125 Adaptive Neural Network Characterizations of Driver Longitudinal Control Behavior

Charles MacAdam
Zevi Bareket

University of Michigan
Transportation Research Institute
(UMTRI)

Ann Arbor, MI 48109, USA
Phone: USA (734)-936-1062
Fax: USA (734)-936-1068
E-mail: cmacadam@umich.edu

ABSTRACT

This paper examines how neural network methods may be used to represent driver manual control of throttle position during headway-keeping tasks. The findings of the study indicate that the neural network methodology employed here can be used to characterize a variety of driver longitudinal control behaviors, provided that the input data exhibit strong similarities to the data used to train the network. Otherwise, the network architecture and methodology utilized here is not considered adequate to predict driver control responses for *unseen* data not represented by the training set. Shortcomings in extending the trained network to predict accurate driver control responses for unseen data can stem from a variety of reasons, including the intermittent nature of driver longitudinal control behavior. While neural networks can be used to represent adaptive longitudinal control behavior of drivers and their associated variability during active control engagements, determining when active driver control engagements are actually occurring and selecting that data for training purposes is a confounding factor.

Keywords / driver, control, neural, network, headway, longitudinal, adaptive, behavior

1. INTRODUCTION

This paper examines how neural network methods may be used to represent driver manual control of throttle position during headway-keeping tasks. Recent studies [1-4] of passenger car headway control systems have increased interest in the longitudinal control behavior of actual drivers. Much of this interest is focused on understanding the range of driving behavior present in the highway traffic population in order to better match the control characteristics of new headway-keeping technologies to the preferences of drivers when such systems are activated. The neural net approach examined here offers one possible approach for identifying and modelling adaptive longitudinal control behavior of drivers engaged in headway-keeping or related tasks. The resulting control model characterization(s) might then be used as a basis for control algorithm development in ITS headway control systems. It can also have utility within the context of ITS warning/control packages that require a continuously updated characterization of driver control behavior.

A previous paper [4] demonstrated the capability to represent driver throttle control behavior as a function of range and range rate using a fairly simple two–layer neural network architecture for specific instances of tracking control behavior. An example result from that paper is seen in Figure 1 showing the level of agreement achieved between the neural net representation and an actual measurement of driver throttle control during normal highway driving. Although the type of result seen in Figure 1 was typical of modelling *specific* instances of driver control behavior with a neural net, further analysis indicated that the same model was not capable of predicting driver throttle control activity with the same degree of accuracy at other encounter times (unseen data not included in the network training). It was hypothesized that additional training data for each driver and additional vehicle information such as speed, and road grade information, would likely improve the network's ability to predict throttle control behavior with unseen data not contained in the initial training set.

This paper now extends that initial work to include additional sequences of data with which to train the neural network and also adds forward speed as an additional network input. Alternate network architectures were also considered within the study as additional methods for improving the prediction capabilities with unseen data. It was hoped that these modifications would further enhance the adaptive capabilities of the network.

2. METHODOLOGY

2.1 Driver Data

Experimental data were collected from a group of 36 drivers taking part in a research program on headway control systems [1, 4]. A subset of these data was then used to train candidate neural network architectures. The network inputs were range, range-rate, and speed of the test vehicle sampled at 5 Hz. The network output was driver throttle control position. The experimental data corresponded to normal highway driving in the U.S. under moderate traffic conditions. A test vehicle equipped with an infrared range sensor and on-board instrumentation package collected an hour of *manual* (headway control system inactivated) driving data for each of the drivers over the same highway route.

Selected portions of these data from three different drivers were used in this study. The three selected drivers exhibited driving styles that could be categorized as "aggressive," average," and "passive" – reflective of their willingness to pass and overtake other vehicles during their respective driving sessions. For each of the three selected drivers (A, B, and C), representative data for "closing-in" and "tracking" maneuvers were used to train the neural network. It was not known, but suspected, that the drivers were actually engaged in some form of control activity for these selected data. Each training set ranged from about 4 to 8 minutes of such data, depending on the driver. Each training set included six separate encounters with different target vehicles, ranging in duration from about 30 to 90 seconds. The training "clips" were then combined into one large record that was used to train the network in a single session (per driver).

