Modeling of Human Behaviors in Real Driving Situations

Tomoaki Miyazaki, Tetsuji Kodama and Takeshi Furuhashi, and Hiroshi Ohno

Abstract— **A model of human behavior could be used to produce improved human-machine systems and, in particular, an automated highway system to improve the safety of current highways. Pentland and Liu have demonstrated that they can categorize human driving actions very soon after the beginning of the action using dynamic Markov models. The experiment was conducted within a driving simulator instrumented to record driver control input such as steering wheel angle, brake position, and accelerator position. Our work is an attempt to assess the classification accuracy of the modeling approach in real driving situations.**

Keywords— **intelligent transport systems, driving behaviors, hidden Markov model.**

I. Introduction

THE collision avoidance has been investigated to help drivers operate vehicles more safely and effectively, and to address the driver errors, which are cited as the primary cause in about 90% of all crashes involving passenger vehicles, trucks and buses. We are developing a collision avoidance system, which is equipped with the sensor and vehicle control systems required to predict driver errors, and to act through direct vehicle control to prevent the crash. The work presented here was carried out with the particular collision avoidance system (see Fig. 1) in mind. The system is designed to provide a driver with warnings of an impending crash or for automatic collision avoidance by slowing down the vehicle speed in order to stop, where the crash is initiated by the driver of the subject vehicle, and not the other vehicle. In this context, it is assumed that an sub-system equipped with the sensors (video cameras [1, 2] or millimeter wave radars) is able to detect a stop sign that controls an intersection or an impending crash, in which the current state of the vehicle (position, velocity, and acceleration) is modeled as a set of differential equations. The work presented here focuses on the detection of the driver's intended action, in which the driver's steering, acceleration, and braking patterns are modeled as a set of hidden Markov models (HMMs). The ability to detect which action the driver is beginning to initiate can allow intelligent cooperation by the vehicle. In the case of collision avoidance, it performs certain safety checks. For instance, when the vehicle is approaching an intersection controlled by a stop sign and the driver is not beginning to initiate a stopping action, the safety checks alert the system that will warn the driver and/or start automatic control of the vehicle in order to stop. If the driver is beginning to initiate a stopping action, the safety checks do nothing.

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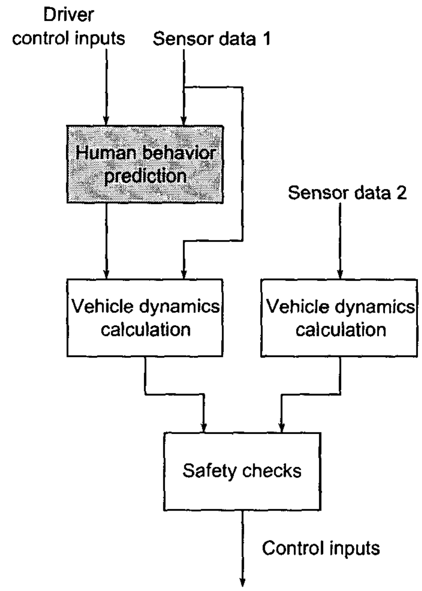

Fig. 1. Block diagram of a collision avoidance system.

In some application, the state of the vehicle that can be modeled as a set of differential equations is used to predict the future state. This type of prediction is useful only for short time periods up to a second. The time that is required to prevent an impending crash or the vehicle from entering the intersection, on the other hand, is estimated to be several seconds. Pentland and Liu [3] used dynamic Markov models (a set of dynamic models sequenced together by a Markov chain) to recognize human driving behaviors from sensory data and to predict the human's behaviors over a few seconds time, in which the human considered as a device with a large number of internal mental states, each with its own particular control behavior, and interstate transition probabilities. Such a model of human behaviors could be used to collision avoidance systems. However, the experiment was conducted within a driving simulator that consists of the front half of a vehicle and an image projected onto the wall facing the driver. In this article we are characterizing the patterns of steering, acceleration, and braking that will be able to define the driver's intended action by use of HMMs based on the experimental data recorded in real-world driving.

II. Methods

There are several possible choices for what type of statistical model is used for characterizing the properties of real-world signals. Examples of such statistical models include Gaussian processes, Poisson processes, Markov processes, and hidden Markov processes. The HMMs are very rich in mathematical structure and work very well in practice for several important applications in machine recognition of speech [4], handwriting, and gesture [5], etc. To implement HMMs, the choice of type of model, choice of model size, and choice of observation symbols must be made depending on the signal being modeled [4]. In this article we use fully connected HMMs, in which every state of the model could be reached in a single step from every other state of the model, and assume that the number of states in the model is $N = 4$ as illustrated in Fig. 2.

