Designing an Automated System using Wearable Devices for Compliance Monitoring and Activity Detection in Scoliosis Patients

by

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- AIS: Adolescent Idiopathic Scoliosis – A type of medical condition in adolescents related to an irregularity in the curvature of the spine.
- TLSO: Thoracolumbosacral orthosis – A type of back brace prescribed to help prevent worsening of the AIS condition.
- PCB: Printed Circuit Board – Hardware board made of semi-conductors consisting of circuits and sensors used for data acquisition
- FSR: Force Sensitive Resistor - Commonly referred to as Force Sensor
- RTC: Real-time clock – This is a clock which is included in the circuit, and is used to generate time-stamps in a dataset.
- LIE: Lying activity – The patient is asked to lay down while performing this activity
- SIT: Sitting activity – The patient is asked to sit still on a chair while performing this activity
- SND: Standing activity – The patient is asked to stand still while performing this activity
- WLK: Walking activity – The patient is asked to walk at a normal pace while performing this activity
- RUN: Running activity – The patient is asked to run while performing this activity
- STR: Stairs activity – The patient is asked to climb stairs while performing this activity

Abstract

The use of wearable devices in healthcare and rehabilitation programs is growing exponentially. This thesis focuses on wearable sensors and technology used to monitor treatment compliance in patients with a medical condition known as Adolescent Idiopathic Scoliosis (AIS). Patients with AIS are prescribed to wear a thoracolumbosacral orthosis (TLSO) – a type of back brace, to help prevent worsening of their condition. Scoliosis is a medical condition which occurs in adolescents, where an individual's spine develops curvature. Adolescent Idiopathic Scoliosis (AIS) occurs in children aged 16 years or younger. Brace treatment with TLSO is known as one of the most effective non-surgical treatment for scoliosis. The brace is designed to be worn continuously for long periods of time without any supervision. Therefore, it is vital to carry out the proper procedures for measuring the effectiveness of the treatment, and to accurately evaluate the amount of time of the brace being worn. To successfully monitor compliance with brace treatment, a wearable multi-modal sensor solution is to be embedded into the patient's brace. This thesis proposes an end-to-end system to help improve monitoring brace treatment by continuously observing the amount of force inside the brace. In addition to compliance monitoring, my research is extended to detecting the patient’s daily activities by implementing a novel data-mining method to identify different trends and patterns associated with the activities performed by the patient. This thesis attempts to implement wearables in such an application, and anticipates realizing a successful relationship between monitoring and improving compliance.

CHAPTER I: INTRODUCTION

Idiopathic scoliosis is an abnormal curvature of the spine that can worsen throughout growth, making it vital for doctors to treat it during the early stages. For that reason, physicians focus on skeletally immature adolescents who show signs and symptoms of idiopathic scoliosis. Today, 3% of children below the age of 16 years are diagnosed with adolescent idiopathic scoliosis (AIS). The severity of scoliosis in a patient is measured by the Cobb angle. The Cobb angle refers to magnitude of the spinal curvature as measured on a posteroanterior plain radiograph of the spine. In order to ensure that the treatment is successful, it is important to monitor the quality and duration of brace wear. The total number of hours of brace wear correlates to the lack of spinal curve progression (Rahman *et al.*, 2005; Katz *et al.*, 2010; Weinstein *et al.*, 2013). A braced curve that remains ≤45°-50° at skeletal maturity is considered a treatment success, as bracing is no longer effective once patients are skeletally mature. Curves that are ≤45°-50° at skeletal maturity are not likely to progress during adulthood (Asher and Burton, 2006). Several studies provided convincing evidence about the effectiveness of this treatment given appropriate usage (Sapountzi-Krepia *et al.*, 2006). By embedding the brace with force and motion sensors, the duration of brace wear can be accurately monitored. The objective is to design a 'smart brace' capable of automatically monitoring the duration of brace wear, in addition to properly detecting certain activities the patient performs. In this thesis, I designed a system to monitor and evaluate the duration and quality of brace wear by correlating the force, acceleration and angular velocity collected by a multi-modal sensor solution. With the increase in usage of wearable technology in the health field, the data analysis associated with such a device can help doctors monitor the patient's treatment process.

1.1 Problem Statement

The most common form of treatment of AIS in skeletally immature individuals is a thoracolumbosacral orthosis (TLSO) back brace. While the brace does not provide a solution to fix the curvature, it helps prevent worsening of the curve throughout the adolescent's growth. If progression of the spinal curvature is prevented, then surgery can be avoided and this is considered a brace treatment success (Katz *et al.*, 2010). The brace is designed to be worn continuously for long periods of time without any supervision. Therefore, it is vital to carry out the proper procedures for measuring the effectiveness of the treatment, and to accurately evaluate the amount of time of the brace being worn. Prescribed hours of brace-wear ranges from 12 to 23 hours per day depending on the severity of the patient's spinal curve. Both Katz et al. (Katz *et al.*, 2010) and Weinstein et al. (Weinstein *et al.*, 2013) have demonstrated a dose-response curve, in which duration of brace wear is positively associated with the rate of treatment success. Weinstein et al. reported that patients who wore the brace for 0 to 6 hours daily had a success rate of 42%, whereas patients who wore the brace for at least 12.9 hours had success rates of 90 to 93%. Therefore, the duration and quality of brace wear is an important parameter in the effectiveness of the brace treatment. However, monitoring brace compliance is a challenging task. Previous studies have demonstrated that when brace wear is accurately monitored with a temperature sensor, adherence to brace wear is frequently overestimated (Rahman *et al.*, 2005; Asher and Burton, 2006; Katz *et al.*, 2010; Weinstein *et al.*, 2013). Morton et al. found that patients wore the brace for 47% of the prescribed time, although physicians, orthotists, parents, and patients estimated that the brace be worn for 64%, 66%, 72%, and 75% of the prescribed time, respectively (Morton *et al.*, 2008). Katz et al. reported that patients wore the brace for the same number of hours regardless of whether the prescribed time was 16 hours or 23 hours (Katz *et al.*, 2010). As a result, the effectiveness of treatment depends on the duration of wear and tightness of the brace. To successfully monitor compliance with brace treatment, a wearable multi-modal sensor solution is embedded into the patient's brace.

1.2 Monitoring Brace Treatment

This thesis proposes an end-to-end system to help improve monitoring brace treatment by continuously observing the amount of force inside the brace. The data provides an accurate and valuable insight on the amount of force being exerted by the patient during their regular daily activities. A custom-designed hardware solution is fabricated in a TLSO brace for an empirical evaluation. The custom-designed hardware consists of a sensor board, a force sensor, an accelerometer and a gyroscope. The force sensor records the force being exerted on the patient's back, while the accelerometer and gyroscope generate cues to determine the patient's activities and lifestyle. This thesis is extended to detection of the patient’s daily activities by implementing a novel data-mining method to identify different trends and patterns associated with the different activities performed by the patient. Using machine learning techniques, the model will be designed to detect certain pre-defined activities. The main aim is to design a context-aware remote monitoring system for ubiquitous evaluation and enhancement of brace treatment compliance of AIS patients. In addition to monitoring and evaluating the effectiveness of brace treatment pervasively, the thesis aims to provide a statistical insight to the physicians by performing activity detection using a motion sensor. Data is collected using the sensors and can be stored on a SD card, or uploaded in real-time to a cloud for longitudinal analysis. The data received from the wearable sensors will help monitor TLSO brace compliance in an attempt to improve monitoring brace treatment. In current practices, physicians lack bio-feedback with respect to remote treatment monitoring in patients with AIS. This thesis attempts to implement wearables in such applications, and anticipates realizing a successful relationship between monitoring and improving compliance.