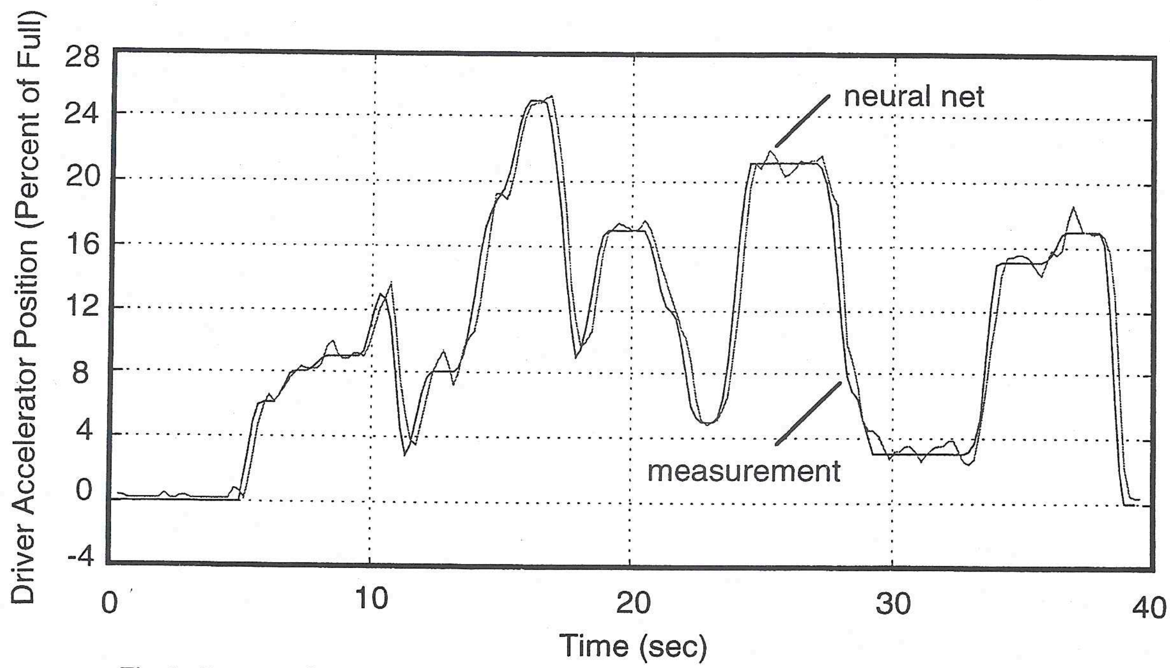

Fig. 1. Representing Driver Longitudinal Control Behavior with a Neural Net, from [4].

Once trained, the resulting model for each driver was then challenged by comparing its predicted throttle control behavior against similar *unseen* data at other encounter times. This procedure was repeated for each of the three drivers.

2.2 Network Architecture

Figure 2 shows a diagram depicting the basic network architecture used in this study. It contains 15 first-layer neurons with sigmoid activation functions. These are then combined into a single linear output-layer neuron representing the driver throttle control activity. Several other architectures involving fewer and greater numbers of neurons were initially examined before selecting this particular network which provided a reasonable compromise between accuracy and training speed. The inputs to the networks are range, range-rate, vehicle speed, and two lagged counterparts of each respective input, making a combined total number of inputs equal to nine. The lagged inputs can help provide time derivative information to the network. The lag value used in these calculations was 2 seconds. An example set of network inputs (range, range-rate, and velocity) and the corresponding target output (accelerator / throttle position) is seen in Figure 3. (The range and speed units are feet and feet / second, respectively.) This particular time history set corresponds to a closing-in and tracking maneuver. As noted above, six of these types of time history data streams were combined into one contiguous data set for training purposes for each of the three drivers. MatLab [5] was used to conduct the calculations. The Levenberg-Marquardt back-propagation algorithm was selected for training and required about 150-200 epochs to achieve satisfactory matching. Figure 4a shows an example result comparing the predicted network output of throttle control and the corresponding training data for driver A (sum squared output error level of about 10 after 200 epochs). Figure 4b shows a portion of the same data on an enlarged time scale.