Fig. 7 shows experimental data of steering wheel angle, brake position, accelerator position, and vehicle velocity (chosen as a stopping example) that were recorded at 1/10 seconds intervals and have a resolution of 8 bits per signal. The system to acquire sensory data has been installed in a vehicle of the Toyota. Test runs have been performed on roads around the Toyota Central Research and Development Laboratories in Japan under normal conditions for approximately 60 minutes. Using the data, we built 4-state models of each type of driver action (stopping and do nothing). The 20 sets of patterns of steering, braking, acceleration, and velocity for approximately 2.5 seconds before the onset of the stopping action (Fig. 3) are used for the model of driver's intended action of stopping. The 20 sets of the patterns for approximately 2.5 seconds in which the driver does nothing or drives normally with no turns lane changes are used for the model of do nothing.

Although the continuous density HMMs appear to be a promising tool for characterizing the set of the signals, it is expensive in terms of computing time and resources, which will be a weakness of the system that renders it unsuitable for real-time implementations of the algorithm on a microprocessor. In order to be in a form suitable for discrete density HMMs, the set of the signals must be quantized via codebooks, etc. The quantization process requires that a decision be made on the number of discrete symbols allowed for each signal. It is common practice to make histograms drawn from each signal and let symbols stand for the peaks in order to reduce serious degradation associated with the quantization. Fig. 4 shows a histogram representing the probabilities for observing each value of steering wheel angle in a test run. In the case of Fig. 4 , we represent the signal of steering wheel angle as a time sequence consisting of 3 symbols, O_{s0}, O_{s1}, and O_{s2}. The signals of steering wheel angle, brake position, accelerator position, and vehicle velocity are quantized and represented as time sequences consisting of 4, 3, 3, and 2 symbols, respectively, and then mixed together to form a time sequence consisting of 72 symbols, which is used for the observable output of the HMMs. We adjust the model parameters using the Baum-Welch method to maximize the probability of the observation sequence given the model, in which we choose random initial estimates of the HMM parameters so that the maximum is the global maximum.

III. Results and Discussion

In order to do driver's intended action detection, we carried out a feature analysis of the set of the signals by calculation of model likelihoods for both models of the stopping and do noth-

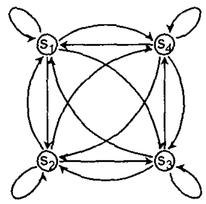

Fig. 2. A 4-state fully connected hidden Markov model.

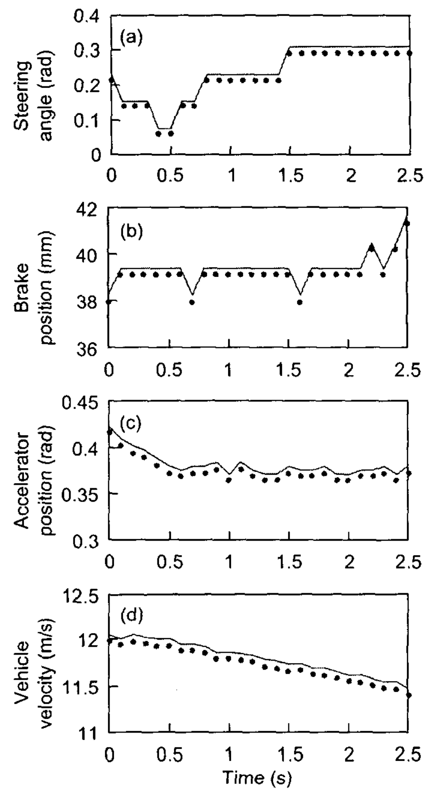

Fig. 3. A set of patterns for 2.5 seconds before the onset of the stopping action.

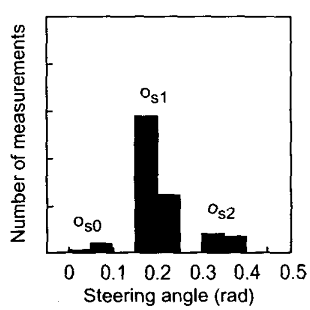

Fig. 4. A histogram representing the probabilities for observing each value of the steering wheel angle in a test run.