1.3 Related Work

Currently, temperature sensors are the only commercially available options for monitoring brace compliance in AIS. The iButton (Maxim Integrated, San Jose, CA) and Orthotimer (Pro-Tech Orthopedics, Raynham, MA) are temperature sensors that can be integrated in a TLSO. Both devices periodically measure the inside temperature of the brace. Physicians and orthotists can download temperature readings and view daily brace wear patterns using specialized software at clinic visits. In the study by Katz et al., authors recorded wear time once the temperature stabilized between 90°F and 99°F (Katz *et al.*, 2010). Temperatures were recorded every 15 minutes. Once the temperature dropped below 90°F, the wear time for an episode was stopped. Similarly, Weinstein et al. recorded temperatures every 15 minutes and considered that the brace was being worn when the temperature reached 82.4°F or higher (Weinstein *et al.*, 2013). Although temperature sensors have been shown to be effective at monitoring brace compliance in AIS by measuring the duration of brace wear, these sensors are unable to monitor the quality of brace wear (i.e., whether the brace is being worn correctly, as fitted by the physician and orthotist) (Rahman *et al.*, 2005; Asher and Burton, 2006; Katz *et al.*, 2010; Weinstein *et al.*, 2013). A few studies have also evaluated the use of pressure sensors to monitor compliance with brace wear in a clinical setting (Chase, Bader and Houghton, 1989; Wong *et al.*, 2000; Périé *et al.*, 2003). Lou and colleagues have investigated the use of force sensors to monitor compliance with brace wear in idiopathic scoliosis (Lou, Hill and Raso, 2010; Lou *et al.*, 2011; Chalmers *et al.*, 2015). However, the studies acknowledged that the force data changed (decrease over time) constantly happened during the period of the brace treatment. They were unable to determine whether the decrease in force was secondary to redistribution of forces in the brace over time. The authors believe that it might be due to the fact that force is low resolution data with low degrees of freedom so that I can extract more information from the real-life situation and train more robust models.

A system with multiple sensors and multiple modalities would be able to measure higher resolution data which has not yet been studied in a clinical setting. Inertial motion sensors have been successfully used for ubiquitous activity and motion monitoring applications. The sensors are capable of collecting and processing physical activity data continuously, remotely, and in real-time, which in turn facilitates design of timely interventions in a variety of applications such as activity recognition, activity estimation and joint angle estimation (Robertson *et al.*, 2015; Vikas *et al.*, 2016)

1.3.1 Compliance Monitoring

To properly evaluate the effectiveness of brace treatment, doctors monitor the duration of brace wear, to confirm whether the patient is complying to their prescribed treatment. Depending on the severity of the condition, physicians recommend that the brace needs to be worn for up to 23 hours a day for the treatment to be effective. A study by Weinstein et al. showed that TLSO treatment significantly reduced the curve progression in patients with AIS (Weinstein *et al.*, 2013). They found that longer hours of brace wear proved to provide a greater benefit to the patients. Rahman et al. developed a methodology to determine the duration of brace wear by the patient by using a temperature sensor (Rahman *et al.*, 2005). The brace was considered to be worn if the temperature recorded was above 26°C. The duration of the brace wear was divided by 23 to calculate the percentage of compliance. Temperature sensors are highly sensitive to minor fluctuations and temperature changes. These changes can be environmental factors such as changes in overall temperature of the weather, or the temperature in an indoors setting. Switching on the air-conditioner in the house can result in a temperature change. Such uncertainties can result in false values. As a result, a temperature sensor can often times over-estimate the duration of brace wear. Moreover, it does not provide a reliable measure of brace fit quality. Karol et al. demonstrated that patients with AIS who received regular feedback about their compliance with brace wear wore their brace for significantly more hours per day as compared to patients who did not receive feedback (Karol *et al.*, 2016). In that study, brace wear was monitored using a temperature sensor embedded inside the brace. Patients who received their brace wear data at their follow-up appointments with the physician had improved compliance. In this thesis, I designed and implemented a reliable heuristic method of evaluating the compliance of brace treatment. I used a more robust method by segmenting the data to provide an accurate calculation of the compliance of brace treatment.

1.3.2 Activity Detection Motion

There has been extensive research in the areas of activity detection from accelerometer and gyroscope readings. Ermes et al. developed a novel method to classify the unsupervised data obtained from a 3D accelerometer placed on the subject's wrist and hip. In addition, data from a GPS receiver was recorded and analyzed for activity identification (Ermes *et al.*, 2008). The total classification accuracy achieved was 89%. Ribeiro et al. developed a MHARS or Mobile Human activity recognition system to monitor different activities performed by patients (Ribeiro Filho *et al.*, 2016). The authors used accelerometer data, heart rate, altitude and body temperature to monitor the activities and the patient's health status. They achieved an accuracy of 86.7% in classifying patient data into different activities. Capela et al. designed a unique methodology which takes into account the transition between different phases of sitting, standing and lying to detect the three activities (Capela, Lemaire and Baddour, 2015). They achieved an accuracy of 96% for sitting, 98.7% for standing and 100% for lying. Pereira et al. used accelerometers in a mobile phone for activity detection. They used different features such as, mean acceleration for each axis, standard deviation and absolute average difference to classify different activities (Pereira *et al.*, 2016). The authors achieved an overall accuracy of 91.7%. Bao et al. used a combination of 5 accelerometers including four on the limbs and one on the hip to detect different activities (Bao and Intille, 2004). They achieved an overall accuracy of 84.6% for activity recognition.

1.4 Overview of the Proposed System

In this thesis, I intend to discover an innovative and effective treatment-monitoring methodology by implementing a context-aware remote sensing solution. The objective of the study is to monitor compliance of the brace treatment, and also to detect certain activities the patient performs. The compliance study indicates the amount of time the patient wore the brace, as compared to the duration of wear prescribed by their doctor. In this work, I introduced a new priori decision tree to automatically annotate the recorded data based off six different activities consisting of: sitting, standing, walking, running, lying and climbing. The effectiveness of the treatment in patients with scoliosis is evaluated using a main parameter: 1) Duration for which the brace was worn by the patient Data from the force sensor is used to determine the compliance, in addition to the baseline force. The proposed solution consists of two stages: 1) remote sensing and data acquisition and 2) data mining. For the remote sensing module, I designed and fabricated a sensor board to capture data from the patient's body. The data mining module handles processing and the analytical procedure performed on the captured data. To accomplish the target goal of monitoring brace treatment, an end-to-end system has been developed. Fig.1 shows the end-to-end data processing instructions.

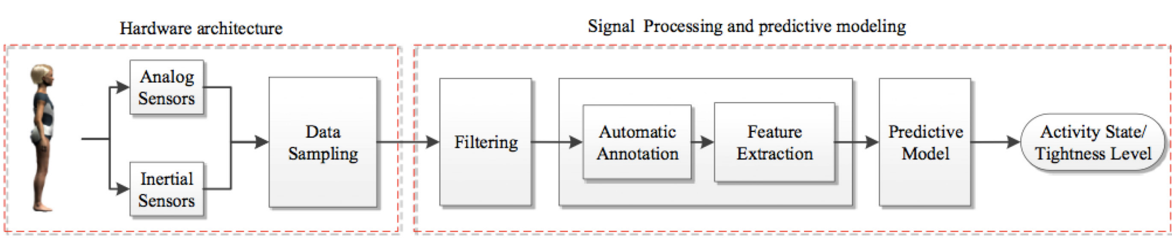


Fig. 1 End-to-end data processing system

CHAPTER II: HARDWARE DESIGN

To provide a reliable and robust method for monitoring compliance in AIS patients, I developed a custom-made PCB hardware solution. The hardware design includes a sensor data acquisition board, a force sensor, and a motion sensor capable of collecting accelerometer and gyroscope values. The equipment is embedded in the brace, and data is continuously collected for analysis.