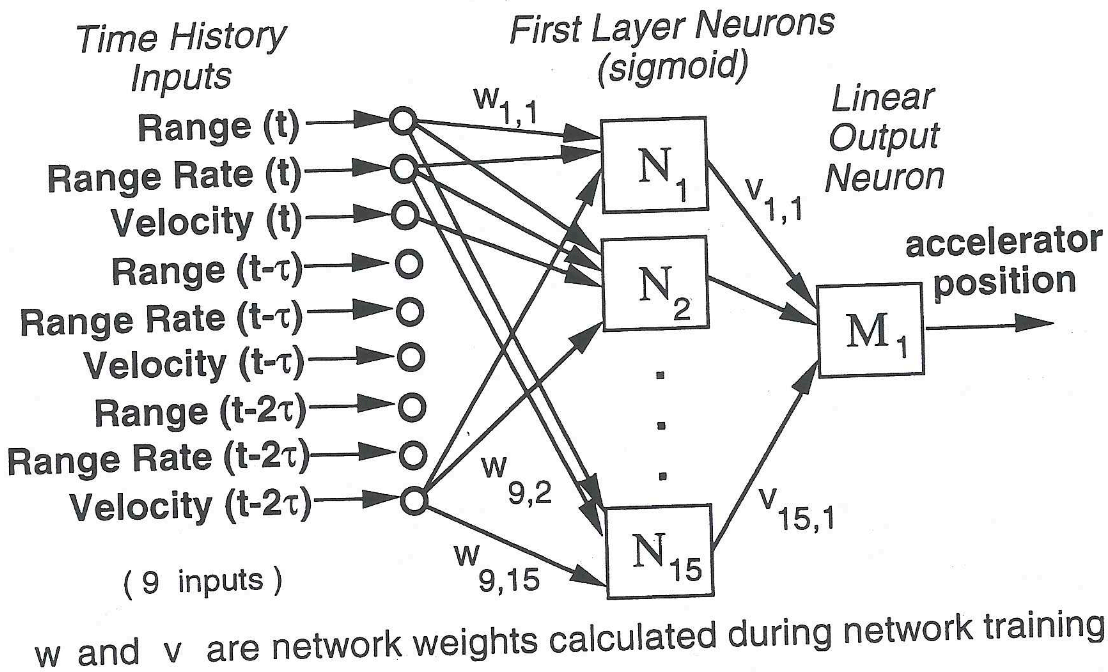

Fig. 2. Neural Net Architecture Used in Study.

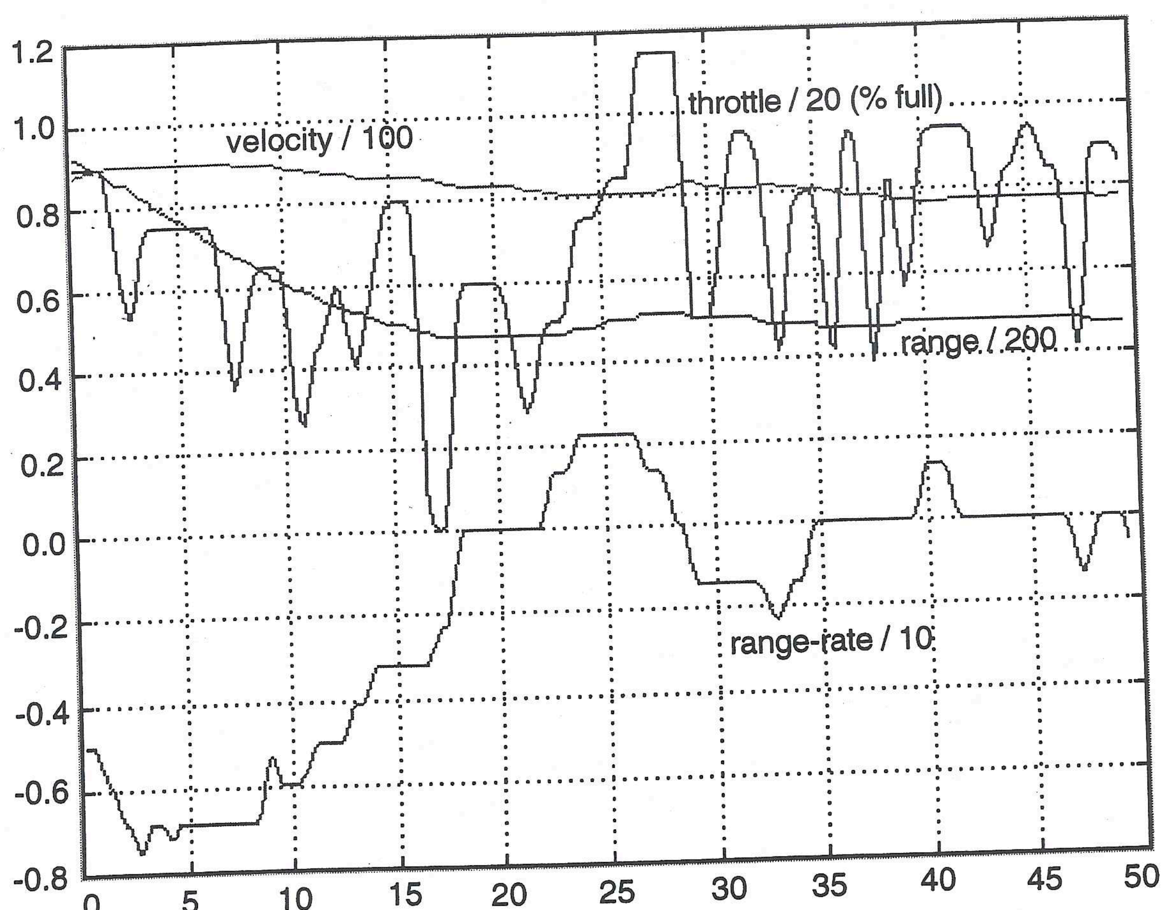

Fig. 3. Example Network Inputs and Target Output Training Signals.

