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A Driver Behavior Recognition Method Based on a Driver Model Framework

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ABSTRACT

A method for detecting drivers' intentions is essential to facilitate operating mode transitions between driver and driver assistance systems. We propose a driver behavior recognition method using Hidden Markov Models (HMMs) to characterize and detect driving maneuvers and place it in the framework of a cognitive model of human behavior. HMM-based steering behavior models for emergency and normal lane changes as well as for lane keeping were developed using a moving base driving simulator. Analysis of these models after training and recognition tests showed that driver behavior modeling and recognition of different types of lane changes is possible using HMMs.

INTRODUCTION

Vigorous efforts are under way today to research and develop partially or fully automated driver assistance systems, such as those for headway distance control or lane keeping control, which make use of Intelligent Transportation System (ITS) technologies(1) (2). In developing these systems, it is important to adopt approaches aimed at improving the performance of the whole driver-vehicle cooperative system by regarding driving as interaction between the driver and the vehicle. Achieving smooth control mode transitions from automated to manual operation is one issue of human-machine interaction in these systems. Such transitions can be divided into instances of forced return to the manual mode when the system encounters non-supported situations or when it fails and instances initiated spontaneously by a driver. In the latter cases, it is important not to automatically interfere with driver induced evasive maneuvers in emergency situations and also to avoid feelings of incongruity in ordinary driving. Accordingly, establishing a technique for detecting the driver's intentions or for recognizing driver behavior is imperative to facilitate smooth and appropriate control mode transitions. The development of effective driver behavior recognition methods requires a thorough understanding of driver behavior and the construction of a model capable of explaining and reproducing drivers' behavioral characteristics. Among various driving actions, this study focused on lane change maneuvers. Some methods have been developed previously to estimate a driver's lane change intention, for example, by making a comparison with the maximum steering angle during ordinary lane keeping, or by using the vehicle's yaw angle relative to the traffic lane and steering data (3). However, these methods are not human model-based. We focus on information processing models of human driver behavior generation and utilize them to adopt a model based approach in the development of a lane change detection and recognition model. The primary components are skilled low level maneuvers whose initiation is managed by higher level decision making components. Development, analysis, and application of this model using a driving simulator are described in this paper.

DRIVER BEHAVIOR RECOGNITION BASED ON DRIVER MODEL

COGNITIVE APPROACH

The cognitive process underlying human actions has been researched extensively over the years. One of the most famous approaches to modeling human-machine interaction concerns the model proposed by Rasmussen (4). In Rasmussen's model, information processing is divided into three hierarchically organized levels based on demand complexity: knowledge base, rule base, and skill base. In the driving context, an identical classification is possible. Michon showed the thought that the organizational structure well suited for driver modeling contains a strategic, a tactical and an operational level which roughly correspond to the knowledge, rule, and skill division in Rasmussen's model (5). Boer et al. proposed an integrated driver model (IDM) which borrows from Rasmussen's and Michon's model and incorporates the concept of the dynamic aspects of driver behavior as well as an important role of driver needs (6, 7). The concept of their model is shown in Figure 1. Incorporating the idea of attention management, this model focuses on the switching of intra- or inter- process levels. It can explain not only the selection of maneuvers in manual driving but also the operation of mode transitions in driver assistance systems. An understanding of attention management or the characteristics of each process level is closely related to an understanding of the driver's intentions.

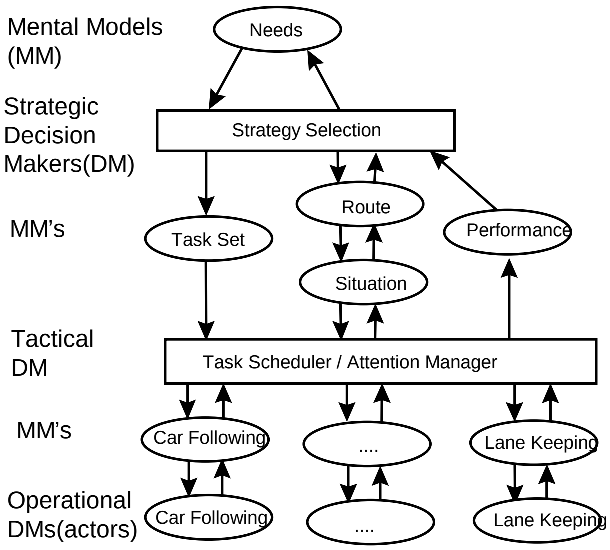


Figure 1. Conceptual Configuration of Integrated Driver Model

Primary focus in this paper is on the tactical and operational levels. The tactical level models driver's task scheduling in terms of determining when which maneuvers are appropriate. This can be characterized by a set of heuristics or rules that translate a particular environmental condition into a set of appropriate tasks. The operational level models execution of maneuvers that are learned and automated process thereby falling in the category of skill-based activities.

