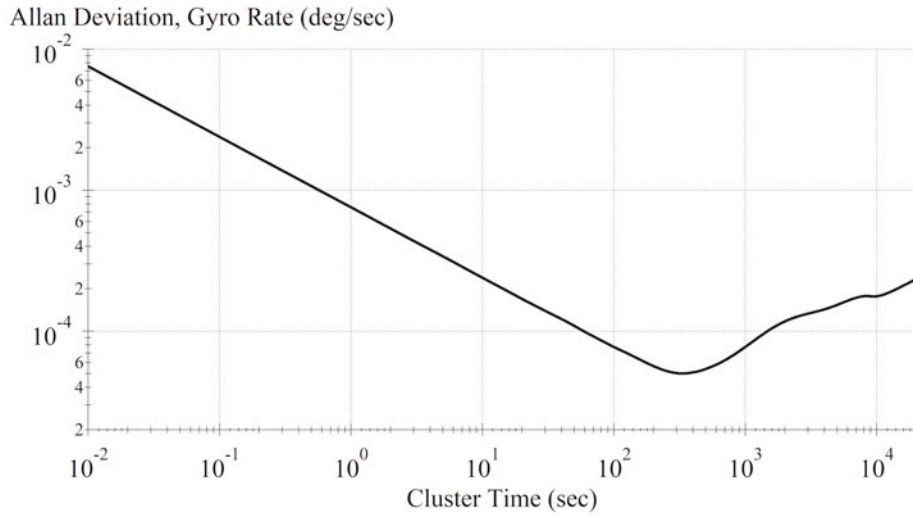


Figure 6.3 Allan deviation, rate gyroscope

IEEE Std 952 recommends the use of an empirical curve fit to measured Allan variance to determine the coefficients associated with each class of noise in fiber-optic gyroscopes [114]. The standard form of the fitting function is as follows:

$$\sigma_A^2(n\Delta t) = \frac{R_A^2(n\Delta t)^2}{2} + \frac{K_A^2 n\Delta t}{3} + \frac{2B_A^2 \ln(2)}{\pi} + \frac{N_A^2}{n\Delta t} + \frac{3Q_A^2}{(n\Delta t)^2} \quad (6.53)$$

The terms to right of the equal sign correspond to ramp instability (R_A), rate random walk (K_A), bias instability (B_A), angle random walk (N_A), and quantization (Q_A).

For the rate gyroscope examined in Figure 6.3, angle random walk dominates the signal for cluster times less than or equal to 100 seconds. This manifests as a slope of -1/2, due to the logarithmic scaling. Angle random walk is estimated using the value of Allan deviation for a 1-second cluster time, which is 7.56×10^{-4} deg/s. This implies the following coefficient for angle random walk:

$$N_A = 7.56 \times 10^{-4} \text{ deg}/\sqrt{s} = 0.0454 \text{ deg}/\sqrt{h} \quad (6.54)$$

Often, angle random walk is specified in alternate units, as shown.

None of the other idealized mechanisms described in IEEE Std 952 fit the data for cluster times above 100 seconds very closely. However, addition of rate random walk and ramp instability improves the curve fit for cluster times between 100 seconds and ½ hour:

$$R_A = 1.03 \times 10^{-7} \text{ deg/s}^2, K_A = 1.38 \times 10^{-6} \text{ deg/s}^{3/2} \quad (6.55)$$

The actual spectral content of the rotation rate signals approximated the idealized (one-sided) spectral density function, S_Ω , expected using the three noise parameters derived in the Allan variance analysis:

$$S_\Omega(2\pi f) = \frac{R_A^2}{(2\pi f)^3} + \frac{K_A^2}{(2\pi f)^2} + N_A^2 \quad (6.56)$$

The actual spectral content is flat, and approximates white noise rotation rate, for frequencies above 0.002 Hz. As frequency decreases below 0.002 Hz, the spectral density increases. For frequencies below 0.0005 Hz, the contributions of rate random walk and ramp instability effects outpace angle random walk.

Other relevant observations from the three trials include:

- For the test examined in Figure 6.3, the standard deviation with the bias removed was 0.00752 deg/s. This is the value of the Allan deviation for a cluster time of 0.01 seconds (i.e., using 1-point clusters).
- Auto correlation using 20,000 sampled data points did not produce a value above 0.5 percent of the signal variance for a non-zero lag. This implies that the signal is dominated by white noise at high frequencies.
- Normalized probability distributions produced values of skew below 2×10^{-3} and excess Kurtosis below 2.6×10^{-2} .
- Normalized probability distributions produced Kolmogorov-Smirnov test for normality scores of 0.00504-0.00546. The high number of samples ($> 6,400,000$) implies confidence that the distribution is not normal, yet a similar level of confidence that the cumulative distribution differs from normality by less than 0.0055.

6.4.3 GPS Outputs

Figure 6.4 shows the Allan deviation for GPS height collected over 3.0 hours. These data included RTK corrections, and carrier phase ambiguities resolved to “narrow-lane integers.” The empirical function in Equation (6.53) produces a reasonable fit to the data for cluster times less than 10 seconds, but not the rest. Inspection of the autocorrelation function reveals the presence of several distinct noise sources with specific time constants and characteristic frequencies. (See Figure 6.5.) The same is true of GPS pitch inclination and GPS roll inclination.

It is likely that tightly coupled integration with the GPS system would be required to capture the noise sources evident in the Allan deviation and autocorrelation functions. For simplicity, the measurement model for all of the GPS outputs only includes normally distributed random noise. These are quantified using estimates of standard deviation.

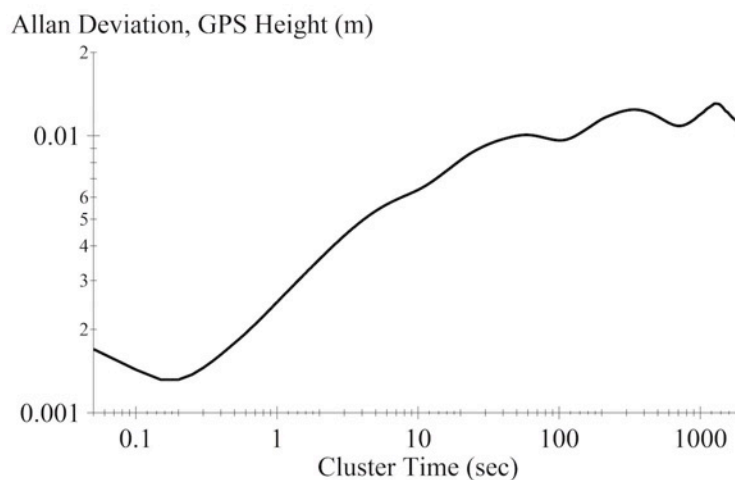


Figure 6.4 Allan deviation, GPS height

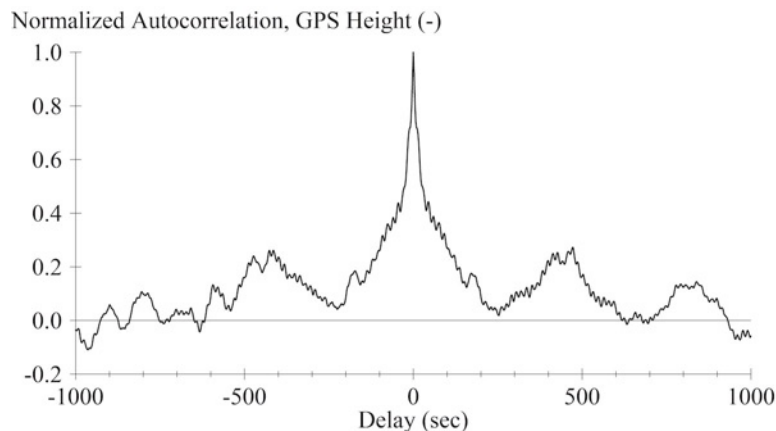


Figure 6.5 Normalized autocorrelation, GPS height

6.4.4 Tuning

Table 6.1 summarizes the approach used to tune the Kalman filter. The table lists each error quantity, the associated symbol for standard deviation, the corresponding model (measurement or process), and the value. The table also identifies which values were established before tuning and fixed, and which values were tuned based on the outcome of preliminary test runs.

Table 6.1 Kalman filter tuning approach

Error Estimate	Symbol	Model	Status	Value
GPS height	σ_{p_z}	Measurement	Fixed	0.012 m
GPS vertical velocity	σ_{v_z}	Measurement	Fixed	0.03 m/s
GPS pitch inclination	σ_{θ}	Measurement	Fixed	0.12 deg
GPS roll inclination	σ_{ϕ}	Measurement	Fixed	0.2 deg
Acceleration	σ_a	Process	Tuned	6×10^{-4} g
Acc. random walk	$\sigma_{a'}$	Process	Tuned	5×10^{-8} m/s ³
Roll rate	σ_{ω_1}	Process	Fixed	7.7×10^{-3} deg/s
Roll rate random walk	$\sigma_{\omega'_1}$	Process	Tuned	4.2×10^{-6} deg/s ²
Pitch rate	σ_{ω_2}	Process	Fixed	7.7×10^{-3} deg/s
Pitch rate random walk	$\sigma_{\omega'_2}$	Process	Tuned	2.2×10^{-4} deg/s ²
Yaw rate	σ_{ω_3}	Process	Fixed	0 deg/s

Of the 11 estimates of standard deviation, only 4 were designated for tuning. Preliminary analysis revealed that tuning the full set of values improved the results. However, it required a very complicated optimization process that was not guided by insight into the system kinematics or knowledge of signal processing. Further, the reported performance of the system would have been difficult to reproduce in a practical application.

Fixed quantities were set using information that could be easily obtained, as follows:

GPS height, GPS roll inclination, and GPS pitch inclination: The GPS provided a real-time estimate of standard deviation with each observation of height, roll, and pitch. Table 6.1 lists the median values of those estimates observed during preliminary runs, excluding bounce tests and quiescent tests. Use of the individual estimates in real time may lead to some improvement, but was not found to be necessary. Note that the performance reported in this chapter is not maintained if the carrier phase ambiguities

are not resolved to “narrow-lane integers,” except in the constant height and attitude reference implementation.

GPS vertical velocity: The manual for the GPS hardware and firmware reported “velocity accuracy” to less than 0.03 m/s.

Pitch and roll rate: Standard deviation values for pitch rate and roll rate are fixed at 0.0077 deg/s. This is the average value from the three laboratory tests used to examine Allan deviation. This value can be obtained by monitoring the output of each sensor over several minutes of zero-input operation.

Yaw rate: Since the influence of yaw rate on system performance for the test runs used in this demonstration is small, a value of zero is used for its standard deviation. Using a value of zero for yaw rate changes the results very little. However, this may not be the case for a testing program that includes operation on a curve.