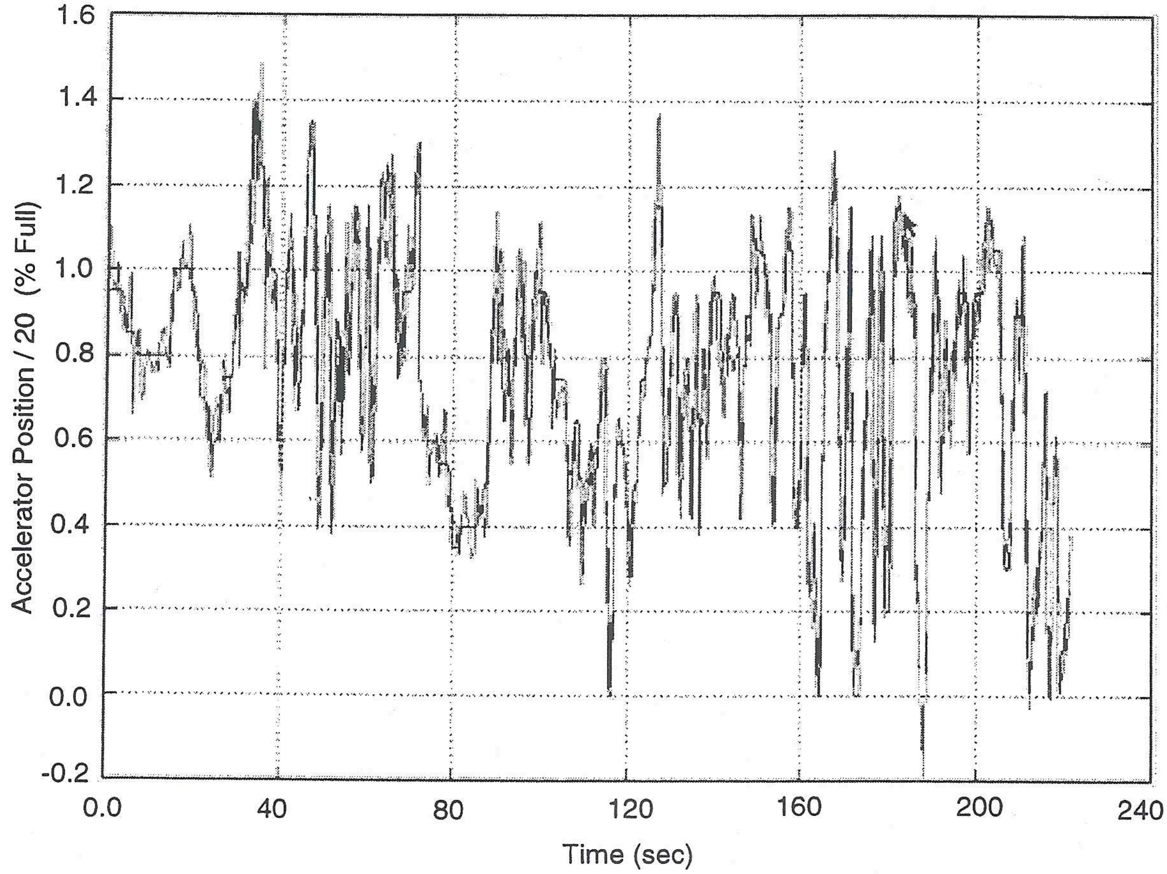

Fig. 4a. Example Comparison of Neural Net Prediction vs. Training Data (Driver A).