2.1 Printed Circuit Board (PCB) Design

The sensor board contains an Atmega32u4 Atmel baseband data processor, a 9-axis MEMS MPU-6050 motion sensor from InvenSense, which communicates using the I^2C channel, and a custom-designed Honeywell FSB1500NSB force sensor placed at the analog channel using a 10-bit resolution A/D converter. The design also includes a micro SD card as a data logger and nRF8001 from Nordic as a Bluetooth low energy module. Figure 2 displays the hardware schematic and Figure 3 displays the sensor board that the proposed hardware architecture is implemented.

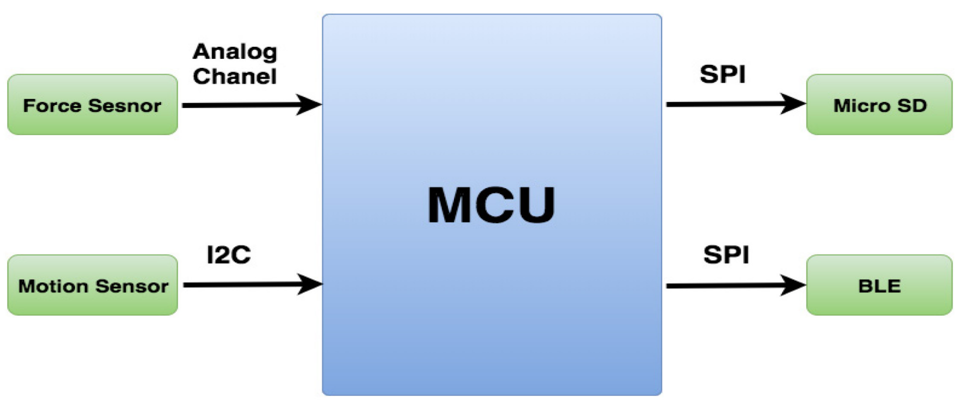


Fig. 2 Hardware Schematic

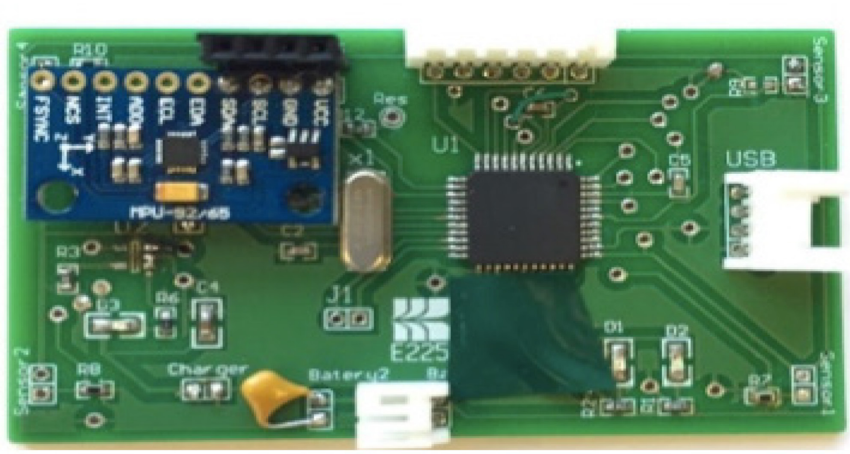


Fig. 3 Printed Circuit Sensor Board

The proposed solution consists of our hardware design system embedded in a Boston-type TLSO. The motion sensor and force sensor are connected to the PBC, and the system is installed into the brace. The TLSO brace is custom-designed to provide the ability of embedding the electronics. Fig 4(a) shows the customized brace with direction of axes of the motion sensor. Fig 4(b) demonstrates the position of the force sensor inside the customized brace.

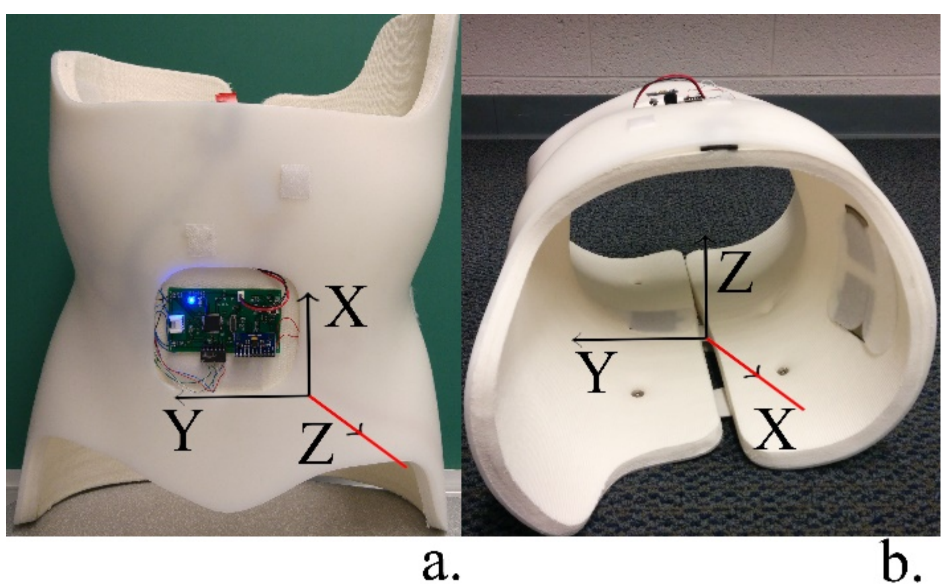


Fig. 4(a) Sensor board embedded in the TLSO & 4(b) Position of force sensor

2.2 Research and Development of Force Sensor

Initially, I began the testing process with an off-the-shelf force sensor as shown in Figure 5. Because of its square shape, this FSR-406 INTERLINK sensor reads the force being exerted on the entire square sensor. Due to the fact that the force is not concentrated and is distributed on a greater surface area, I had to use a sensor that measures force applied at a specific point. This provides a more accurate value.

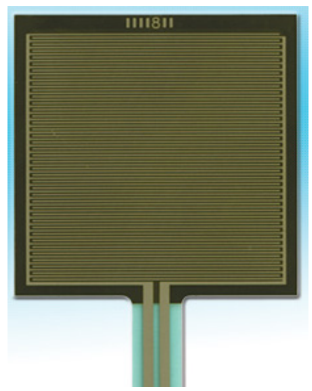
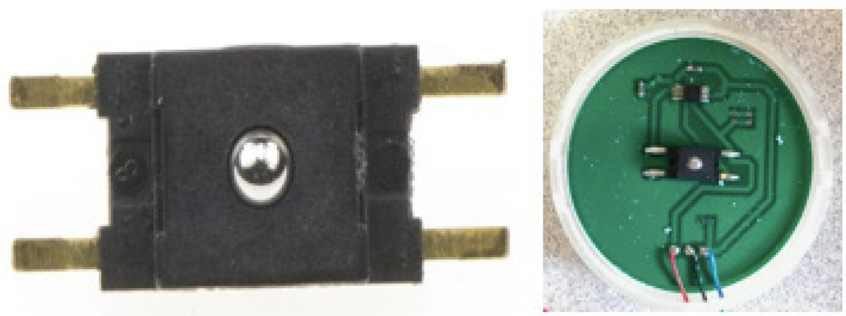


Fig. 5 FSR-406 INTERLINK Force Sensor

Certain studies have been carried out on applications in the domain of health-care that use the Force Sensitive Resistor (FSR), to measure force at specific point of body. Lukowicz et al. used such a sensor to detect a patient's activity by analyzing the frequency domain of the force data (Lukowicz *et al.*, 2006). The main challenge with selecting the appropriate force sensor for this application is to ensure that the data being recorded is accurate and consistent. Overnight tests were performed on the sensor by placing a fixed amount of weight on the sensor for a number of hours. There was a change in reading after a certain amount of time. The fluctuation and inconsistency of the data readings did not make this sensor effective for this study. The overnight testing results showed a gradual 20% increase in the force being measured over time. Thus, proving that the sensor was not stable or consistent. This is similar to the concept of sensor drift, which implies that after a given time, certain sensor values begin to drift away from the actual value. To overcome the inconsistency of the FSR sensor, I designed a more reliable and accurate custom-made sensor.