Tuning of the remaining four quantities using profiles from the left- and right-side using at least six test runs is recommended: (1) constant speed of 8 km/hr or less, (2) constant speed of 72 km/hr or greater, (3) braking at 0.15-0.2 g, (4) braking at 0.3 g or greater, (5) a stop no more than 2 seconds long preceded by braking at 0.3 g or greater, and (6) a stop no less than 5 seconds long preceded by braking at 0.2 g or less. In the braking runs, the final speed should be at least 25 km/hr. In the runs with stops, the speed before braking begins should be greater than 40 km/hr.

In this research, the tuning procedure optimized the same quantities in the preliminary runs that are used here to report the performance of the system in the regular test runs. This includes: (1) maximizing cross correlation for all preliminary runs, (2) maximizing agreement in average IRI for preliminary runs at constant speed, and (3) maximizing agreement in peak IRI at the critical location for all runs with braking and stops. The “critical location” is either the location of a stop, or the location where the brakes were released for runs with braking, but no stop. Visual inspection of short-interval roughness profiles, PSD plots, and filtered profile plots is recommended.

Although a tuning process based on blind optimization would have succeeded, some preliminary constraints on the process were applied:

1. Set the values for pitch rate random walk and roll rate random walk at the level derived from the Allan variance analysis described above. If the required test data are not available, use values of zero.
2. Define a space of error estimates for acceleration and acceleration random walk that perform as well or better than the nominal profiler for the constant (high) speed run (i.e. do no harm) and the run with light braking. In this case, the “nominal profiler” means profile derived with this system using only the body-fixed component of vertical acceleration, the height sensor, and the distance encoder.
3. Using the lowest values found in step 2, define the range of values for pitch rate random walk that maximizes performance for the run with heavy braking and improves performance for the runs with stops. Prioritize the left side profile. Deprioritize values of pitch rate random walk that degrade performance for the runs examined in step 2.
4. Using the lowest values found in steps 2 and 3, define the range of values for roll rate random walk that maximizes the performance for the run at low speed and the run with heavy braking. Prioritize the right side profile. Deprioritize values of roll rate random walk that degrade performance on the other runs.
5. Repeat steps 2 through 4 until no incremental performance improvement is observed. Each time step 2 is re-applied, fix pitch rate random walk and roll rate random walk at the lowest values found in the previous iteration.
6. Fix the acceleration error estimate. Find the combination of the three random walk error estimates that provide the best collective performance for all preliminary runs. This will often require a trade-off between maintaining performance at constant speed and improving performance with braking.

Blind optimization beginning with results from the steps above may further improve performance. However, if performance improvements depend on adjustment of the error estimates to a precision level lower than several percent, it is less likely the same level of performance will exist in all conditions. With the tuning approach described here, the overall performance of each Kalman filtering and smoothing implementation presented in this chapter is maintained for changes in each standard deviation value in Table 6.1 of up to 40 percent. (The

variations were tested using scale factors with a constant step on a logarithmic scale of $\frac{1}{2}$ octave.) That is, the performance does not depend on precise tuning.

The overall objective of the tuning is to determine the frequency range where the inertial sensors (i.e., the process model) dominate the content within the kinematic state variables, the frequency range where the GPS observations dominate, and the frequency range where their influence is of the same order of magnitude. Note that the three random walk values represent the collective influence of several factors, including slowly varying sensor bias, omissions in the process model, numerical imprecision, and imprecise sensor mounting.

6.5 Implementation for Profile Calculation

Figure 6.6 summarizes the flow of sensor outputs used to calculate profile with the Kalman smoother. Inertial sensors (accelerometers and rate gyroscopes) drive the process model within the Kalman filter, and GPS sensors provide inputs to the measurement model. The Kalman filter passes estimates of the system state and state error covariance to the Kalman smoother. The system state variables include floating reference height. The Kalman smoother produces refined estimates of the system state and updated estimates of covariance based on stored readings from the inertial sensors and stored Kalman filter outputs. The smoother requires stored signals, because it steps backward in time through them to make the calculations.

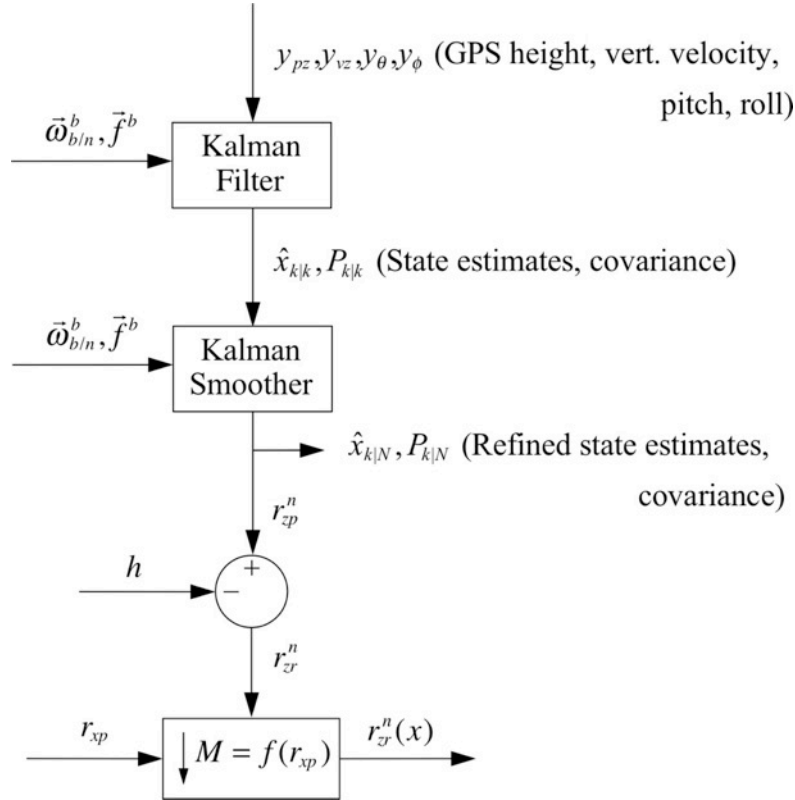


Figure 6.6 Sensor signal flow for profile computation

Profile elevation (r_{zr}^n) at each time step (k) is calculated as follows:

$$r_{zr,k}^n = r_{zp,k}^n - h_k \quad (6.57)$$

Where $r_{zp,k}^n$ is the floating reference height produced by the Kalman smoother, and h_k is the height-sensor reading. The temporal profile (i.e., road elevation versus time), $r_{zr,k}^n$, is decimated to obtain spatial profile, $r_{zr}^n(x_k)$, as a function of distance at a constant interval of 5.08 mm. The decimation factor, M , varies with host-vehicle speed and depends on longitudinal travel distance, r_{xp} . An optical distance encoder measures longitudinal distance.

This system uses a constant time step of 1/16,000 seconds, because analog data from the height sensors, vertical accelerometers, and longitudinal accelerometers were digitized at 16,000 Hz. However, the rate gyroscopes and the lateral accelerometer update their readings at 100 Hz, and the height sensors provide readings at a rate near 3,240 Hz. At each time step, the calculations use the most recent reading from each sensor.

The GPS provides updates at a rate of 20 Hz. As such, the Kalman filter only applies a measurement update at time steps when a new GPS observation is available. The Kalman smoother performs all of its calculations at 16,000 Hz, because it depends on estimates of the state and state error covariance calculated at 16,000 Hz in the forward-running Kalman filter.

Independent Kalman filters and smoothers are applied for each of the left and right profiles. The measurement system included accelerometers (vertical and longitudinal) and height sensors on both sides of the vehicle. Profiles from each side depend on readings from the same rate gyroscopes, lateral accelerometer, optical distance encoder, and GPS. This chapter presents results for the left profile.

6.6 Results

Use of the additional sensors with Kalman smoothing improved profile measurement accuracy at low speed, during braking, and at stops considerably. Three mechanisms contributed to the improvement.

First, three-dimensional measurement of acceleration and rotation rate provided a more accurate measurement of profiler vertical motion. Resolution of acceleration into the direction aligned with gravity reduced the artificial vertical curvature that appeared in the floating-reference-height signal during braking, particularly in locations where the brakes were released. However, it did not reduce the bias in the integrated accelerometer signal (v_{zp}) in the range leading to and during a stop sufficiently to avoid large levels of artificial localized roughness.

Second, use of a Kalman filter to incorporate GPS measurements of height and velocity arrested drift in the floating-reference-height signal. Similarly, incorporation of GPS measurements of pitch and roll inclination arrested drift in the estimates of pitch and roll orientation. The independent measurements by the GPS were necessary because of slowly varying bias in the inertial sensors.

Third, the use of a Kalman smoother provided necessary additional reduction in drift of the floating-reference-height signal. Use of past and future measurements to refine estimates of the system states reduced erroneous low-frequency responses to disturbances that appeared as drift. The backward pass by the Kalman smoother allowed absolute measurements by the GPS

sensors to better influence the estimates of low-frequency system response, and confined the influence of the inertial sensors to the high-frequency range.

Results are provided below using: (1) three-dimensional measurement of kinematics by inertial sensors with incorporation of the GPS using Kalman filtering, and (2) additional refinement of state estimates from the Kalman filter using a Kalman smoother. Results are also provided for three additional implementations of the Kalman smoother:

1. Height-sensor reflection: When the host-vehicle speed is less than 0.16 km/hr, this procedure uses the height-sensor signal as an independent measurement of floating reference height in place of GPS measurements. This is based on the assumption that the road surface elevation at a point is constant, and that equal and opposite fluctuations should appear in the floating-reference-height signal and the height-sensor signal.
2. Constant attitude reference: This implementation of the Kalman smoother replaces GPS measurement of pitch and roll inclination with a constant estimate of zero. This is intended to demonstrate the potential performance of the system if GPS-based attitude measurement is not present or is experiencing an outage.
3. Constant height and attitude reference: This implementation of the Kalman smoother replaces all GPS measurements with a constant estimate of zero. This is intended to demonstrate the potential performance of the system during a GPS outage. In this mode of operation, no actual measurements are provided to the Kalman smoother. Rather, the “constant reference” signals (and the associated elements of the measurement noise covariance matrix) place a limit on the absolute level of position and orientation drift, and the Kalman smoother functions as a high-pass filter.