DRIVER BEHAVIOR RECOGNITION METHOD BASED ON THE HIDDEN MARKOV MODEL

Previous studies have found that driver behavior can be characterized as sequence of basic actions each associated with a particular state of the driver-vehicle-environment and characterized by a set of observable features (8) Pentland et al. researched the modeling of human action, taking into account this observation, and represented driver behavior as a transition of states internal to the driver. They posited that only driving actions can be observed and proposed a driver intention detection method using a hidden Markov model (HMM) to capture the sequential nature of these unobservable internal states that are each associated with a set of observable variables that shape drivers' external behavior (9). An HMM is a superior method for recognizing temporal data patterns, that can be expressed as stochastic transitions among finite discrete states, and is a mainstream speech recognition method (10). Its application to manipulator movement recognition in telerobotics is also being studied (11).

Liu et al. validated their model in an experiment conducted with a driving simulator (12). The objective of that validation test was to recognize different maneuvers such as a right turn, a left turn, or stopping. However, in order to apply such a model to a driver support system, we believe that it is necessary to assess to what degree the HMM based behavior recognition model also provides a plausible model of human behavior generation. This knowledge may not only offer better insight into selecting a particular HMM structure but also provide better insight into potential limitations of the characterization in situations that were not part of the training set that was used to identify the HMM coefficients. Therefore, a detailed analysis was performed on HMM-based models of lane changes and its applicability to a lane-change-recognition driver-assist system critically evaluated.

The HMM-based driver behavior recognition model described here characterizes three different maneuvers: emergency lane change, normal lane change, and lane keeping. Each of these low level maneuvers can be thought of as skills at the operational level in the integrated driver model proposed by Boer et al., whereas the decision to initiate any one of them is mediated at the tactical level. In other words, it recognizes different processes as well as the related switching between them.

DEVELOPMENT OF THE HMM DRIVER BEHAVIOR RECOGNITION MODEL IN LANE CHANGES

MEASUREMENT OF DATA

Apparatus

A driving simulator capable of simulating a motorway traffic environment was used to measure driver behavior data. An image of the road ahead was generated by

Figure 2. Motion Based Driving Simulator

computer graphics and projected on a large field of view, 120 degrees in the horizontal by 30 degrees in the vertical. In addition, a hexapod cooperative motor-driven motion system provided a sense of motion and a digital sound system generated sound while driving (13). The appearance of the driving simulator and the system configuration are shown in Figures 2 and 3 respectively.

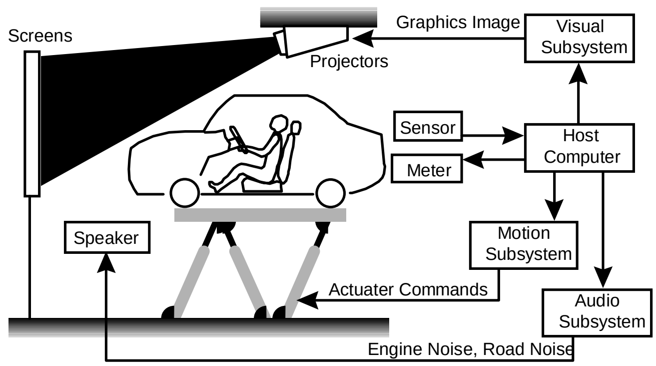


Figure 3. System Configuration of Driving Simulator

Measurement

Subjects were asked to drive in the left lane (slower traffic lane in Japan) of two lanes of traffic at a constant speed of approximately 80 kph (50 mph). Driver behavior data were measured in the following situations.

1) Ordinary lane change: When a text message indicating a lane change was superimposed on the screen showing the forward road view, a subject changed to the right lane in the same way as in ordinary driving.

2) Emergency lane change: A large truck was suddenly presented as an obstacle in front of a subject without any prior warning. Upon seeing it, the subject executed an evasive steering maneuver. The position of the parked truck was set at a forward distance equal to the vehicle speed times 2.5 seconds. Subjects did not know in advance when the obstacle would be presented. They were instructed to change to the right lane immediately upon discovering the truck so as to avoid it.