After conducting detailed research, I decided to use the FSS1500NSB from Honeywell point sensor as shown in Fig 6(a). This sensor collects the force reading that is focused at a specific point. It has a smaller surface area over which the force is collected as compared to the square sensor shown previously. Overnight tests of the point sensor show a great improvement in the stability of force readings. There seemed to be very minimal fluctuation with regards to a change in force readings. After conducting several overnight tests, it was obvious that the point sensor provided more accurate and consistent data.



(a) (b)

Fig. 6(a) FSS1500NSB sensor and 6(b) PCB for the sensor

After ensuring that this force sensor yielded the expected results, I then used a CMOS amplifier to boost the voltage readings from the force sensor. Figure 6(b) shows the PCB for the force sensor, including resistors and the amplifier. The FSB1500NSB sensor has a range of measuring force between 0 to 15N. Since this is not a significant range for measuring changes in force readings, I amplified this range. I used a INA2322 CMOS TI Instrumentation Amplifier with two resistors of values, R_1=27kΩ and R_2=87kΩ, to amplify the numerical value of the force sensor. The amplifier circuit is shown in Figure 7. Using this combination of resistors yield in a 21.2 gain factor. This is done to provide higher-density and more precise analysis to the physician about changes in force readings. Ultimately, the maximum value which can be recorded with the modified force sensor is 1048. Given that the maximum value the force sensor can output is 15N, using the resistors and amplifier yields in an amplification of 70.

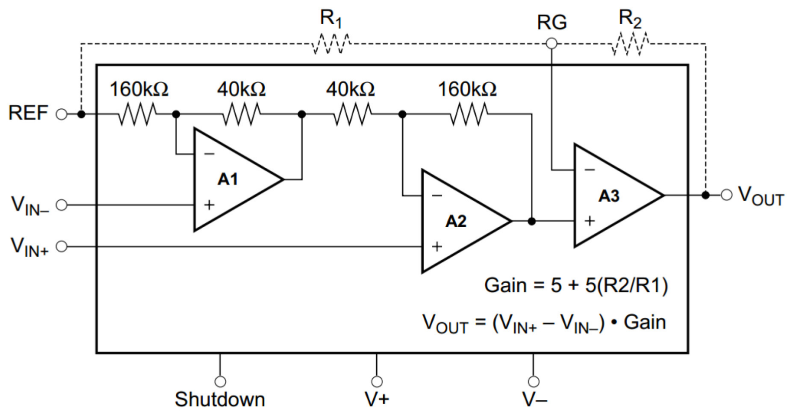


Fig. 7 TI amplifier circuit

After completion of the PCB design for the sensor, the housing for the PCB was desined using a 3D model. Figure 8 shows the sensor housing design. This force sensor housing is designed for Honeywell FSS Low profile force sensor, and the housing itself can handle more than 5 N force. The housing should be thin enough to not cause any discomfort to the patient, and also sturdy enough to withstand the abnormal impact.

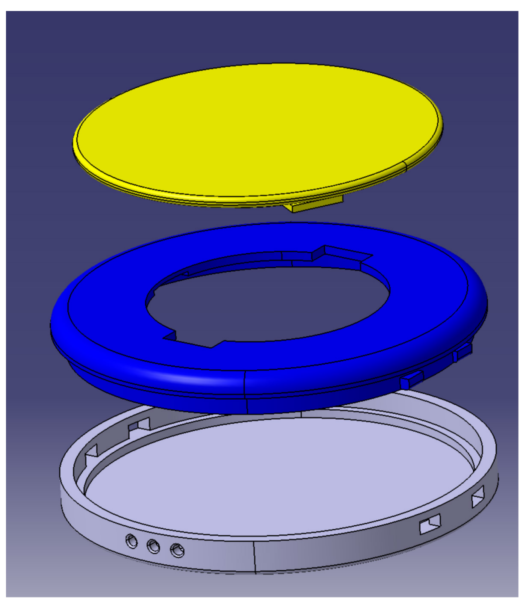


Fig. 8 Sensor Housing Design in a 3D model

2.3 Motion Sensor and Real-time Clock Implementation

To capture the patient's activities, I decided to use a MPU-6050 motion sensor from InvenSens. The MPU-6050 consists of a 3-axis gyroscope, 3-axis accelerometer, and a Digital Motion Processor. With its dedicated I^2C sensor bus, it directly accepts inputs from an external 3-axis compass to provide a complete 9-axis fusion output. The accelerometer provides data associated with the speed and acceleration of a patient's movement. While the gyroscope provides data regarding the orientation of the brace. The x-axis readings of the accelerometer indicate upward movement of the patient. The y-axis and z-axis readings give sideways and forward movement of the patient respectively.

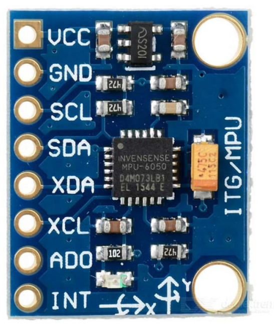


Fig. 9 MPU-6050 Motion Sensor

While collecting data, it is vital to ensure that the data can be used to initially train the model. To do so, training data was extracted from the dataset. In order to capture data in real-time, I introduced the concept of generating time-stamps in my dataset. To do so, I used a DS1307 RTC from Adafruit. The RTC also uses an I^2C communication channel, similar to the motion sensor. It provides seconds, minutes, hours, day, date, month, and year information. The end of the month date is automatically adjusted for months with fewer than 31 days, including corrections for leap year. The clock operates in the 12-hour format with the AM/PM indicator. The DS1307 has a built-in power-sense circuit that detects power failures and automatically switches to the backup supply. Fig. 10 shows the RTC used in my design.

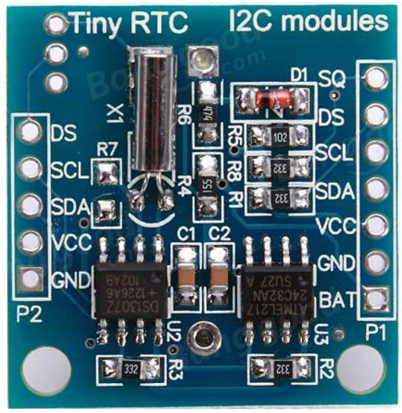


Fig. 10 DS1307 RTC used for generating time-stamps

CHAPTER III: EXPERIMENTS AND DATA ACQUISITION

3.1 Data collection

Data acquisition is a key component to the success and precision of this project. All data collection relates to the data being collected from the TLSO worn by the subjects. Force and motion data is collected and analyzed. In order to process the data, and make meaningful conclusions based off the results, it is vital to ensure that data acquisition is carried out properly and effectively. In this study, I collected data in two different experimental scenarios: 1) In-lab testing and 2) Patient testing.