6.6.1 Kalman Filter

Table 6.2 provides roughness and cross correlation results for profiles processed using the Kalman filter without the smoother. Peak roughness is the highest value in the short-interval roughness profile in the range from 180 m to 228 m from the test section start. This is the area where the host vehicle came to a stop in the stop-and-go runs or released the brakes in the braking runs without a stop. In the reference profile, the peak roughness is 2.4 m/km. The percentage error in average roughness for the 160.9-m-long test section is provided. When a

large error in peak roughness occurs, it accounts for most of the error in average roughness. Cross correlation values provide a rating of agreement to the reference profile in the waveband of interest for the IRI on a scale from -1 to 1. High cross correlation ensures that the details of the profile, as well as the overall roughness and spatial distribution of roughness, agree with the reference profile. Cross correlation of 0.92 or above is required for adequate profile agreement per AASHTO R56-14 [87], and 0.98 is required to demonstrate reference-grade performance.

Table 6.2 Results for the Kalman filter

Run Designation	Peak Roughness (m/km)	Average Roughness Error (Percent)	Cross Correlation
S&G, 1.1-sec stop, 0.17 g	4.6	7.8	0.629
S&G, 1.1-sec stop, 0.20 g	3.3	3.0	0.840
S&G, 2.1-sec stop, 0.33 g	12.9	40.3	< 0.2
S&G, 5.8-sec stop, 0.17 g	21.8	73.0	< 0.2
S&G, 5.7-sec stop, 0.20 g	17.1	52.4	< 0.2
S&G, 5.8-sec stop, 0.20 g	15.7	50.6	< 0.2
S&G, 10.7-sec stop, 0.20 g	27.5	90.7	< 0.2
NS, 72-11 km/hr, 0.20 g	2.7	5.5	0.921
Brk, 71-30 km/hr, 0.19 g	2.7	8.2	0.915
Brk, 72-29 km/hr, 0.39 g	2.6	4.3	0.930
Brk, 49-22 km/hr, 0.16 g	2.6	3.7	0.915
Brk, 49-23 km/hr, 0.18 g	2.4	1.8	0.944
Brk, 49-23 km/hr, 0.18 g	3.2	7.2	0.904
Brk, 49-20 km/hr, 0.25 g	3.4	6.6	0.882
Brk, 49-34 km/hr, 0.84 g	2.5	6.6	0.914
16 km/hr	2.3	1.5	0.986
5 km/hr	2.4	2.7	0.855

Reference peak roughness value: 2.4 m/km. Adequate cross correlation > 0.92.

For the test runs with braking, but no stop, the Kalman filter offered some improvement in road profile measurement over the basic temporal algorithm examined in Chapter 5. However, the adaptive high-pass filtering algorithm offered better performance and did not require additional sensors beyond the nominal inertial profiler design. The Kalman filter failed to produce adequate cross correlation in five of the braking runs.

Without the smoother, the Kalman filter produced large errors peak roughness and commensurately low cross correlation. This is because the Kalman filter did not suppress drift sufficiently to eliminate artificial roughness caused by drift in the floating-reference-height signal at locations where the host vehicle stops. Figure 6.7 provides an example for the test run with a 10.7-second-long stop. The figure compares the floating-reference-height signal produced

by the Kalman filter to the GPS height observations provided to the filter as measurements. During the stop (from 15.7 to 26.4 seconds), the net change in height measured by the GPS was 17.5 mm downward. The height sensor measured a similar decrease in distance between the profiler and the road surface of 18.4 mm during this time increment.

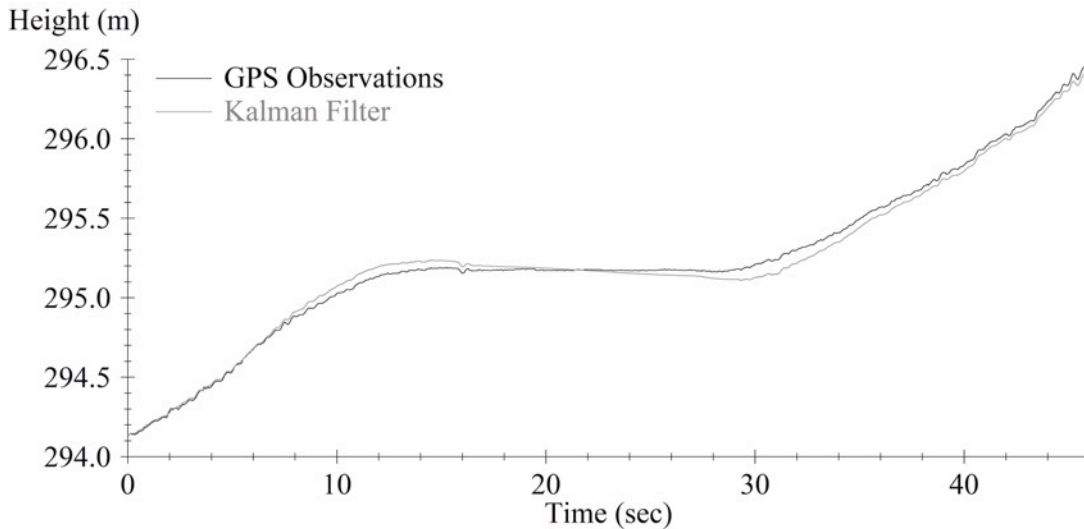


Figure 6.7 Drift in Kalman filter output, 10.7-second-long stop

Braking, which began at 5.3 seconds in this test run, caused the floating-reference-height signal to drift. During the stop, the net downward change in floating reference height is 0.09 m. The portion of this change that was not compensated by the height sensor appears in the profile as a step change in elevation at the location of the stop. The combined effects of drift at the stop and in the low-speed range near the stop caused an artificial peak in the short-interval roughness profile of 27.5 m/km.

After the onset of drift the Kalman filter enforced abrupt corrections to the floating-reference-height signal each time it obtained a new observation from the GPS. Figure 6.8 provides an example using a close-up view of a portion of the traces in Figure 6.7. In this region, the floating reference height has drifted 0.06 m above the prevailing GPS readings. Between GPS observations, the inertial sensors and the process dynamics solely determine the progression of floating reference height. Each 0.05 seconds a GPS observation is available, and the Kalman filter imposes a correction to the floating-reference-height signal that appears as a step change. For the range shown in Figure 6.8, these are downward step changes of approximately 2 mm. These step changes appear in the final profile as artificial roughness.

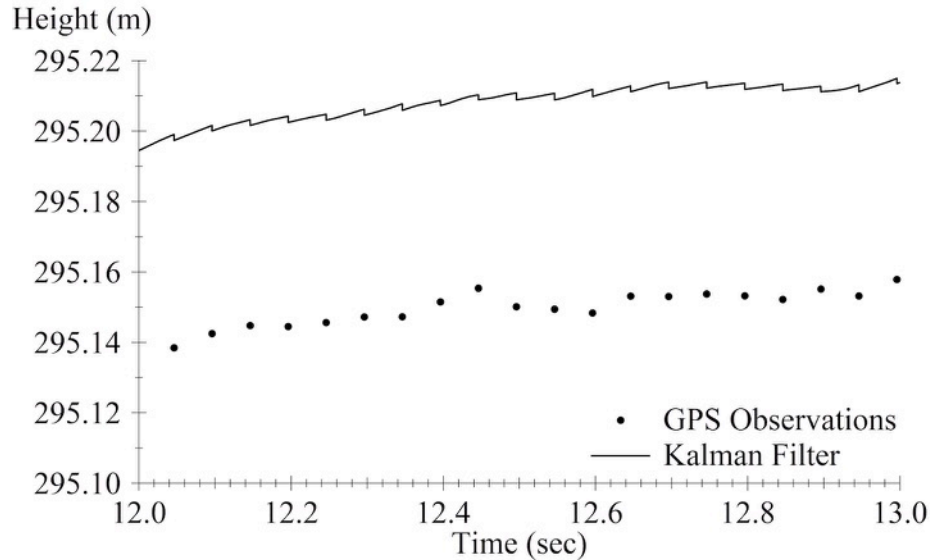


Figure 6.8 Kalman filter corrections during drift, 10.7-second-long stop

Drift of the floating-reference-height signal relative to the GPS observations is attributed to the recursive nature of the Kalman filter and resulting delay in its low-frequency response. Reduction in the process noise covariance estimate associated with acceleration random walk (i.e., a reduction in the ratio of σ_a^2 to σ_r^2) reduces this drift. However, it raises the relative influence of GPS height readings on the content of the state estimates, such as the floating-reference-height signal. This causes noise in the GPS height readings to contaminate the profile in the wavelength range of interest, particularly in areas that do not include braking and in test runs performed at constant speed.

Since the Kalman filter did not produce results as good as the best temporal or spatial error suppression algorithms described in Chapter 5, sensor augmentation with the Kalman filter (and no smoother) is not expected to provide a return on the additional sensor cost.

6.6.2 Kalman Smoother

Relative to Kalman filtering alone, the smoother provided additional suppression of drift in the floating-reference-height signal. For example, Figure 6.9 compares the floating-reference-height signal produced by the Kalman smoother to the GPS height measurements for the test run with a 10.7-second-long stop. Much less drift appears relative to the output of the Kalman filter, and the artificial downward change in elevation in the profile is reduced from 72 mm to less than 2.5 mm.

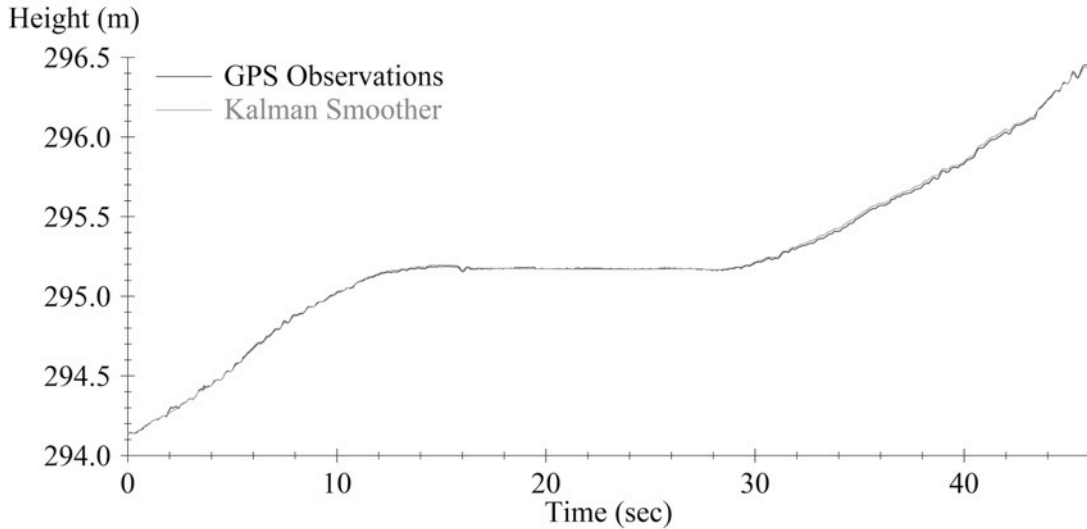


Figure 6.9 Drift in Kalman smoother output, 10.7-second-long stop

Table 6.3 provides roughness and cross correlation results for profiles processed using the Kalman smoother. All braking test runs without a stop correlated to the reference pass with a score above the AASHTO requirement of 0.92, and many were at the “reference quality” level of 0.98 [87]. Further, the error in average roughness was less than 5 percent and the upward bias in peak roughness was less than 10 percent relative to the reference pass in eight of the nine test runs. Much of the variation in peak roughness among these runs is attributed to variations in lateral tracking.