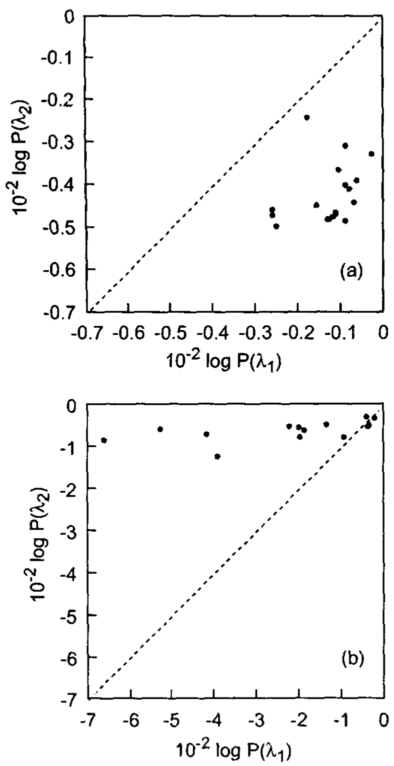

Fig. 5. Results for unknown sets of patterns: (a) in which the driver does nothing or drives normally with no turns lane changes; (b) before the onset of the stopping action.

ing. The probability computation is performed using the Viterbi algorithm. Figs. 5a, 5b show the results for 20 unknown sets of patterns in which the driver does nothing or drives normally with no turns lane changes, and for 20 unknown sets of patterns before the onset of the stopping action, respectively. The notations λ_2 and λ_1 indicate the complete parameter set of the model of the stopping and do nothing, respectively. (To obtain unbiased estimates of classification performance, we employed the leaving one out method.) As can be seen, the system is able to classify the driver's intended actions accurately. The classification accuracies of Figs. 5a, 5b were 100% and 90%, respectively, and the mean classification accuracy was approximately 95%.

If we use the sets of patterns from a few seconds to τ seconds before the onset of the stopping action for the model of driver's intended action of stopping, the mean classification accuracy of the system was decreased with increasing the time τ. A plot of the time τ versus the mean classification accuracy is shown in Fig. 6. The mean classification accuracy was approximately 85% in the case of using the sets of patterns from a few seconds to 1.0 second before the onset of the stopping action, indicating that the models could be used to the collision avoidance system that we are developing.

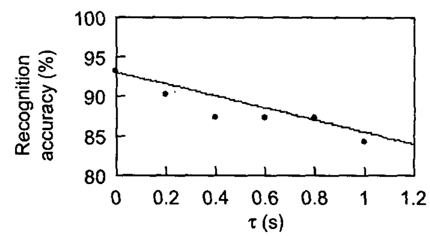

Fig. 6. Variation of the mean classification accuracy as a function of the time τ.

IV. Concluding Remarks

We have described the first tests of our modeling approach in real driving situations by categorizing driver's intended actions of stopping and do nothing. Modeling of other driver's intended actions is currently under development.

Acknowledgments

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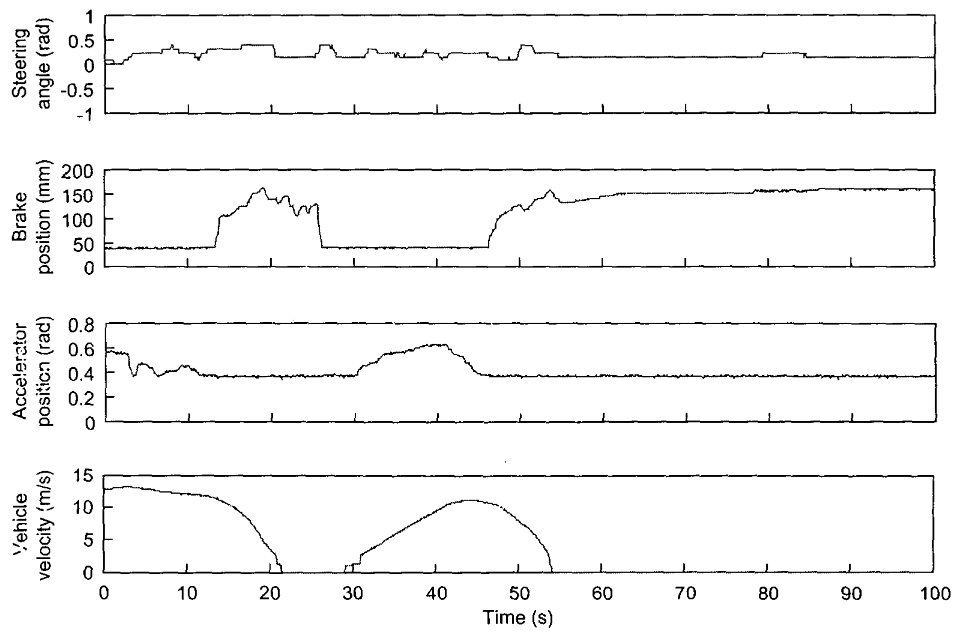

Fig. 7. Real data representing a stopping example.