3.2 Experimental Scenarios

The in-lab subject and actual patient were asked to perform the pre-defined activities: LIE, SIT, SND, WLK, RUN and STR for a duration of 2 minutes each. This data was used to train the model for activity detection. The patient was required to wear the brace for 23 hours a day, as prescribed by the orthotist. During this time, data was continuously recorded on a secure, digital SD card. The patient noted down the timings of specific activities they performed each day in a logbook provided to them. This helped me make a connection of the data collected to the activities performed by the patient for evaluation purposes. I designed a novel priori decision tree to automatically annotate the training data. I specifically employed a decision tree for this purpose in order to benefit from interpretability of the resulting model (i.e. rule-base) and use it for high level knowledge acquisition. This allows me to detect different activities using the trained classifier/model.

3.2.1 In-lab Testing

This first test was a controlled/supervised in-lab experiment. In this experiment, the subject was asked to perform six different activities (standing, sitting, lying down, walking, running and climbing the stairs) for duration of 2 minutes each. The test was repeated for 4 different levels of tightness. This allows me to investigate whether there is some similarity in the data patterns from which I can establish a certain trend. For each level, the subject performed the activities performed lasting 2 minutes each. In total, there were 24 tests conducted with 48 minutes of test data that was collected for the patient. Figure 11 illustrates 4 lines on the strap associated with the 4 levels of strap tightness named L1, L2, L3 and L4. The tightest level (L4) was the reference brace tightness level as fitted by the orthotist for the respective subject. The tightness levels have been defined by the orthotist. The remaining markers, L1-L3, are selected to demonstrate several levels of looseness that might degrade the effectiveness of the brace treatment. With the above-mentioned setup, I aimed to evaluate the ability of the compliance monitoring system to distinguish the appropriate tightness from several levels of looseness in the lab environment as a proof of concept. For our data acquisition, I set 2 minute sessions for each activity performed at each level of tightness. I started with L1 and collected 2 minutes of LIE, SIT, SND, WLK, RUN, and STR. Subsequently, these activities were repeated for all other levels of tightness. I collected 4800 samples per data channel during each session (sampling rate of 40 Hz).

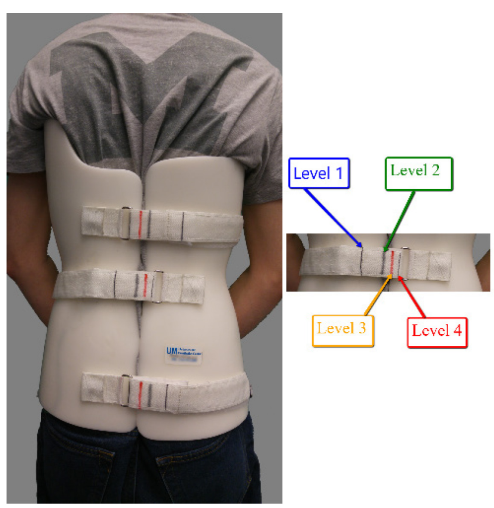


Fig. 11 4 lines on the strap associated with the 4 levels

3.2.2 Patient Testing

I evaluated the monitoring system on a volunteer patient who participated in experiments to conduct 26 days of semi-supervised and unsupervised data collection. The patient was a 12-year-old female who was receiving treatment at the University of Michigan Health System. She was asked to write a log of certain activities they performed during the day. Similar to the in-lab testing, the patient was also asked to perform the six activities of: LIE, SIT, SND, WLK, RUN, and STR. This is considered as semi-supervised data. The patient recorded semi-supervised data for 6 days. After the initial period of 13 days, the patient continued to wear the brace for another 13 days. A total of 26 days of unsupervised data was collected. I utilized markers and ground truths to examine the system in the experimental setup towards automatic detection of the brace wear compliance in unsupervised situations. Time and frequency analysis of the observations demonstrated promising results in terms of accuracy and reliability of the proposed embedded sensor-based monitoring system.

CHAPTER IV: SENSOR-BASED AUTOMATED MONITORING SYSTEM

To reach the quality measurement with minimum detection error, I employed a two-stage activity brace force monitoring design. In the first stage, I segmented the data to monitor compliance, based off the force sensor readings. In the second stage, I identified the current subject activity from 6 pre-defined classes of activities including LIE, SIT, SND, WLK, RUN and STR. This is considered as activity-specific monitoring. Activity-specific refers to the concept of identifying the activity being performed by the patient at any given time.

4.1 Signal Processing and Filtering

For processing data in such an application, filter design is vital. For the first step, I filtered the data received from the motion sensor, which is sampled at 40 Hz, by the means of a 5 Hz Low-Pass Filter. This initial filtering process removes common noise and artifacts from the motion data recorded from each axis. The data collected from the sensor board via Bluetooth or an SD card is fed to the feature extraction module. The priori decision tree uses the features to annotate the semi-supervised data automatically. The annotated data containing class labels is used to create the predictive model.

The data analysis phase contains two aspects: 1) Determining compliance of brace treatment using segmentation, and 2) Activity Detection and Classification. Duration of the brace wear is one of the major factors that impacts the treatment of patients with scoliosis. Compliance is important to physicians and patients as it provides important information about the patient's ability to wear the brace. If the patient has difficulties in wearing the brace, physicians can develop strategies to help increase the compliance.

4.2 Compliance Monitoring Algorithms

This is measured by segmentation of the data from force sensor to evaluate the total number of hours the brace was worn. Segmentation of data correlates to distinguishing the data from when the brace was worn, versus when it was not worn. In this paper, I designed a method to segment the force sensor data to estimate the duration of brace wear. The segmentation process allows in-brace data to help train the predictive mode. The force sensor data is divided into windows of 4 seconds with a window increment of 1 second. In the segmentation by mean process, the average force inside the brace is calculated for each window. I divided the patient data into rectangular windows of 4 seconds each, assuming that the signal is stationary in that window. The breathing pattern of the patient, which is captured from the force sensor, is quasi periodic, with peaks which are about 1.5 seconds apart. By choosing a smaller window size of 1 second, it is not possible to extract the frequency content of the signal. A larger window may contain more than two different activities of the patient and will not generate accurate results. An optimal window size of 4 seconds is chosen for the purposes of analysis.

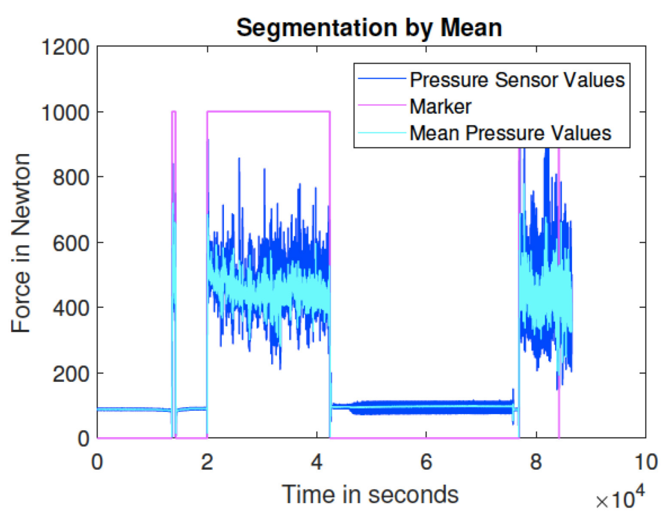


Fig. 12 Data segmentation by mean for complaince montioring

Ultimately, to calculate the total hours of brace wear, the following formula is used, and computed using a MATLAB script:

$$\text{Duration of brace wear} = \frac{\text{Number of samples}}{\text{Sampling Frequecny}}$$

4.3 Activity Detection System Design

The data analysis process for activity detection is as follows: 1) Feature Extraction: after segmentation, the in-brace data is passed to the feature extraction block. The acceleration is along a specific axis for some of the day-to-day activities of the patient. For instance, when the patient climbs up or down the stairs, the direction of acceleration lies mainly on the x-axis. When the patient walks, the acceleration along z-axis is dominant. These properties and values can help distinguish between the two activities. For stationary activities like sitting, standing or lying down, orientation of the brace or the angle of rotation of y-axis (pitch), can be used as a discriminative feature. The number of footsteps in a 10-second window is another discriminative feature that I employed in this work. To improve the identification accuracy of the predictive model, I used three features: Resultant x-axis acceleration, the pitch, and number of footsteps in a 10-second window. These features are used to train the predictive model. Figure 13 depicts the data modeling process.