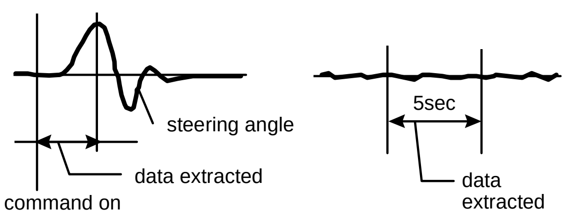
3) Lane keeping: While a subject stayed in the same lane on a straight segment, data were arbitrarily measured by the operator.

Examples of the computer images presented at the onset of each task are shown in Figure 4. During the lane-keeping task, data were measured over particular time intervals whose lengths correspond to those of a lane change. The order in which the tasks were executed was randomized. Ten subjects (five males and five females) who had a driving license participated in the experiment. The participants were in their 20s and 30s. Six runs were executed for each condition per subject.

DEVELOPMENT OF THE HMM-BASED RECOGNITION MODEL

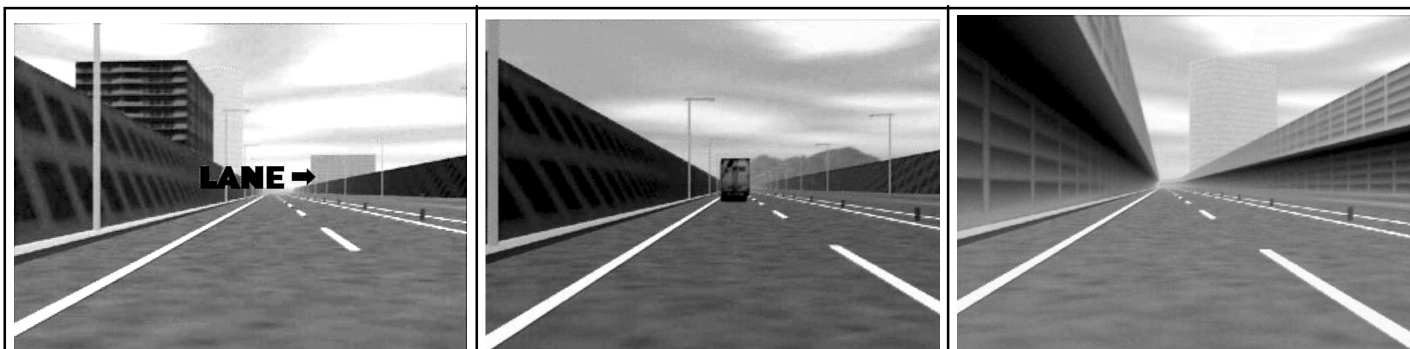
Development tool

Using the measured driver behavior data, an HMM consisting of three recognition categories--emergency



(a) lane change (LCE, LCN) (b) lane keeping (LKN)

Figure 5. Data Extraction Method



1) ordinary lane change | 2) emergency lane change | 3) lane keeping

Figure 4. Example Images at Command Presentation

lane change (LCE), ordinary lane change (LCN), and lane keeping (LKN)--was developed. For the two types of lane change situations, data were extracted in the period between command presentation and the first peak of the steering angle. For lane keeping, data were extracted for a five-second interval from the original data measured with the driving simulator. Figure 5 shows the data extraction method. The HMM was developed using HTK software which is a product of Entropic Inc. (14).

Definition of HMM grammar

A unique grammar concept was introduced for model development that differs from the general approach for three reasons. Firstly, it would be irrational to have the same HMM structure (i.e. same number of states and same set of transitions between them) because of large differences with respect to number of clearly identifiable stages in the action profile for each of the three maneuvers (e.g. the characteristic steering profile of a lane change does naturally not appear in lane keeping). Secondly, the emergency lane change would involve a large steering angle change whereas an ordinary lane change would involve little change. To improve specificity of the recognition model, these two manifestations of the same maneuver should be characterized separately. Thirdly, it was necessary to have a model that could perform continuous recognition, as will be explained later. The adopted approach is one in which a basis sub-HMM is used as a building block for a more complex model. The selected grammar is defined such that LCE and LCN had m and n number of sub-HMMs lcei and lcni respectively and each sub-HMM proceeded in a normal order with the lapse of time, such as from lce1 to lcem in LCE and from lcn1 to lcnn in LCN.