Five of the seven runs with a stop produced cross correlation values above the AASHTO requirement. The largest upward bias in peak roughness compared to the reference value was 1.0 m/km. The reduction in peak roughness errors for runs with a stop demonstrates the additional removal of drift in the floating-reference-height signal offered by adding the Kalman smoother.

The run with braking from 71 km/hr to 30 km/hr at 0.19 g offers a good illustration of the quality in profile and roughness measurement at the cross correlation threshold levels. Figure 6.10 compares the short-interval roughness profiles for the reference pass to the run with braking processed using the Kalman filter only. Comparison of the two profiles produced a cross correlation level of 0.915. (See Table 6.2.) This is near the threshold for adequate agreement. The average roughness agrees to within 8.2 percent, and many of the details of the distribution of roughness throughout the section are similar, as shown in Figure 6.10.

Table 6.3 Results for the Kalman smoother

Run Designation	Peak Roughness (m/km)	Average Roughness Error (Percent)	Cross Correlation
S&G, 1.1-sec stop, 0.17 g	3.4	2.6	0.886
S&G, 1.1-sec stop, 0.20 g	3.0	0.1	0.957
S&G, 2.1-sec stop, 0.33 g	2.7	3.0	0.963
S&G, 5.8-sec stop, 0.17 g	3.0	6.2	0.925
S&G, 5.7-sec stop, 0.20 g	2.9	0.9	0.904
S&G, 5.8-sec stop, 0.20 g	2.4	3.0	0.954
S&G, 10.7-sec stop, 0.20 g	2.5	2.9	0.938
NS, 72-11 km/hr, 0.20 g	2.4	2.1	0.977
Brk, 71-30 km/hr, 0.19 g	2.4	1.7	0.978
Brk, 72-29 km/hr, 0.39 g	2.3	-0.8	0.975
Brk, 49-22 km/hr, 0.16 g	2.3	-0.8	0.963
Brk, 49-23 km/hr, 0.18 g	2.3	-0.9	0.978
Brk, 49-23 km/hr, 0.18 g	2.7	0.9	0.981
Brk, 49-20 km/hr, 0.25 g	2.5	1.2	0.985
Brk, 49-34 km/hr, 0.84 g	2.6	3.9	0.942
16 km/hr	2.3	-0.6	0.988
5 km/hr	2.4	-1.8	0.973

Reference peak roughness value: 2.4 m/km. Adequate cross correlation > 0.92.

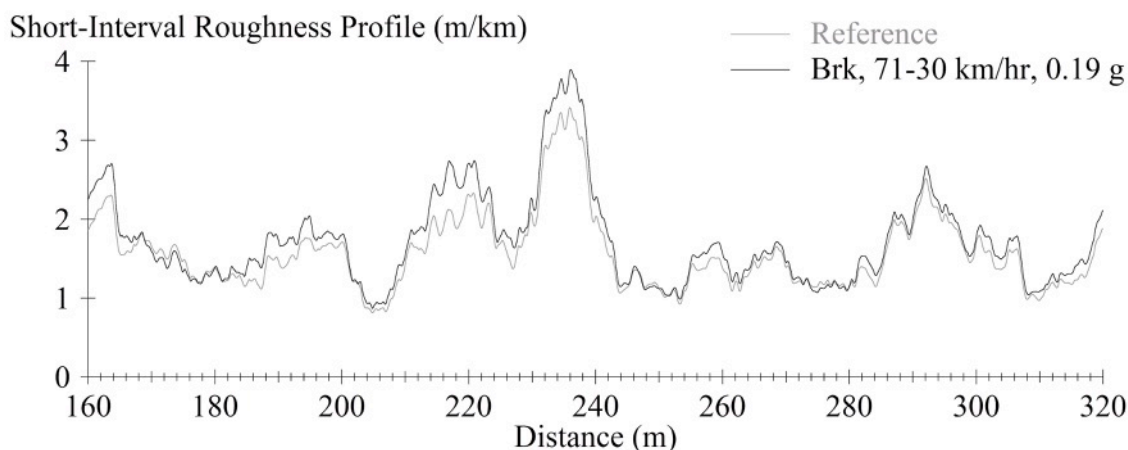


Figure 6.10 Short-interval roughness profile comparison, Kalman filter

Figure 6.11 compares the short-interval roughness profiles for the reference pass to the run with braking processed using the Kalman smoother. Comparison of the two underlying profiles produced a cross correlation level of 0.975. (See Table 6.3.) This is near the threshold for “reference level” agreement. In this case, the average roughness agreed to within 2 percent. In addition, the details of the two short-interval roughness profiles are very similar throughout the section. (The reference trace is not visible behind the trace from the run with braking in many

areas.) A high cross correlation value is only possible if agreement exists in the overall roughness, the spatial distribution of roughness, and the shape of the underlying features in the profile.

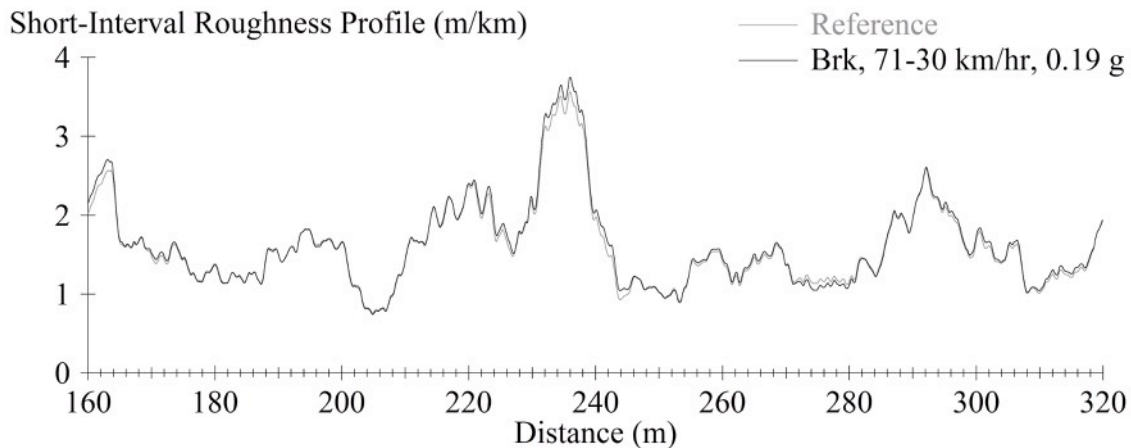


Figure 6.11 Short-interval roughness profile comparison, Kalman smoother

The Kalman smoother also improved measurement of profile at low speed. As described in Chapter 5, high-pass filtering of the accelerometer signal eliminated numerical integration errors for the test run at 5 km/hr. Application of the filters produced cross correlation to the reference pass of 0.938. The Kalman smoother offered a much greater improvement in measurement quality for this test run, due to elimination of errors associated with accelerometer alignment. As speed decreases, sensor alignment errors caused by pitch and roll dynamics of the host-vehicle sprung mass correspond to progressively shorter wavelengths. In turn, the resulting measurement error has a progressively larger effect on content within the profile that affects the IRI. The motion is exacerbated at very low speed by difficulties maintaining a consistent throttle command. Resolution of acceleration into a consistent vertical direction reduced alignment errors, and produced a cross correlation value of 0.973.

The additional sensors and Kalman smoothing algorithm proposed in this research removed most of the measurement error that was present when the test runs are processed using only elements of the basic inertial profiler design (i.e., the nominal sensor set and the basic temporal profile calculation algorithm). In addition, the system proposed here improved reproduction of the reference profile significantly over the best error suppression algorithms described in Chapter 5, which use only the nominal sensor set that appears in a typical

commercial profiler. However, this system did not achieve adequate performance for all of the runs with a stop. The remaining error is caused primarily by drift in the GPS height signal that occurs while the profiler is stopped, which is introduced into the floating-reference-height signal during the measurement update in the Kalman filter. The following section describes a specialized provision that is proposed for mitigating this error source.

6.6.3 Kalman Smoother with Height-Sensor Reflection

Height-sensor reflection offers further reduction of profile measurement error at stops. This procedure switches to an alternate mode of operation when the host-vehicle speed is less than 0.16 km/hr. In the “stopped” mode, the Kalman filter replaces the GPS with the height sensor as an external source of position information. This is based on the assumption that at very low speed the road surface elevation is constant and changes to the height-sensor signal are caused solely by vertical motion of the profiler reference point. This is not universally true when speed is below 0.16 km/hr. However, GPS readings of height are prone to drift over time intervals of several seconds or more. (See Figure 6.4.) This is not included in the measurement error model. As such, the height sensor is considered a more accurate measure of profiler reference point movement during a stop. Height-sensor reflection is implemented using the four provisions described here.

The first provision replaces fluctuations in GPS measurements with fluctuations in height sensor measurements in the very low speed range.

$$y_{rz,k} = y_{rz,ref} + (y_{h,ref} - y_{h,k}) \quad (6.58)$$

Where $y_{h,k}$ is the height-sensor reading at each time step. The quantities $y_{rz,ref}$ and $y_{h,ref}$ are the last values of GPS height and height-sensor output, respectively, obtained before initiation of the stopped mode. These remain constant throughout the very low speed interval, and are included in the calculation to offset the fluctuating height-sensor signal to a level consistent with the prevailing GPS height. This changes the measurement equation for height to the following:

$$y_{h,k} = r_{z,k}^n + c_{\theta_k} (s_{\phi_k} l_y + c_{\phi_k} l_z) + y_{rz,ref} + y_{h,ref} + e_{h,k} \quad (6.59)$$

The error term, $e_{h,k}$, represents noise in the height sensor. (See Equation (6.48) for the unmodified version.)

The second provision replaces $\sigma_{r_z}^2$ with σ_h^2 in the measurement covariance matrix to account for the modified source of measurement noise, where:

$$\sigma_h = 0.0015 \text{ m} \quad (6.60)$$

This value is higher than the prevailing noise level in the height sensor. Tuning of σ_h using preliminary test runs was required, and the final value depended on host-vehicle pitch dynamics as it approached the stop.