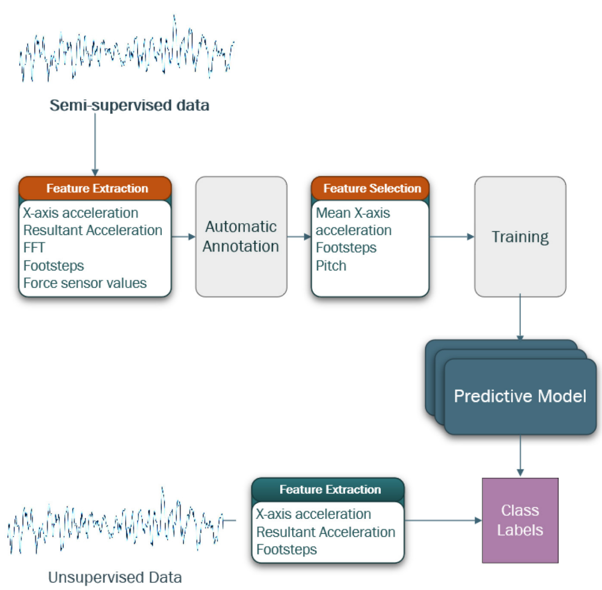


Fig. 13 Signal processing & Modeling process

2) Detection of Footsteps: the number of footsteps is a discriminative feature used to differentiate stationary from non-stationary activities. Sitting, standing and lying show no footsteps, as they are stationary activities. The number of footsteps is also used to differentiate walking from running.
3) FFT Analysis: FFT analysis was carried out to help distinguish between different activities such as running and walking. The frequency peak for running is achieved at approximately 1.5Hz, equivalent to 2 steps/sec. The frequency peak for walking is 1Hz, while the frequency peak for sitting was between 0.5Hz to 1Hz. This analysis helped further establish our decision tree to detect and distinguish activities. 4) Automatic Annotation using Priori Decision tree. After the number of footsteps is detected and the FFT analysis is carried out, I can automatically annotate the semi-supervised data using a priori decision tree. The decision tree is depicted in Figure 14. In the decision tree, I used four features: 1) Number of footsteps in a 10-second window, 2) Peak of the FFT in a 10-second window, 3) X-axis acceleration and 4) Orientation of the brace which is measured by the angle of rotation of y-axis (normalized pitch). 5) Classification: This can be depicted in Figure 13. I used 10-fold cross-validation and employ a fine KNN classifier with different values of K. I also use a complex decision tree classifier, and a SVM classifier with a Gaussian Kernel for activity identification.

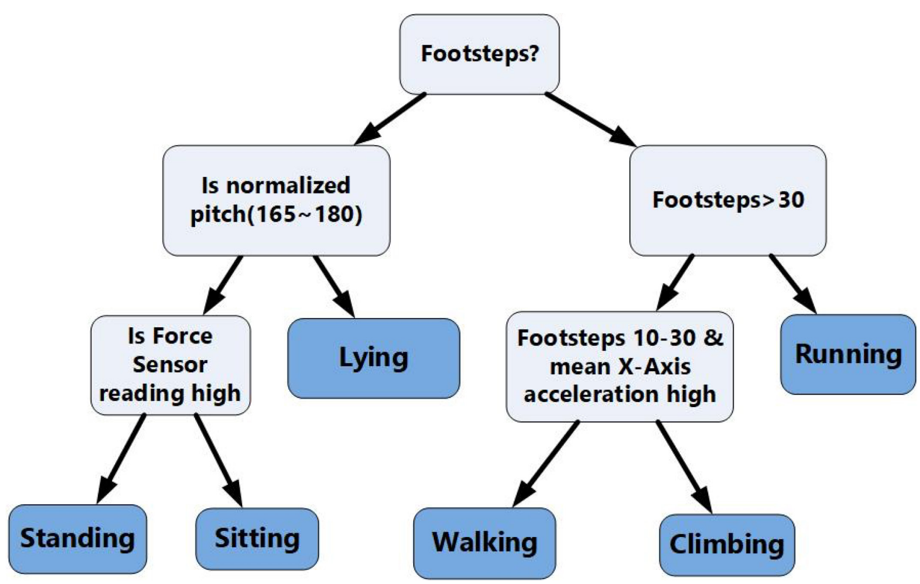


Fig. 14 Context prediction model and features

Furthermore, I used the following equations to compute the following features:

- Resultant Acceleration:

$$A_r = \sqrt{(A_x)^2 + (A_y)^2 + (A_z)^2}$$

- Resultant gyroscope values:

$$G_r = \sqrt{(G_x)^2 + (G_y)^2 + (G_z)^2}$$

- Pitch:

$$pitch = \frac{A_y}{\sqrt{(A_x)^2 + (A_z)^2}}$$

4.4 Experimental Results

In this work, I implemented a multi-modal sensor monitoring solution including a custom designed multi-sensor board and a data processing algorithm suite with a two-stage classification design to accurately detect the quality of brace wear. I incorporated inertial motion sensing capability that can capture valuable patient activity and motion information for activity segmentation. Then, multiple force sensor data is recorded and analyzed for activity specific to brace quality detection with almost a 100% accuracy. The experimental results are shown below for the in-lab testing, as well as the patient's test data.

4.4.1 In-lab Results

The in-lab experiment is designed based on 4 in-lab data collection sessions from a 21-year-old male using a custom designed back brace designed for him. This protocol consists of the 6 activities: LIE, SIT, SND, WLK, RUN and STR, which are performed for 4 different days conducted in a semi-controlled setting. An analysis was performed to investigate whether data can be distinguished into 4 different levels. Figure 15 shows the separation between tightness levels after refining the data from artifacts and normalizing the data. Ultimately, a comparison was done to understand the force levels associated with each level. These results are depicted in Figure 16.