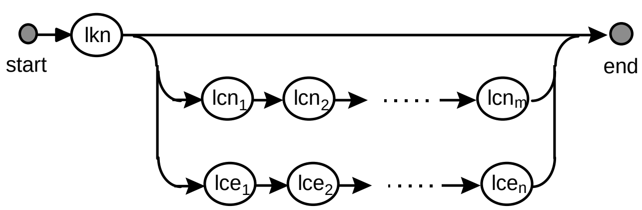


Figure 6. Grammar in Lane Change HMM

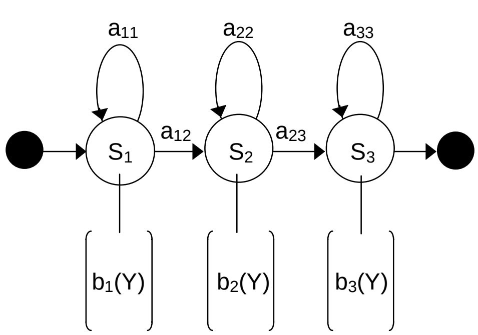


Figure 7. Structure of the HMM

A single sub-HMM, lkn, was established for LKN. In the lane change situations in this experiment, the reaction time domain continued until a subject initiated a steering maneuver after command presentation. In the model, that time period was assumed to be the same as for lane keeping. Accordingly, lane change data for LCE, for example, proceeded in the manner of "lkn, lce1, ... , lcem" along with the grammar. A conceptual diagram of the grammar adopted in this study is shown in Figure 6.

Structure of the HMM

Figure 7 shows the structure of the sub-HMM used in this study. Three sub-HMMs were used for both LCN and LCE. Each sub-HMM consisted of three states with a left-to-right configuration which did not allow for skipping of states or backward state transition. The steering angle, steering angle velocity, and steering force were used for the observation data sequence. Different subsets of these three measurements were used to identify the three maneuver models.

Training of the HMM

The HMM was trained to estimate the parameters $a_k(i)$ and $b_k(Y)$ and to maximize $\Pr(Y|\lambda)$, where λ is the parameter vector. Parameter estimation was completed in three stages.

First, an initial set of parameter values was obtained from the training data based on a more or less arbitrary segmentation of the data (i.e. collecting statistics of the measurements in each state as represented by the segments). That was followed by repeated use of Viterbi alignment to re-segment the training data. The Viterbi algorithm can be viewed as a special form of the forward-backward algorithm where only the maximum path of transitions through the states at each time step is taken instead of all paths. This optimization reduces the computational load and additionally allows the recovery of the most likely state sequences. The most likely state sequence determines the new segmentation of the observation sequence, and the parameters of each state are re-estimated according to this new segmentation. Second, a Baum-Welch re-estimation of individual HMMs was performed using the training set. Here, the probability of being in each state in each time frame is calculated using the forward-backward algorithm. A new estimate for the respective output probability can be assigned.Since either the forward or backward algorithm can be used to evaluate the posterior probability with respect to the previous estimation, this technique can be used iteratively to converge the model to some error criterion. Third, parameter re-estimation was performed using an embedded training version of the Baum-Welch algorithm. In this case, all model parameters were simultaneously re-estimated from unsegmented training data. Further details about these procedures can be found in (10).

PERFORMANCE OF THE MODEL

Lane Change Recognition

Lane change recognition using the trained HMM was executed. Recognition by the HMM involved calculating the probability that the given observation data sequence Y would be generated by one of the three models li. The model associated with the highest likelihood is used as the recognition result.

To recognize whether drivers are performing or initiating a particular maneuver, one compares the pattern of driver behavior to the HMM of that particular maneuver. That is, given an observation sequence and a model, the probability that the observed sequence would be generated by the model is needed. The forward-backward algorithm is often used in practice to compute this probability. Using this algorithm, once this probability has been evaluated for all competing models for an observation data sequence, then the model with the highest probability supports recognition of the maneuver it characterizes. In other words, one of three categories, LKN, LCE, or LCN, is output as a recognition result for each set of driving action data given. Figure 8 shows the configuration of the HMM-based lane change recognizer. To obtain the recognition result for novel driving action data, the leave-one-out method was used. This involves training the model using data for 9 of 10 subjects and executing a recognition test for the one subject left out and then repeating the procedure for all 10 subject cases. The recognition rate by category for different observation data is shown in Table 1. LCE was recognized correctly with all combinations of data. For LCN and LKN, a recognition rate of 100% was obtained by only using the steering angle and steering angle velocity for the observation data sequences. These results suggest that the use of an HMM is a promising lane change recognition technique. They also indicate the importance of observation data selection in building an HMM-based recognizer.