The third provision removes the influence of the other GPS observations. The measurements provided to the Kalman filter are replaced as follows:

$$\begin{aligned} y_{vz,k} &= y_{vz,ref} \\ y_{\theta,k} &= 0 \\ y_{\phi,k} &= 0 \end{aligned} \quad (6.61)$$

Where $y_{vz,ref}$ is the last observation of GPS vertical velocity obtained before initiation of the quasi-stopped mode. Values of zero are maintained for pitch and roll inclination. Estimates of standard deviation for GPS vertical velocity and pitch inclination angle are increased by a factor of 10. This removes their influence on the state estimates throughout the stop. No factor is applied to the standard deviation for the measurement of roll inclination, because excessive drift in roll inclination introduced drift into the measurement equation for the reference height of the right-side profiler.

The fourth provision accommodates the sampling rate of the height sensor. In this implementation, the process dynamics are updated at a rate of 16,000 Hz, whereas the height sensor provides measurements at a rate near 3,240 Hz. As such, the Kalman filter applies the measurement update when a new reading from the height sensor is available. No change to the format of the Kalman smoother is required.

Table 6.4 lists the roughness and cross correlation results for test runs with stops using the Kalman smoother with height-sensor reflection. All seven test runs produced cross correlation values above the AASHTO requirement and above the cross correlation produced by the Kalman smoother without height-sensor reflection. In some cases, peak roughness values were lower than the reference value. This is due in part to variations in lateral tracking of the profiler, and in part to exclusion of actual roughness from the measurement in the area where

height-sensor reflection was applied. The average roughness was within 5 percent of the reference values in all runs.

Table 6.4 Results for the Kalman smoother with height-sensor reflection

Run Designation	Peak Roughness (m/km)	Average Roughness Error (Percent)	Cross Correlation
S&G, 1.1-sec stop, 0.17 g	2.1	-1.8	0.969
S&G, 1.1-sec stop, 0.20 g	2.2	-2.3	0.963
S&G, 2.1-sec stop, 0.33 g	2.4	1.9	0.972
S&G, 5.8-sec stop, 0.17 g	2.5	4.4	0.949
S&G, 5.7-sec stop, 0.20 g	2.2	-1.5	0.952
S&G, 5.8-sec stop, 0.20 g	2.2	2.3	0.967
S&G, 10.7-sec stop, 0.20 g	2.7	3.0	0.958

Reference peak roughness value: 2.4 m/km. Adequate cross correlation > 0.92.

6.6.4 Kalman Smoother with a Constant Attitude Reference

This implementation of the Kalman smoother demonstrates the potential performance of the system if GPS-based attitude measurement is not present or is experiencing an outage. GPS measurement of pitch and roll inclination are replaced with constant estimates of zero:

$$y_{\theta,k} = 0, y_{\phi,k} = 0 \quad (6.62)$$

GPS measurements of height and velocity remain intact, and the Kalman filter applies the measurement update at 20 Hz using actual height and velocity measurements together with the artificial attitude measurements. The net effect of imposing a constant reference signal on pitch and roll rotation is removal of their low-frequency content. That is, the constant attitude reference functions within the Kalman filter as a high-pass filter on integrated outputs from the rate gyroscopes.

The specific outcome of using the constant attitude reference depends on estimates of standard deviation provided to the measurement covariance matrix:

$$\sigma_{\theta} = 5 \text{ deg}, \sigma_{\phi} = 2 \text{ deg} \quad (6.63)$$

Further, the performance of this implementation for test runs with a stop depended on application of height-sensor reflection provisions described above. During the stopped mode, the error estimate for height measurement is increased as follows:

$$\sigma_h = 0.07 \text{ m} \quad (6.64)$$

Preliminary calculations showed that performance of the system was not very sensitive to these values within a “valid” range. However, a sufficiently high value was needed for each item to retain valid measurement of vehicle dynamic response within the state estimates, and a sufficiently low value was needed to mitigate the effect of drift. Tuning of the error estimates using preliminary test runs was required, and the final values were influenced by the host vehicle’s propensity for dynamic motion in pitch and roll.

Table 6.5 lists the roughness and cross correlation results for test runs processed using the Kalman smoother with a constant attitude reference. The constant attitude reference produced results equivalent to using actual measurements of pitch and roll attitude when both options applied height-sensor reflection at stops. The lowest cross correlation value is well above the threshold of 0.92 for adequate performance. Note that reproduction of this result depends on tuning as described above, and is not guaranteed for profilers mounted to a host vehicle with a greater propensity for misalignment in pitch and roll.

Table 6.5 Results for the Kalman smoother with a constant attitude reference

Run Designation	Peak Roughness (m/km)	Average Roughness Error (Percent)	Cross Correlation
S&G, 1.1-sec stop, 0.17 g	2.1	-1.6	0.973
S&G, 1.1-sec stop, 0.20 g	2.2	-2.2	0.953
S&G, 2.1-sec stop, 0.33 g	2.5	2.6	0.968
S&G, 5.8-sec stop, 0.17 g	2.4	3.7	0.957
S&G, 5.7-sec stop, 0.20 g	2.1	-1.9	0.949
S&G, 5.8-sec stop, 0.20 g	2.3	2.6	0.964
S&G, 10.7-sec stop, 0.20 g	2.5	2.4	0.967
NS, 72-11 km/hr, 0.20 g	2.5	2.1	0.976
Brk, 71-30 km/hr, 0.19 g	2.4	1.6	0.980
Brk, 72-29 km/hr, 0.39 g	2.3	-0.7	0.976
Brk, 49-22 km/hr, 0.16 g	2.2	-0.8	0.963
Brk, 49-23 km/hr, 0.18 g	2.3	-0.7	0.979
Brk, 49-23 km/hr, 0.18 g	2.7	0.6	0.983
Brk, 49-20 km/hr, 0.25 g	2.4	1.0	0.987
Brk, 49-34 km/hr, 0.84 g	2.6	4.2	0.942
16 km/hr	2.3	-0.7	0.987
5 km/hr	2.3	-2.5	0.963

Reference peak roughness value: 2.4 m/km. Adequate cross correlation > 0.92.

6.6.5 Kalman Smoother with a Constant Height and Attitude Reference

This implementation of the Kalman smoother demonstrates the potential performance of the system if the GPS is not present or is experiencing an outage. All GPS measurements are replaced with constant estimates of zero:

$$y_{rz,k} = 0, y_{vz,k} = 0, y_{\theta,k} = 0, y_{\phi,k} = 0 \quad (6.65)$$

Since all GPS readings are simulated, and the Kalman filter applies the measurement update at every time step. In this implementation, the measurement model within the Kalman filter functions as a high-pass filter on estimates of height, vertical velocity, pitch, and roll produced by the process model.

In addition to the changes specified when using a constant attitude reference, error estimates for height and vertical velocity measurement are altered as follows:

$$\sigma_{rz} = 0.5 \text{ m}, \sigma_{vz} = 1.0 \text{ m/s} \quad (6.66)$$

Like the error estimates for orientation, these values required tuning using preliminary test runs as described above.

Table 6.6 provides the results for the Kalman smoother with the constant height and attitude reference in conjunction with height-sensor reflection. This implementation produced results equivalent to using actual GPS measurements. The ability to apply the Kalman smoother in areas without a sufficient sky view for accurate GPS would make this system much more robust. Eliminating the need for GPS sensors altogether reduces equipment cost. However, additional tuning of the measurement model is required. Further, verification for vehicles with diverse pitch and roll response properties and for a greater number of speed change scenarios may be needed.

Table 6.6 Results for the Kalman smoother with a constant height and attitude reference

Run Designation	Peak Roughness (m/km)	Average Roughness Error (Percent)	Cross Correlation
S&G, 1.1-sec stop, 0.17 g	2.2	-0.8	0.981
S&G, 1.1-sec stop, 0.20 g	2.2	-2.3	0.962
S&G, 2.1-sec stop, 0.33 g	2.5	1.7	0.971
S&G, 5.8-sec stop, 0.17 g	2.6	4.4	0.952
S&G, 5.7-sec stop, 0.20 g	2.2	-1.4	0.949
S&G, 5.8-sec stop, 0.20 g	2.0	1.4	0.974
S&G, 10.7-sec stop, 0.20 g	2.3	1.9	0.970
NS, 72-11 km/hr, 0.20 g	2.4	1.9	0.977
Brk, 71-30 km/hr, 0.19 g	2.4	1.4	0.980
Brk, 72-29 km/hr, 0.39 g	2.3	-0.7	0.977
Brk, 49-22 km/hr, 0.16 g	2.3	-0.8	0.963
Brk, 49-23 km/hr, 0.18 g	2.3	-0.6	0.979
Brk, 49-23 km/hr, 0.18 g	2.7	0.3	0.985
Brk, 49-20 km/hr, 0.25 g	2.5	1.1	0.986
Brk, 49-34 km/hr, 0.84 g	2.6	3.7	0.943
16 km/hr	2.3	-0.5	0.988
5 km/hr	2.3	-2.6	0.957

Reference peak roughness value: 2.4 m/km. Adequate cross correlation > 0.92.

Chapter 7

Conclusions and Recommendations

7.1 Summary

Inertial profilers are limited in their ability to measure IRI during challenging operational conditions. In particular, they are prone to errors in the floating-reference-height signal when the host vehicle travels at low speed, decelerates during braking, or comes to stop. These errors reduce the accuracy of profiles measured on urban road networks and low-speed roadways, and render the measurements of IRI unusable at important locations, such as signalized intersections.

Two important mechanisms contribute to errors in the floating-reference-height signal derived from accelerometer output in typical inertial profilers.

First, the accelerometers are typically fixed in the host-vehicle body. As such, they experience dynamic changes in pitch and roll orientation as the host vehicle reacts to driver inputs, such as braking and steering. Tilt of the sensitive axis causes errors in the measurement of true vertical acceleration and contamination by components of the longitudinal and lateral acceleration. The most common example of this error source occurs when the host vehicle tilts in pitch during braking and a portion of the rearward acceleration projects onto the sensitive axis of the accelerometer. After double integration, this appears as errors in curvature in the floating-reference-height signal, which appears in the profile over the region where the braking occurred.

Accelerometer tilt also causes profile measurement error at very low travel speed, because of dynamic response of the profiler host vehicle in pitch and roll to road roughness. When the host vehicle travels at progressively lower speed, the accelerometer signal is contaminated in a frequency range that increasingly corresponds to the wavelength range of interest for measuring the IRI.

Second, bias in the output of the accelerometers causes drift in the floating-reference-height signal. Causes of bias include road grade, cross slope, local variations in the acceleration due to gravity, and temperature changes. During constant-speed operation, the effects of drift are

typically confined to very low frequencies and do not contaminate the wavelength range of interest within the profile. However, when the host vehicle decelerates to a very low speed or comes to a stop, the temporal drift in floating-reference-height signal appears within the measured profile over a very small distance range. Often, this manifests as a steep change in elevation. This registers as severe localized roughness and a large upward bias in the average roughness for the road section where the stop occurred.