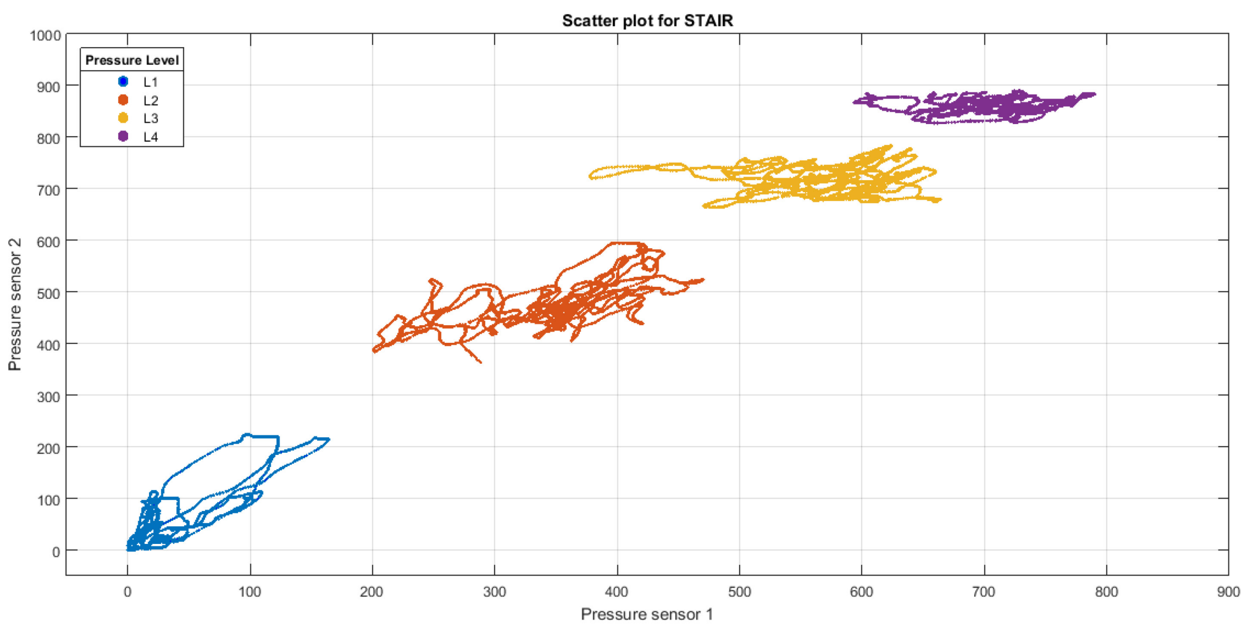


Fig. 15 Data classification for the 4 different levels

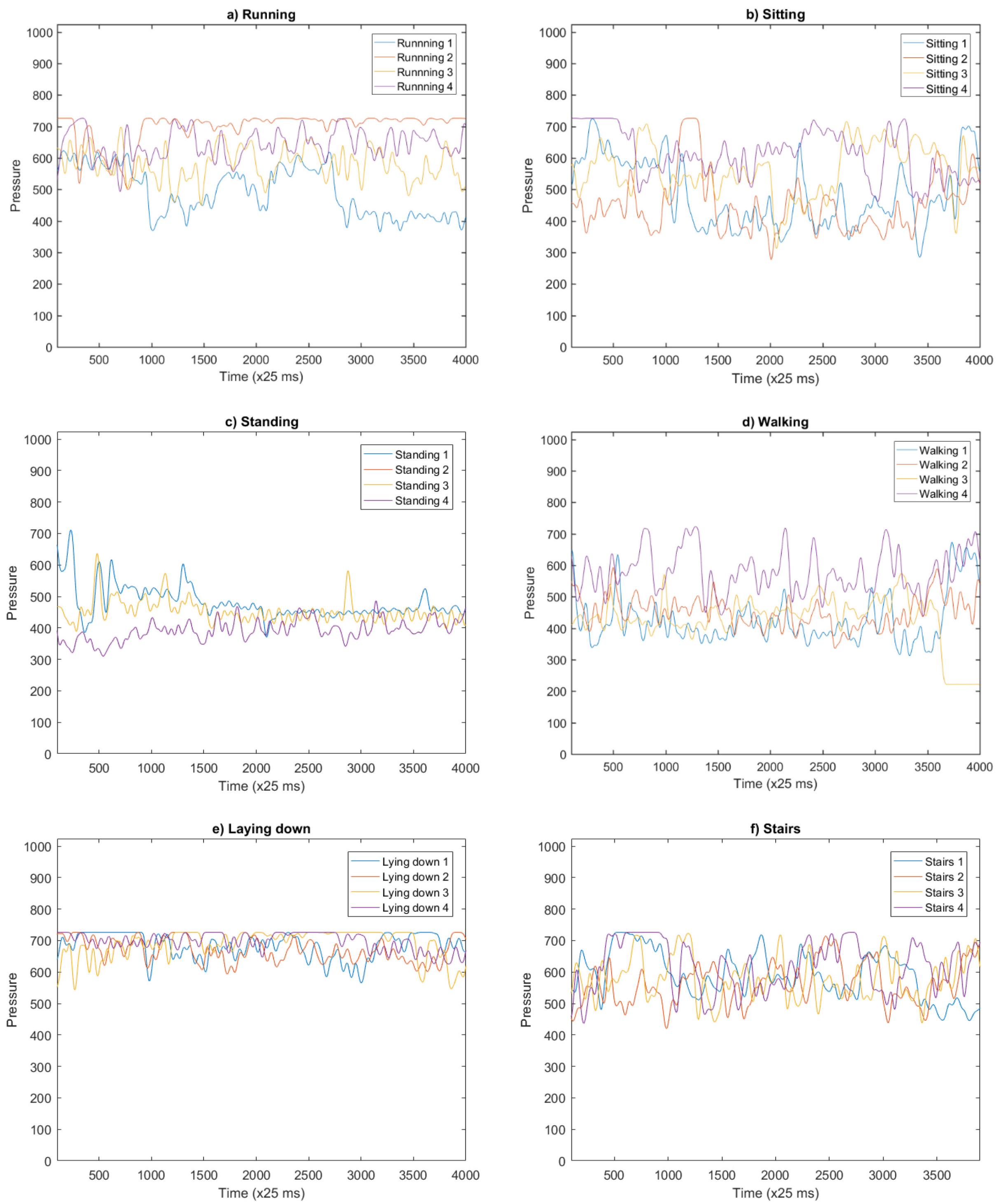


Fig. 16 Six different activities performed over 4 days on different levels

4.4.2 Patient Results

After collecting semi-supervised and unsupervised data from the patient, an anlayis was done on both experimental scenarios. Table I. shows force and compliance percentages. Compliance percentage represents how well the patient is complying to the duration for which they wear the brace, as prescribed by the physician. It was observed that initially, after the first 4 days, the patient begins to become accustomed to the brace. On day 1, they wear the brace for 2 hours. It was also observed that there was a gradual reduction in the force exerted by the brace, which indicates that the brace was getting looser, which could be due to the patients wearing TLSO loosely or due to patient's curvature reducing while wearing the TLSO. This information is important to the physician as a loose brace may not be able to adequately control the spinal curvature. Figure 17 depicts a relation between the number of hours of brace wear and the force exerted by the brace. The remote sensor system was able to detect 1) Compliance of brace treatment by evaluating the duration of brace wear by the process of segmentation and, 2) The quality of brace-fit by estimating the duration of the activities as performed daily by the patient.

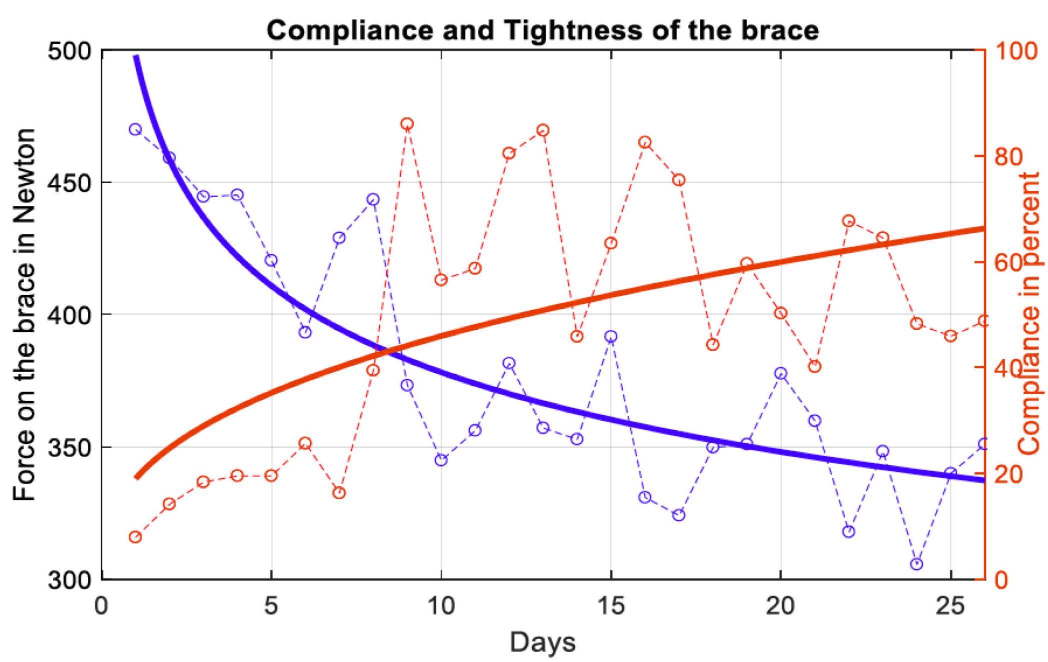


Fig. 17 Relationship between Force and Compliance of brace wear

TABLE I.