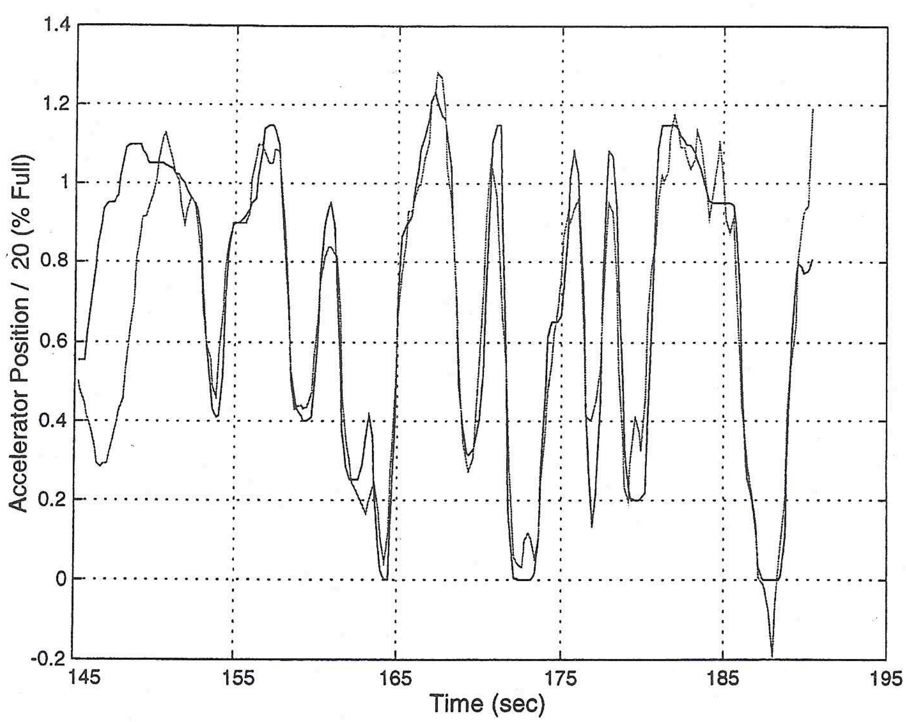

Fig. 4b. Enlarged Time Scale.

3. RESULTS FOR THREE DRIVERS

Corresponding sample results for each of the three drivers (A, B, and C) are seen in Figure 5. This figure shows a typical comparison between the neural net prediction and portions of the data used to train the network. In contrast, Figure 6 shows sample results for the same network configuration and weight values, but now comparing driver accelerator control responses predicted by the trained network with data not used in the training session (unseen data). As indicated here, the level of agreement is considerably less using the unseen data as input to the network.