This research developed and tested the following options for addressing these sources of profile measurement error:

Error suppression algorithms: These algorithms use specialized numerical procedures applied at low travel speed combined with standard filtering techniques to reduce artificial roughness measured at a stop. These techniques depend only on the use of output from sensors included in the nominal profiler design. As such, they are proposed as short-term solutions for adapting the processing software in existing profilers, and for new profilers when funds are not available to support the cost of additional sensors. In these algorithms, reduction of artificial roughness at stops comes at the cost of invalid profile measurement at very low speed.

Sensor augmentation: These designs require additional sensors to improve profile measurement at low speed, during braking, and at stops. The additional sensors include body-fixed measurement of profiler acceleration and rotation rate in three dimensions to help resolve acceleration into a consistent vertical direction. The system also includes GPS measurement of host-vehicle height, vertical velocity, pitch inclination, and roll inclination. A multi-rate extended Kalman filter combines the inertial sensors with the GPS outputs to reduce drift in the floating-reference-height signal and errors associated with host-vehicle tilt. Use of an RTS smoother improves the mitigation of drift. Sensor augmentation is proposed as a long-term solution, because it requires major changes to profiler hardware and software design.

A custom measurement system was developed and built for this research to enable an experimental demonstration of profile measurement errors caused by accelerometer misalignment and an investigation of the effectiveness of the proposed solutions. The measurement system included the nominal set of sensors that appear in typical profilers, and several additional sensors to support the augmentation approach described above.

The nominal measurement system demonstrated excellent performance in three ways. First, it demonstrated accurate sensor calibration and very low system noise in stationary tests, such as the bounce test and the quiescent test. Second, it measured profile with a high degree of repeatability in the wavelength range of interest for the IRI. Third, it reproduced profiles measured by an inclinometer-based reference device accurately in the wavelength range of interest for the IRI. The system obtained cross correlation for repeatability and accuracy above the level expected for a reference device, but only under specific conditions. These include: (1) operation at a constant speed of 24 km/hr and above, and (2) consistent lateral tracking for the two measurements under comparison to within 12 cm or less.

The relative performance of error suppression algorithms and sensor augmentation proposed in this research was evaluated using the results from several test runs collected under challenging conditions, including operation at low speed, braking, and operation through a stop. For all test runs, performance is quantified using standard measures for accuracy of longitudinal profile and IRI used by road agencies for pavement network quality assurance and pavement network management [87,92]. These include:

1. Reduction of bias in the peak value of short-interval roughness profiles relative to a reference measurement in test runs with braking and a stop. Peak values are reported in the region where braking ended or the test vehicle came to a stop. This is where the most severe bias typically occurs.
2. Agreement to a reference measurement of average IRI measured over a 160.9-m test section.
3. Cross correlation to a reference profile measurement using the output of the IRI algorithm over a 160.9-m test section. Cross correlation of 0.92 or higher is deemed adequate.

Unfortunately, the test runs performed at low speed, with braking, and with stops passed over a track well beside the track followed by the inclinometer-based device. To reduce the confounding effects of tracking errors, the reference profile was measured using a test run at 72 km/hr with similar tracking to the evaluation runs.

Table 7.1 summarizes the performance of the suppression algorithms and sensor augmentation options examined in this research. The options appear in three groups: (1) temporal profile calculation algorithms using the nominal sensor set, (2) spatial profile calculation

algorithms using the nominal sensor set, and (3) the use of an augmented sensor set and Kalman filtering. In each group, results are provided for incremental improvements on the basic option or alternative implementations, where the basic option represents common practice used by existing commercial profilers.

Table 7.1 provides cross correlation results and percent error in roughness for selected test runs at low speed, with braking, and with stops. Cells with cross correlation above a threshold value of 0.92 are shaded. Some cells in Table 7.1 are marked with a dash. In those instances, the results are the same as in the cell above, because the improvement to the algorithm over the one listed in the row above was not in effect for that test run.

In Table 7.1, the basic temporal and spatial algorithms represent use of the nominal inertial profiler sensors and no improvements to the baseline profile calculation algorithm. These algorithms suffer from large errors in measured roughness at low speed, during braking, and at stops. The adaptations “with high-pass filtering” apply the high-pass filters to the accelerometer signal prior to each stage of integration. Application of high-pass filtering in this manner is recommended for both spatial and temporal profile measurement architectures. Although pre-integration high-pass filtering alone does not offer sufficient improvement, it is recommended as an error mitigation strategy.

Adaptive high-pass filtering is recommended for architectures with temporal profile calculation, and high-pass filtering with timer distortion and height-sensor reflection is recommended for architectures with spatial profile calculation. Note that each of these algorithms greatly reduces (i.e., suppresses) the erroneous peak roughness for the test runs with the stop and the near stop. However, the algorithms do so by removing both valid and invalid content at low speed, and they both underestimate roughness for the test run at 5 km/hr. These algorithms offer a short-term option for reducing the largest errors in measured roughness in cases where the funds do not exist for implementing the sensor augmentation strategy proposed in the research.

Table 7.1 Cross correlation to the reference test run for selected conditions

Algorithm	Constant Speed 5 km/hr	Constant Speed 16 km/hr	Braking 49-23 km/hr 0.18 g	Near Stop 72-11 km/hr 0.20 g	Stop & Go 2.1-sec stop 0.33 g	Stop & Go 10.7-sec stop 0.20 g
Basic Temporal Algorithm (TA)	< 0.2 (1622.7)	0.863 (9.2)	0.605 (27.9)	< 0.2 (195.3)	< 0.2 (862.6)	< 0.2 (13,139.7)
TA with High-Pass Filter (HPF)	0.940 (-4.2)	0.985 (-0.7)	0.963 (0.6)	0.578 (17.7)	0.256 (36.8)	< 0.2 (99.5)
TA with Adaptive HPF	0.322 (-51.9)	0.985 (-0.8)	0.955 (1.0)	0.793 (4.9)	0.581 (17.5)	0.724 (9.3)
Basic Spatial Algorithm (SA)	< 0.2 (928.5)	0.985 (0.2)	0.621 (27.2)	< 0.2 (190.8)	< 0.2 (852.5)	< 0.2 (8,607.7)
SA with Spatial HPF	0.746 (14.5)	0.927 (-1.0)	0.900 (1.8)	0.713 (8.1)	< 0.2 (231.3)	< 0.2 (4,946.6)
SA with HPF, Timer Distortion, and Height-Sensor Reflection (HSR)	< 0.2 (-86.6)	—	—	0.756 (3.4)	0.587 (11.7)	0.678 (11.8)
Kalman Filter (KF)	0.855 (2.7)	0.986 (1.5)	0.904 (7.2)	0.921 (5.5)	< 0.2 (40.3)	< 0.2 (90.7)
KF with smoother (KS)	0.973 (-1.8)	0.988 (-0.6)	0.981 (0.9)	0.977 (2.1)	0.963 (3.0)	0.938 (2.9)
KS with HSR	—	—	—	—	0.972 (1.9)	0.958 (3.0)
KS with HSR and a Constant Reference	0.957 (-2.6)	0.988 (-0.5)	0.985 (0.3)	0.977 (1.9)	0.971 (1.7)	0.970 (1.9)

Shaded cells correspond to cross correlation above 0.92. Percent error in roughness is shown in parentheses.

Sensor augmentation with Kalman filtering offered substantial improvement over the basic temporal and spatial algorithms, but was not universally better than the error suppression algorithms. However, the Kalman smoother produced results well above the cross correlation threshold of 0.92. Values close to 0.98 imply high-quality measurement of average IRI, peak roughness, and of details within the profile in the wavelength range of interest for the IRI. Further improvement is evident using height-sensor reflection, which uses the height-sensor signal to help mitigate drift in the floating-reference-height signal during stops.

Sensor augmentation and the use of the Kalman smoother with height-sensor reflection is recommended as a long-term option for improving profile measurement at low speed, during braking, and at stops. Implementation of this option is strongly encouraged for road network survey vehicles with profilers that already include some of the additional sensors for other functions, and for any network survey vehicle that is expected to operate on urban and low-speed roads.

The “constant reference” option uses the Kalman filter and smoother, but replaces GPS outputs with artificial signals. Rather than using GPS observations to correct low-frequency content in the integrated outputs from the inertial sensors, the constant reference serves as a limit on drift in the position and orientation estimates. This method is recommended as an “urban canyon” mode for systems with GPS sensors. The constant reference option also offers the possibility to reduce sensor cost and mounting complexity.

7.2 Contributions

The following describes contributions made in this research:

- The research demonstrated the fundamental kinematic and dynamic causes of inertial profile measurement errors related to accelerometer bias and misalignment analytically, and verified the findings experimentally.
- The research developed and executed testing and analysis methods for establishing the sensitivity of road profilers to challenging operational conditions. The research demonstrated these methods by characterizing the status of several in-service profilers, and as a means to quantify the relative success of provisions for reducing measurement errors. The research also demonstrated the confounding influence of

lateral tracking on profiler accuracy and repeatability testing, and the need to control, or at least measure, lateral position during profiler certification testing.

- The research demonstrated existing and novel methods for reducing profile measurement errors during stop-and-go operation using only the sensors available on typical inertial profilers. These methods included several options that account for diverse data collection architectures present in the existing commercial profiling fleet.
- The research proposed and validated the use of additional sensors to improve the accuracy of inertial profilers at low speed, during braking, and through a stop. The additional sensors include those typical of a strap-down navigation system and GPS. Sensor outputs were processed using a novel application of a multi-rate extended Kalman filter with an RTS smoother. The research also proposed and validated an implementation that provides acceptable performance during and GPS outage.

7.3 Suggestions for Future Research

7.3.1 Practical Implementation

The measurement system developed for this research benefited from several advantages that may not exist in typical inertial profilers. These include: (1) mounting of the profile measurement hardware directly to the host-vehicle frame, (2) a high level of protection from electrical noise, (3) recording raw signals at a high rate, (4) redundant provisions to synchronize signals from different subsystems, and (5) the selection of a host vehicle with favorable dynamics. The field performance of a system using the techniques recommended in this research depends, to some extent, on all of these factors. To facilitate retrofit of existing inertial profilers, an examination of these issues is recommended. In particular, work is needed to determine the maximum performance that is possible using a less favorable host vehicle (e.g., shorter wheelbase, higher center of mass) and less favorable mounting practices (e.g., trailer hitch).