Days	Force on brace	Compliance %
1	469.8	7.91
2	459.1	14.1
3	444.5	18.3
4	445.1	19.5
5	420.4	19.5
6	393.1	25.6
7	428.9	16.2
8	443.4	39.4
9	373.2	86.5
10	344.8	56.2
11	356.1	58.6
12	381.5	80.4
13	357.1	84.7

Force and Compliance Percentages

I achieved an overall accuracy of activity recognition of a 100%. Patients were instructed to wear the brace for 2 hours a day initially, gradually increasing to 23 hours a day. This was proven by the analysis, as compliance was observed to increase from 20% to 80% after 4 weeks. Naturally, the brace is tightest when the patient begins treatment. As they continue wearing the brace daily, they start to “break-in”, making the brace more comfortable to wear. The results support this theory. A comparison was made with the accuracy of activity identification in this study with the previous research work, as shown in Table II. This methodology and analysis is the most accurate to date.

TABLE II.

Activities	**Ernes et. al** (Ermes *et al.*, 2008)	**Pereira et. al (**Périé *et al.*, 2003)	**Morton et al.** (Morton *et al.*, 2008)	**My methodology**
Sitting	97%	90%	96%	99%
Standing	90%	91%	87%	80%
Walking	71%	87%	94%	99%
Climbing	-	80%	61%	99%
Lying	98%	89%	-	100%
Running	91%	88%	98%	100%
Total	89%	83%	92%	100%

Comparison of Accuracies of Activity Identification in previous research work

REFERENCES

Asher, M. A. and Burton, D. C. (2006) 'Adolescent idiopathic scoliosis: natural history and long term treatment effects', *Scoliosis*, 1(1), p. 2. doi: 10.1186/1748-7161-1-2.

Bao, L. and Intille, S. S. (2004) 'Activity Recognition from User-Annotated Acceleration Data Pervasive Computing', *Pervasive Computing*, 3001, pp. 1–17. doi: 10.1007/978-3-540-24646-6_1.

Capela, N. A., Lemaire, E. D. and Baddour, N. (2015) 'Improving classification of sit, stand, and lie in a smartphone human activity recognition system', in *2015 IEEE International Symposium on Medical Measurements and Applications, MeMeA 2015 - Proceedings*, pp. 473–478. doi: 10.1109/MeMeA.2015.7145250.

Chalmers, E. *et al.* (2015) 'An advanced compliance monitor for patients undergoing brace treatment for idiopathic scoliosis', *Medical Engineering and Physics*, 37(2), pp. 203–209. doi: 10.1016/j.medengphy.2014.12.010.

Chase, A. P., Bader, D. L. and Houghton, G. R. (1989) 'The biomechanical effectiveness of the boston brace in the management of adolescent idiopathic scoliosis', *Spine*, 14(6), pp. 636–642. doi: 10.1097/00007632-198906000-00018.

Ermes, M. *et al.* (2008) 'Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions', *IEEE Transactions on Information Technology in Biomedicine*, 12(1), pp. 20–26. doi: 10.1109/TITB.2007.899496.

Karol, L. A. *et al.* (2016) 'Effect of compliance counseling on brace use and success in patients with adolescent idiopathic scoliosis', *Journal of Bone and Joint Surgery - American Volume*, 98(1), pp. 9–14. doi: 10.2106/JBJS.O.00359.

Katz, D. E. *et al.* (2010) 'Brace wear control of curve progression in adolescent idiopathic scoliosis', *Journal of Bone and Joint Surgery - Series A*, 92(6), pp. 1343–1352. doi: 10.2106/JBJS.I.01142.

Lou, E. *et al.* (2011) 'An objective measurement of brace usage for the treatment of adolescent idiopathic scoliosis', *Medical Engineering & Physics*, 33(3), pp. 290–294. doi: 10.1016/j.medengphy.2010.10.016.

Lou, E., Hill, D. L. and Raso, J. V. (2010) 'A wireless sensor network system to determine biomechanics of spinal braces during daily living', *Medical and Biological Engineering and Computing*, 48(3), pp. 235–243. doi: 10.1007/s11517-010-0575-4.

Lukowicz, P. *et al.* (2006) 'Detecting and interpreting muscle activity with wearable force sensors', in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, pp. 101–116. doi: 10.1007/11748625_7.

Morton, A. *et al.* (2008) 'Accuracy in the prediction and estimation of adherence to bracewear before and during treatment of adolescent idiopathic scoliosis', *Journal of Pediatric Orthopaedics*, 28(3), pp. 336–341. doi: 10.1097/BPO.0b013e318168d154.

Pereira, J. D. *et al.* (2016) 'A movement activity recognition pervasive system for patient monitoring in ambient assisted living', in *Proc 31st Annu ACM Symp Appl Comput - SAC '16*, pp. 155–161. doi: 10.1145/2851613.2851689.

Périé, D. *et al.* (2003) 'Boston brace correction in idiopathic scoliosis: A biomechanical study', *Spine*, 28(15), pp. 1672–1677. doi: 10.1097/00007632-200308010-00008.

Rahman, T. *et al.* (2005) 'The association between brace compliance and outcome for patients with idiopathic scoliosis', *Journal of Pediatric Orthopaedics*, 25(4), pp. 420–422. doi: 10.1097/01.bpo.0000161097.61586.bb.

Ribeiro Filho, J. D. P. *et al.* (2016) 'MHARS: A mobile system for human activity recognition and inference of health situations in ambient assisted living', *Journal of Applied Computing Research*, 5(1). doi: 10.4013/jacr.2016.51.04.

Robertson, K. *et al.* (2015) 'Prompting technologies: A comparison of time-based and context-aware transition-based prompting', *Technology and Health Care*, 23(6), pp. 745–756. doi: 10.3233/THC-151033.

Sapountzi-Krepia, D. *et al.* (2006) 'The experience of brace treatment in children/adolescents with scoliosis', *Scoliosis*, 1(1). doi: 10.1186/1748-7161-1-8.

Vikas, V. et al. (2013) 'Measurement of robot link joint parameters using multiple accelerometers and gyroscope', in *ASME 2013 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, pp. V06BT07A007-V06BT07A007.

Weinstein, S. L. *et al.* (2013) 'Effects of Bracing in Adolescents with Idiopathic Scoliosis', *New England Journal of Medicine*, 369(16), pp. 1512–1521. doi: 10.1056/NEJMoa1307337.

Wong, M. S. *et al.* (2000) 'Effectiveness and biomechanics of spinal orthoses in the treatment of adolescent idiopathic scoliosis (AIS)', *Prosthetics and Orthotics International*, 24(2), pp. 148–162. doi: 10.1080/03093640008726538.