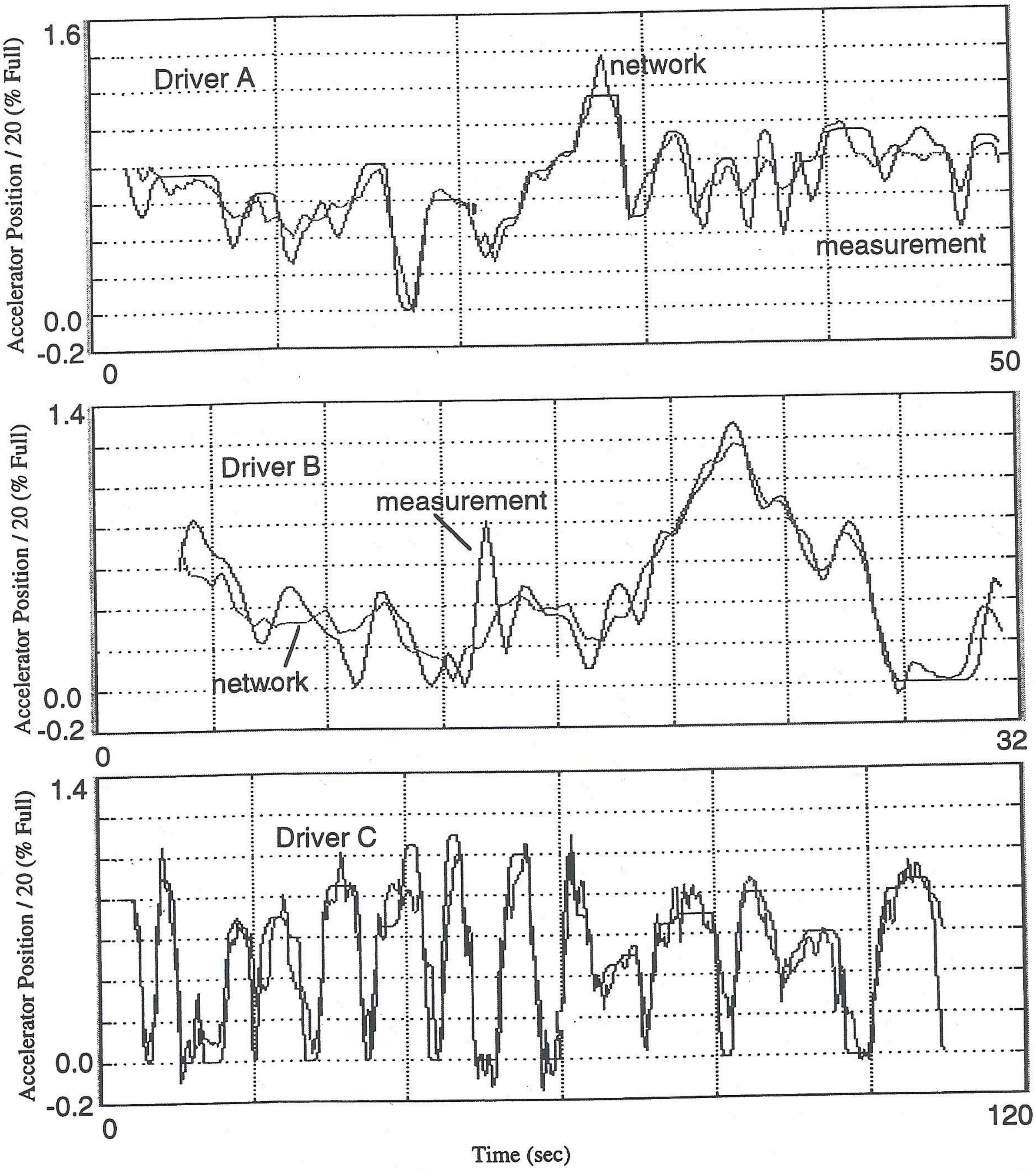

Fig. 5. Example Comparisons Between Network Predictions and Portions of *Training* Data. Drivers A, B, and C.