7.3.2 Three-Dimensional Surface Measurement

Commercial inertial profilers are now available that provide measurements of the road surface in three dimensions. The typical design includes replacement of the height sensors with a sweeping laser, which is mounted high above the road surface to help capture a wide transverse

profile in each sweep. This increases the vulnerability of the range-to-ground measurement to alignment errors. It also places the inertial sensors in a location with a different vibration environment. The methods demonstrated in this research offer potential benefits for those three-dimensional systems. However, some additional provisions may be needed. This includes: (1) consideration of the pitch and roll inclination of the sweeping laser, and (2) development of a custom tuning approach to account for the change in vibration environment.

7.3.3 Alternative Measurement Concepts

This research provided options to reduce or eliminate errors in measured longitudinal road profile by improving measurement of the accelerometer-established inertial platform. This approach was taken to create options for improving the performance of a large existing fleet of inertial profilers. Several other measurement concepts have the potential to measure valid profile without the use of an inertial platform.

Many alternative measurement concepts have been proposed in the classical literature, but were never adapted for use on a road with live traffic. These options, and others, should be considered for two reasons. First, sufficient computing power is available to leverage data processing and fusion techniques, like those demonstrated in this research, to use multiple sensors and benefit from the strengths of each. Second, other options are available to serve as the host vehicle that may provide more favorable dynamics (e.g., drones).

7.3.4 Computational Efficiency

Using the Kalman filter required only a modest computational load, in part because the calculations associated with the measurement model were only needed when the GPS system provided new observations. In contrast, the RTS smoother required heavy computation at the same rate as the analog sensor outputs were digitized, and storage of more than 50 signals for processing after the completion of each test run. Additional research may reveal methods for decreasing the required storage and computational load. Substantial savings are possible if a valid method can be found to reduce the frequency at which the state error covariance and Kalman gain matrices are updated.

This research used a fixed-interval smoother to improve the state estimates from the Kalman filter. Use of a fixed-interval smoother is cumbersome for very long pavement sections

or test runs that include a long stop. A fixed lag smoother offers the option to reduce demands on signal storage at the cost of an increase in computational load. A fixed-lag smoother was not used, because the lag required for an accurate estimate of the floating reference height depends heavily on the host-vehicle speed profile. For example, no lag is needed at constant speed, and a lag that goes well beyond the stop is needed for stop-and-go operation. Development of an adaptive fixed-lag smoother may improve the trade-off between performance and storage demand compared to the fixed-interval smoother used in this research.

Appendix A

Digital Filtering Technical Notes

This appendix describes digital filters used in support of the research. All of the filters are based on a cascaded form of the third-order Butterworth filter.

A.1 Designations

For the high-pass filter, the transfer function, $H(s)$, is:

$$H(s) = \frac{s^3}{s^3 + 2\omega_a s^2 + 2\omega_a^2 s + \omega_a^3} \quad (\text{A.1})$$

Where ω_a is the analog (angular) cut-off frequency and s is the Laplace operator. In this implementation, the filter comprises a first-order Butterworth filter and a complementary second-order stage:

$$H_1(s) = \frac{s}{s + \omega_a} \quad (\text{A.2})$$

$$H_2(s) = \frac{s^2}{s^2 + \omega_a s + \omega_a^2} \quad (\text{A.3})$$

Where $H_1(s)$ is the transfer function of the first-order stage, and $H_2(s)$ is the transfer function of the second-order stage.

Likewise, the cascaded form of the low-pass filter includes the following transfer functions:

$$H_1(s) = \frac{\omega_a}{s + \omega_a} \quad (\text{A.4})$$

$$H_2(s) = \frac{\omega_a^2}{s^2 + \omega_a s + \omega_a^2} \quad (\text{A.5})$$

This document assigns the following designations to the filter stages:

LPF_{B3S1}: Low-pass filter, first-order stage.

LPF_{B3S2}: Low-pass filter, second-order stage.

HPF_{B3S1}: High-pass filter, first-order stage.

HPF_{B3S2}: High-pass filter, second-order stage.

These designations pertain to application of the filters beginning at the earliest available sample and progressing forward. In some cases, these filtering stages are applied in reverse to cancel the phase shift imposed by the forward-running stages. That is, filtering is initiated at the latest available sample and progresses backward. In such cases, the designations include an “R” at the end of the subscript (e.g., HPF_{B3S1R}).

An abbreviated designation for the high-pass filter (HPF_{B3}) and low-pass filter (LPF_{B3}) indicates that the first-order and second-order stages were applied in succession. For example, LPF_{B3} implies the application of LPF_{B3S1} followed by LPF_{B3S2}.

When both stages of the forward and reverse filters are applied without other processing steps between any of them, they are applied in a specific order to minimize initial transient responses: first-order stage, forward; second-order stage, reverse, first-order stage, reverse; and second-order stage, forward. Together, these four stages make up a sixth-order filter. The abbreviated designations for these filter sets are:

HPF_{B3x2}: HPF_{B3S1}, HPF_{B3S2R}, HPF_{B3S1R}, and HPF_{B3S2}.

LPF_{B3x2}: LPF_{B3S1}, LPF_{B3S2R}, LPF_{B3S1R}, and LPF_{B3S2}.

A.2 Digitization

The bilinear approximation recasts the transfer functions into the z-domain:

$$s = \frac{2}{\Delta t} \frac{1 - z^{-1}}{1 + z^{-1}} \quad (\text{A.6})$$

Where Δt is the sampling period of the digital signal. The following substitution accounts for the non-linear relationship between the analog cut-off frequency and the digital cut-off frequency:

$$\omega_a = \frac{2}{\Delta t} \tan(\pi f_c \Delta t) \quad (\text{A.7})$$

Where f_c is the digital cut-off frequency in Hertz.

Manipulation of the z-domain transfer functions into the following form provides the coefficients for the digital filtering equations:

$$H(z) = \frac{\sum_{i=0}^n N_i z^{-i}}{\sum_{i=0}^n D_i z^{-i}} \quad (\text{A.8})$$

Where n is the order of the filter, z^{-i} represents a delay of i samples, and D_i and N_i are filter coefficients. The discrete equation for the forward-running filter is:

$$y(t_k) = \frac{1}{D_0} \left(\sum_{i=0}^n N_i x(t_{k-i}) - \sum_{i=1}^n D_i y(t_{k-i}) \right), \text{ for } k = n+1, n+2, \dots, K \quad (\text{A.9})$$

Where $x(t_k)$ and $y(t_k)$ are the input and output signals at discrete sample number k , and K is the number of samples in each signal. For the backward running filter:

$$y(t_k) = \frac{1}{D_0} \left(\sum_{i=0}^n N_i x(t_{k+i}) - \sum_{i=1}^n D_i y(t_{k+i}) \right), \text{ for } k = K-n, K-n-1, \dots, 1 \quad (\text{A.10})$$

Table A.1 provides the coefficients for the four basic filtering stages. For notational simplicity, the following substitution is used:

$$c = \tan(\pi f_c \Delta t) \quad (\text{A.11})$$

Table A.1 Filter coefficients						
	D_0	D_1	D_2	N_0	N_1	N_2
LPF _{B3S1}	$c+1$	$c-1$	—	c	c	—
LPF _{B3S2}	c^2+c+1	$2(c^2-1)$	c^2-c+1	c^2	$2c^2$	c^2
HPF _{B3S1}	$c+1$	$c-1$	—	1	-1	—
HPF _{B3S2}	c^2+c+1	$2(c^2-1)$	c^2-c+1	1	-2	1

A.3 Initialization

The forward-running filtering stages are initialized as follows.

LPF_{B3S1}:

$$y(t_1) = x(t_1) \quad (\text{A.12})$$

LPF_{B3S2}:

$$y(t_1) = x(t_1), y(t_2) = \frac{1}{D_0} (N_0 x(t_2) + (N_1 + N_2) x(t_1) - (D_1 + D_2) y(t_1)) \quad (\text{A.13})$$

HPF_{B3S1}:

$$y(t_1) = -\frac{D_1}{D_0} x(t_1) \quad (\text{A.14})$$

HPF_{B3S2}:

$$y(t_1) = -\frac{D_1 + D_2}{D_0} x(t_1), y(t_2) = \frac{1}{D_0} (N_0 x(t_2) + (N_1 + N_2) x(t_1) - (D_1 + D_2) y(t_1)) \quad (\text{A.15})$$

The backward-running filtering stages are initialized as follows.

LPF_{B3S1R}:

$$y(t_K) = x(t_K) \quad (\text{A.16})$$

LPF_{B3S2R}:

$$y(t_K) = x(t_K), y(t_{K-1}) = \frac{1}{D_0} (N_0 x(t_{K-1}) + (N_1 + N_2) x(t_K) - (D_1 + D_2) y(t_K)) \quad (\text{A.17})$$

HPF_{B3S1R}:

$$y(t_K) = -\frac{D_1}{D_0} x(t_K) \quad (\text{A.18})$$

HPF_{B3S2R}:

$$y(t_K) = -\frac{D_1 + D_2}{D_0} x(t_K), y(t_{K-1}) = \frac{1}{D_0} (N_0 x(t_K) + (N_1 + N_2) x(t_{K-1}) - (D_1 + D_2) y(t_K)) \quad (\text{A.19})$$

A.4 Cut-off Frequency

The cut-off frequency for these filters is expressed in terms of the cut-off frequency for the third-order filter, which is the cut-off for the combination of the first- and second-order

stages. Note that the gain of the first-order stage is also reduced by 3 dB at the cut-off frequency, because it is a Butterworth filter. The gain of the second-order complementary filter is unity at the cut-off frequency. The gain of the second-order complementary high-pass filter is reduced by 3 dB at $0.78615f_c$, and the gain of the second-order complementary low-pass filter is reduced by 3 dB at $1.27202f_c$.

To obtain 3 dB gain reduction for the sixth-order combination of forward and reverse high-pass filtering stages (i.e., HPF_{B3x2}) at a desired frequency, f_{-3dB} , the cut-off frequency for the third-order filters must be set as follows:

$$f_c = (\sqrt{2} - 1)^{1/6} f_{-3dB} \quad (\text{A.20})$$

For the low-pass filter, the cut-off frequency is:

$$f_c = (\sqrt{2} - 1)^{-1/6} f_{-3dB} \quad (\text{A.21})$$

A.5 Spatial Filtering

Spatial filtering is performed in the distance domain, rather than the time domain. The filters operate as described above. However, the independent variable x_k replaces t_k and the distance increment Δx replaces the time increment Δt . For convenience of interpretation, cut-off values for spatial filtering are expressed in terms of wavelength (λ_c), rather than spatial frequency. To obtain a 3 dB reduction for the sixth-order combination of forward and reverse high-pass filtering stages (i.e., HPF_{B3x2}) at a desired wavelength, λ_{-3dB} , the cut-off wavelength for the third-order filters must be set as follows:

$$\lambda_c = (\sqrt{2} - 1)^{-1/6} \lambda_{-3dB} \quad (\text{A.22})$$

Appendix B

Measurement System Photos



Figure B.1 Left side view



Figure B.2 Right side view



Figure B.3 Lower sensor rack



Figure B.4 Rear view



Figure B.5 Rotational encoder mounting hardware



Figure B.6 Right sensor pod, underside, lower cover removed



Figure B.7 Right sensor pod, upper cover removed



Figure B.8 Center sensor pod, cover removed



Figure B.9 Forward camera and lane tracker camera



Figure B.10 Front left GPS antenna (pitch rover)



Figure B.11 Left front laser



Figure B.12 Vehicle interior

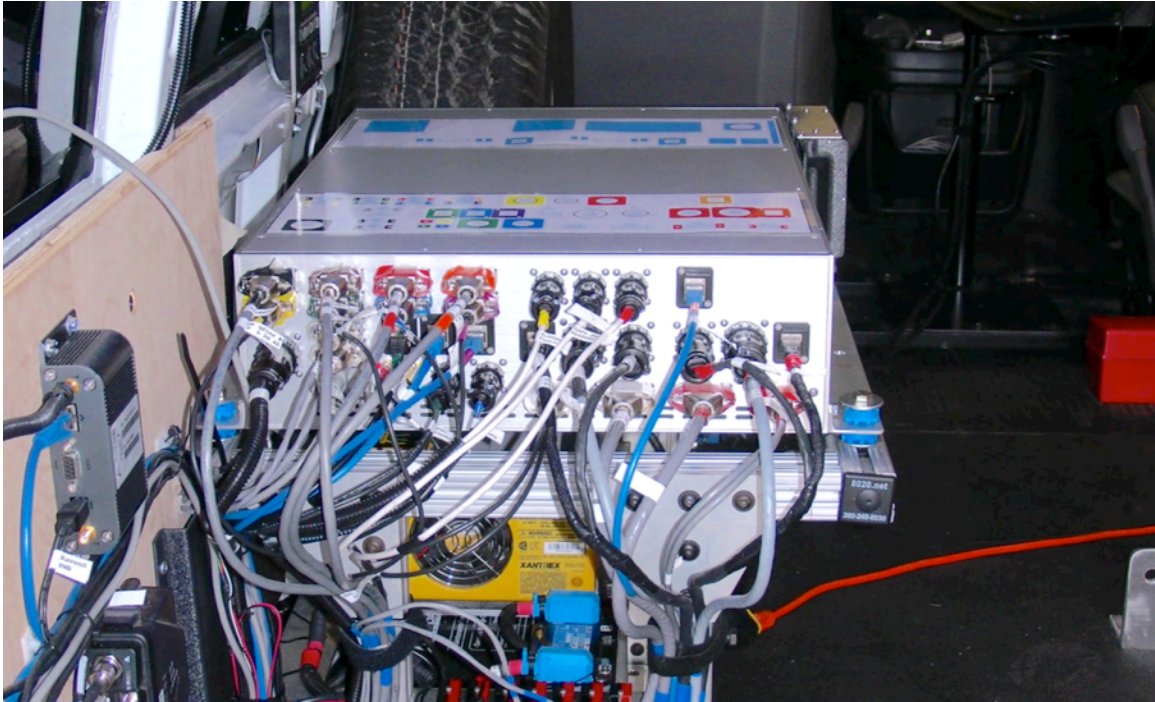


Figure B.13 DAS exterior

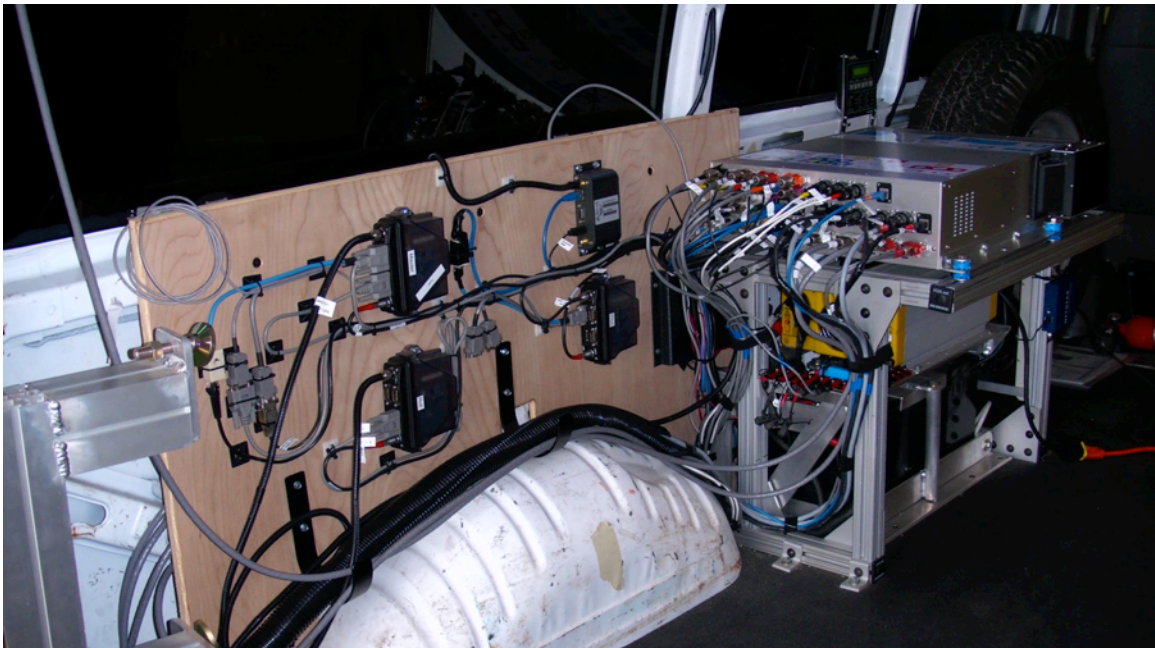


Figure B.14 DAS, power supply, and GPS receivers



Figure B.15 Vehicle interior with outer hardware stowed

Appendix C

Linearized System Equations

This appendix presents the linearized system equations for the extended Kalman filter described in Chapter 6. For ease of interpretation, the subscripts for time step are omitted. Sine and cosine functions are abbreviated as follows:

$$s_\theta = \sin(\theta), c_\theta = \cos(\theta), s_\phi = \sin(\phi), c_\phi = \cos(\phi) \quad (\text{C.1})$$

State vector:

$$x = \{r_{zp}^n, v_{zp}^n, \theta, \phi, \delta_a, \delta_{\omega_1}, \delta_{\omega_2}\}^T \quad (\text{C.2})$$

Linearized state transition matrix:

$$A = \begin{bmatrix} 1 & \Delta t & A[1,3] & A[1,4] & \Delta t^2 / 2 & 0 & 0 \\ 0 & 1 & A[2,3] & A[2,4] & \Delta t & 0 & 0 \\ 0 & 0 & 1 & A[3,4] & 0 & 0 & c_\phi \Delta t \\ 0 & 0 & A[4,3] & A[4,4] & 0 & \Delta t & s_\theta s_\phi \Delta t / c_\theta \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (\text{C.3})$$

Where:

$$\begin{aligned} A[1,3] &= (-c_\theta u_{ax} - s_\theta s_\phi u_{ay} - s_\theta c_\phi u_{az}) \Delta t^2 / 2 \\ A[1,4] &= c_\theta (c_\phi u_{ay} - s_\phi u_{az}) \Delta t^2 / 2 \\ A[2,3] &= (-c_\theta u_{ax} - s_\theta s_\phi u_{ay} - s_\theta c_\phi u_{az}) \Delta t \\ A[2,4] &= c_\theta (c_\phi u_{ay} - s_\phi u_{az}) \Delta t \\ A[3,4] &= -\Delta t (s_\phi (u_{\omega_2} + \delta_{\omega_2}) + c_\phi u_{\omega_3}) \\ A[4,3] &= (c_\phi u_{\omega_3} + s_\phi (u_{\omega_2} + \delta_{\omega_2})) \Delta t / c_\theta^2 \\ A[4,4] &= 1 + (c_\phi (u_{\omega_2} + \delta_{\omega_2}) - s_\phi u_{\omega_3}) s_\theta \Delta t / c_\theta \end{aligned} \quad (\text{C.4})$$

Linearized process noise covariance = WQW^T , where:

$$Q = \text{diag}(\sigma_a^2, \sigma_{\omega_1}^2, \sigma_{\omega_2}^2, \sigma_{\omega_3}^2, \sigma_{a'}^2, \sigma_{\omega_1'}^2, \sigma_{\omega_2'}^2) \quad (\text{C.5})$$

$$W = \begin{bmatrix} \Delta t^2 / 2 & 0 & 0 & 0 & 0 & 0 & 0 \\ \Delta t & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & c_\phi \Delta t & -s_\phi \Delta t & 0 & 0 & 0 \\ 0 & \Delta t & s_\theta s_\phi \Delta t / c_\theta & s_\theta c_\phi \Delta t / c_\theta & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (\text{C.6})$$

Measurement vector:

$$y = \{y_{rz}, y_{vz}, y_\theta, y_\phi\}^T \quad (\text{C.7})$$

Linearized measurement matrix:

$$H = \begin{bmatrix} 1 & 0 & H[1,3] & H[1,4] & 0 & 0 & 0 \\ 0 & 1 & H[2,3] & H[2,4] & 0 & c_\theta(c_\phi l_y - s_\phi l_z) & -s_\theta l_z \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & -\frac{s_\theta s_\phi}{\sqrt{1 - (c_\theta s_\phi)^2}} & \frac{c_\theta c_\phi}{\sqrt{1 - (c_\theta s_\phi)^2}} & 0 & 0 & 0 \end{bmatrix} \quad (\text{C.8})$$

Where:

$$\begin{aligned} H[1,3] &= -s_\theta (s_\phi l_y + c_\phi l_z) \\ H[1,4] &= c_\theta (c_\phi l_y - s_\phi l_z) \\ H[2,3] &= -c_\theta ((u_{\omega_2} + \delta_{\omega_2}) l_z - u_{\omega_3} l_y) - s_\theta (u_{\omega_1} + \delta_{\omega_1}) (c_\phi l_y - s_\phi l_z) \\ H[2,4] &= -c_\theta (u_{\omega_1} + \delta_{\omega_1}) (s_\phi l_y + c_\phi l_z) \end{aligned} \quad (\text{C.9})$$

Linearized measurement noise covariance VRV^T , where:

$$R = \text{diag}(\sigma_{rz}^2, \sigma_{vz}^2, \sigma_\theta^2, \sigma_\phi^2), V = I_4 \quad (\text{C.10})$$

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