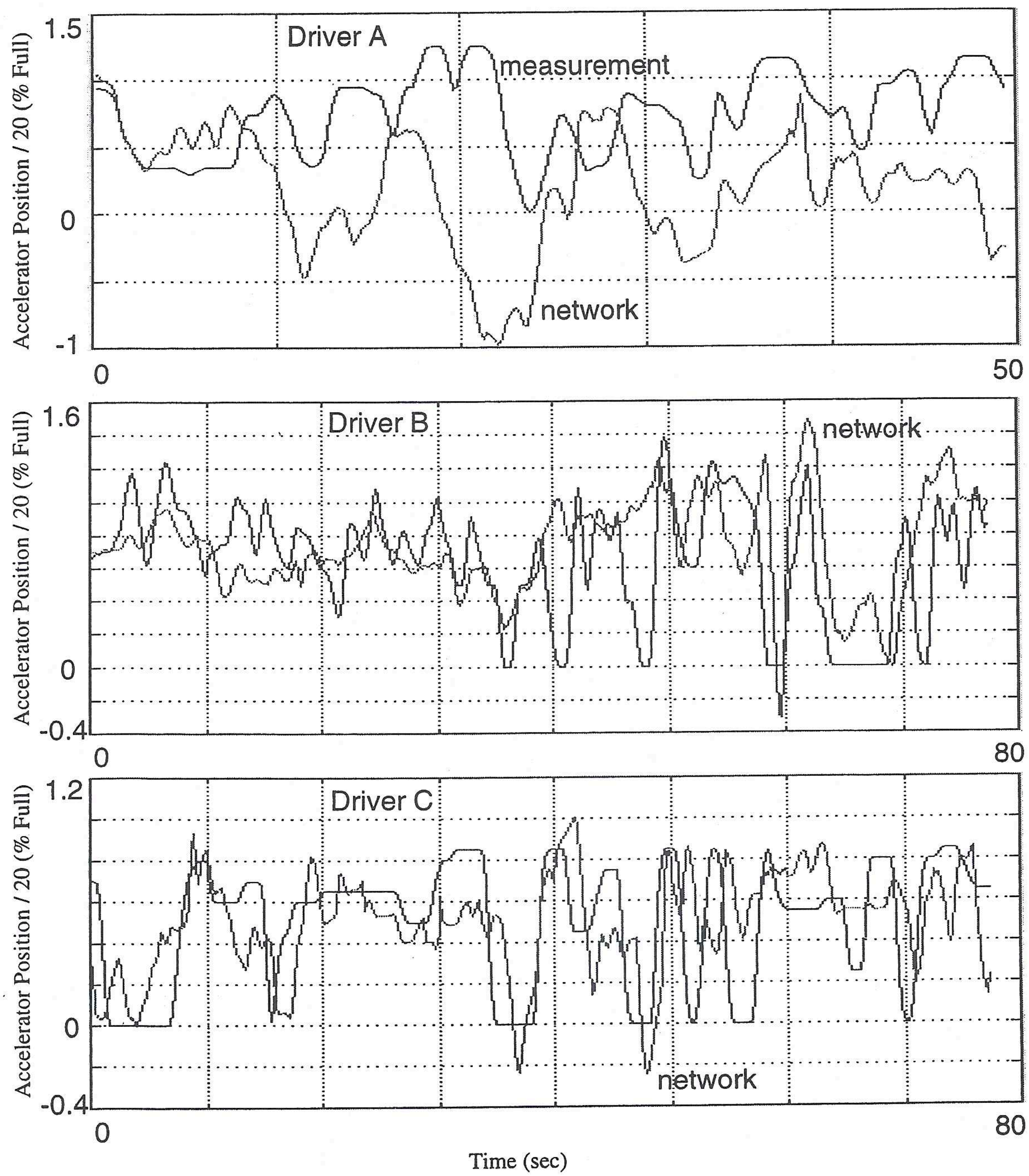

Fig. 6. Example Comparisons Between Network Predictions and *Unseen* Data. Drivers A, B, and C.

4. DISCUSSION

The training data results seen in Figure 5 indicate that a neural net approach can be used to identify different driver control responses under a variety of similar highway driving conditions. However, as indicated by the results of Figure 6, a broader application to unseen data, that attempts to capture an even wider range of longitudinal control behavior of drivers, still presents a challenge. Although certain portions of the unseen data comparisons in Figure 6 demonstrate some agreement with the corresponding measurements, many other portions are clearly lacking. Explanations for some of these results may be related to the variety of activities drivers normally engage in during driving, many of which are not necessarily control-related.

4.1 Intermittent Control Activity

Numerous longitudinal control situations that occur during potential headway-keeping activities come and go and can be fairly intermittent in nature. (An exception to this may be driver control responses under very close following conditions.) Significant leeway is present in many longitudinal control situations thereby providing opportunities for intermittent (or even unrelated) control behavior by drivers. The issue of intermittency can present difficulty to control identification procedures because of the associated variability and inconsistencies in assumed relationships between driver control activity and dependent variables.

If certain basic control relationships exist but are only being exercised occasionally by a driver, the identification of those basic rules or tendencies becomes more difficult. Sometimes, no driver control activity may be present, even though the data may reflect time history traits similar to those exhibited by intentional control engagements by a driver. For example, determining how fast to close in on a target vehicle, or when to pull out and pass, can often be dictated more by the preferred operating speeds of the respective drivers and adjoining traffic conditions than by some continuous longitudinal control processing activity on the part of the driver. In other cases, the driver may be more fully engaged in tracking the lead vehicle. In both cases the range data may appear to exhibit similar basic traits even though the driver control activities are unalike.

Interestingly, these results also contrast with some recent lateral control applications for which neural net approaches have demonstrated reasonable consistency in identifying driver steering control behavior during path-keeping tasks [6, 7, 8]. When considering the differences in these two types of driving tasks and their attendant driver control requirements, some explanation may be related to the continuity of the control task. For example, the lateral path-keeping task, even for simple straight-line driving, does seem to require fairly continuous monitoring and attention by a driver, given the consequences of straying out of a lane or off the road. The roadside and lane markers also provide a type of continuous reminder to the driver in this regard. In a collision avoidance sense, the roadside or lane edge acts as a *persistent obstacle* to be avoided. In contrast, the nature of target vehicles in one's forward view during longitudinal engagements, act as *intermittent moving obstacles* that are encountered with varying frequency depending on one's driving style and the traffic density. In this regard, the more permanent stimulus of control activity for the driver (and perhaps conditioner of attentiveness) arises from lateral control requirements. These differential or asymmetric stimuli to the driver between lateral and longitudinal control requirements may contribute in some way to differences in time-on-task that drivers elect to allocate.

4.2 Looking Through a Straw

Understanding and modelling the longitudinal control behavior of drivers is further constrained by the limited information available from a range sensor alone. Adjacent or following vehicles can often temporarily influence how a driver modulates the throttle, independent of the target vehicle ahead, thereby bypassing any assumed relationship or dependency between driver throttle modulation activity and range information assumed in many longitudinal control formulations. Consequently, use of additional information relating to vehicles located adjacent to and behind a subject vehicle would likely be useful in developing more robust and realistic models of driver longitudinal control behavior.

In light of the above discussion, use of additional sensor data would seem to help achieve a more generalized neural net (or alternate) model of driver longitudinal behavior, particularly for improving predictions of driver control behavior with unseen data. Its success would likely depend on the ability to incorporate additional nearby vehicle information into the formulation, somewhat akin to a collision avoidance system that monitors target threats from multiple directions. Human factors information relating to driver attention and the likelihood of active driver control involvement would also seem helpful in this regard.

5. CONCLUSIONS

The findings of this study indicate that the neural network methodology employed here (utilizing range information and vehicle speed as network inputs) can be used to represent a variety of driver longitudinal control behaviors, provided that the input data exhibit strong similarities to the data used to train the network. Otherwise, the network architecture and methodology utilized here is not considered adequate to predict driver control responses for *unseen* data not represented by the training set.

Shortcomings in extending the trained network to accurate control predictions on unseen data in this application can stem from a variety of reasons. One important reason is the intermittent nature of driver longitudinal control behavior. Unless data selected for the network training calculations are known to involve active control engagements by drivers, the resulting network characterizations will be diminished. Information or indicators about the degree of control engagement by drivers would clearly help determine what data should be used for training purposes. While neural networks can be used to represent adaptive control behavior of drivers and their associated variability during active control engagements, determining when active control engagements are actually occurring and selecting that data for training purposes is a confounding factor.

Incorporation of additional sensor data that provide information about surrounding vehicle movements relative to the subject vehicle would likely improve a network's predictive capability using the same or similar approach described here. Forward range information alone appears to be insufficient for adequately representing a broad range of control behaviors routinely observed in actual drivers. Driver longitudinal control behavior is likely dependent upon a variety of factors and sensory inputs, beyond those just involving range information to a leading vehicle. The data analyses obtained here are also consistent with that view.

Lastly, adaptive control applications often assume a largely fixed structure for the plant/controller which contains an associated set of parameters that vary slowly over time. A broader reality is likely at work in this particular problem in the sense that the nature of the human plant/controller is generally recognized to be variable, intermittent, and time-varying.

ACKNOWLEDGMENT

Portions of this work were supported by the U.S. Department of Transportation and the National Highway Traffic Safety Administration under the Cooperative Agreement entitled "Fostering the Development, Evaluation, and Deployment of Forward Crash Avoidance Systems (FOCAS)," No. DTNH22-94-Y-47106.

REFERENCES

[1] Fancher, P. et al, Fostering Development, Evaluation, and Deployment of Forward Crash Avoidance Systems (FOCAS), U.S. DOT Annual Research Report ARR-12-15-96, UMTRI-96 44, December 1996.

[2] Sayer, J., Mefford, M., and Fancher, P., "Consumer Acceptance of Adaptive Cruise Control Following Experience with a Prototype System," *Proceedings of the Human Factors and Ergonomics Society 39th Annual Meeting*, Santa Monica, CA 1995.

[3] Turrentine, T., Sperling, D., and Hungerford, D., "Consumer Acceptance of Adaptive Cruise Control and Collisions Avoidance Systems," *Transportation Research Record*, No. 1318, 1991, pp. 118-121.

[4] MacAdam, C. C., Bareket, Z., Fancher, P. and Ervin, R., "Using Neural Networks to Identify Driving Style and Headway Control Behavior of Drivers," *Proceedings of the 15h IAVSD Symposium on the Dynamics of Vehicles on Roads and Tracks*, Budapest, Hungary, August 1997.

[5] Demuth, H. and Beale, M., "Neural Network Toolbox for Use with MatLab - User's Guide," Version 2.0a, The MathWorks Inc., 1994.

[6] MacAdam, C.C. and Johnson, G. E., "The Application of Elementary Neural Networks and Preview Sensors for Representing Driver Steering Control Behavior," *Vehicle System Dynamics*, Vol. 25, No. 1, 1996.

[7] Neusser, S. et al., "Neurocontrol for Lateral Vehicle Guidance," *IEEE Micro*, Vol. 13, No. 1, 1993. pp. 57-66.

[8] Lubin, J. M. et al., "Analysis of a Neural Network Lateral Controller for an Autonomous Road Vehicle," *Proceedings, Future Transportation Technology Conference and Exposition*, 1992.

Proceedings of the International Symposium on Advanced Vehicle Control 1998

AVEC '98

International Symposium on Advanced Vehicle Control 1998

September 14(Mon.)-18(Fri.), 1998

Nagoya Congress Center

Sponsored by

Society of Automotive Engineers of Japan, Inc. (JSAE)

Organized by

AVEC '98 Organizing Committee in JSAE

In Association with:

International Association for Vehicle System Dynamics (IAVSD)

International Federation of Automatic Control (IFAC)

The Institute of Mechanical Engineers (I Mech E)

The Japan Society of Mechanical Engineers (JSME)

SAE International

The Society of Instrument and Control Engineers (SICE)