Learning performance of the HMM

The capability of the HMM as a method of driver behavior modeling was analyzed using performance statistics of the identified models. The observation data output

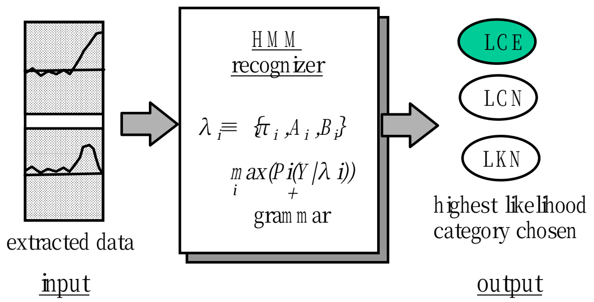
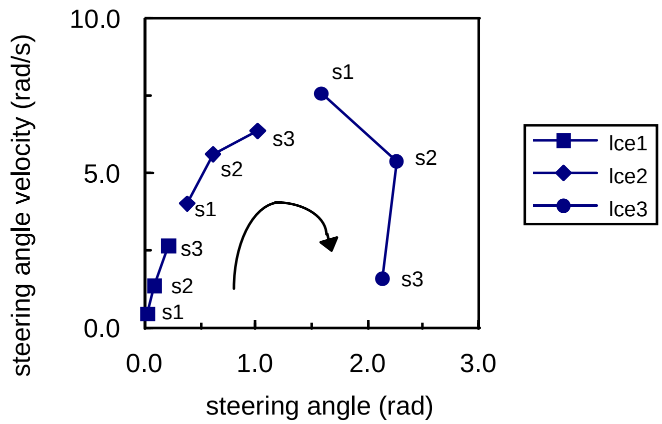


Figure 8. Configuration of a HMM Recognizer

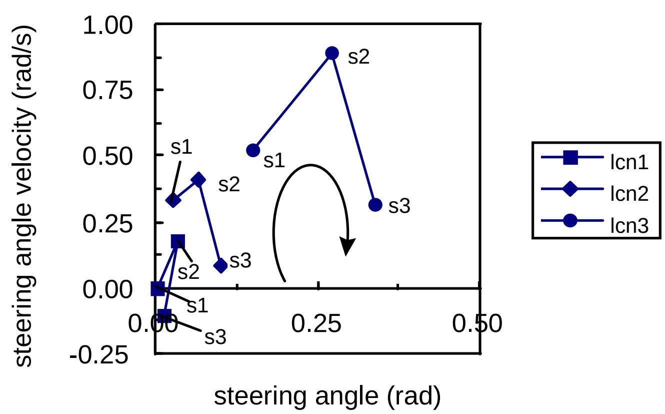
Table 1. Recognition Rate by Category

observation data	recognition rate (%)		
	LCE	LCN	LKN
a	100.0	85.0	100.0
b	100.0	10.0	100.0
c	100.0	90.0	78.3
a+b	100.0	80.0	100.0
a+c	100.0	100.0	100.0

a) steering angle
b) steering force
c) steering angle velocity



(a) LCE



(b) LCN

Figure 9. Learning Result of the HMM

probability of the HMM developed in this study is given in the form of a Gaussian distribution. The change in the average values of the output distribution accompanying state transitions was used to study the performance of the HMM in lane changes. The model examined was the one that provided the best recognition results for both the steering angle and steering angle velocity. The average values of the steering angle and steering angle velocity in each state of the sub-HMMs are shown in Figure 9. It is seen that the change in the steering data in the transition of the LCE sub-HMMs corresponded well to the typical change in steering action. This indicates that the HMM fully learned the characteristics of an emergency lane change. On the other hand, for LCN, although the average of the steering angle velocity of S3 was smaller than that of state S2, the steering angle increased with the progress of the lane change. Furthermore, the minimum absolute average values of the steering and steering angle velocity of each state in LKN were less than 0.003 rad and 0.008 rad/s respectively. In summary, it can be considered that HMMs learn well the characteristics of a temporal change in the steering pattern in a lane change, indicating they that can be used to build a driver behavior recognition model.

CONTINUOUS RECOGNITION OF LANE CHANGES

The recognition method in the previous section generated a single output for each set of data containing a time interval between command presentation and the execution of a steering maneuver for changing lanes. However, in order to recognize a lane change at an early stage when a driver support system is operating, it is necessary to generate output continuously. Using a revised version of the recognition method, the possibility of operating the recognition system continuously was examined and the characteristics of driver behavior were also analyzed based on the recognition results.

EXAMINATION METHOD

Driving action data were divided into fixed time length buffers and HMM recognition was executed for the individually divided data. In addition, grammar constraints

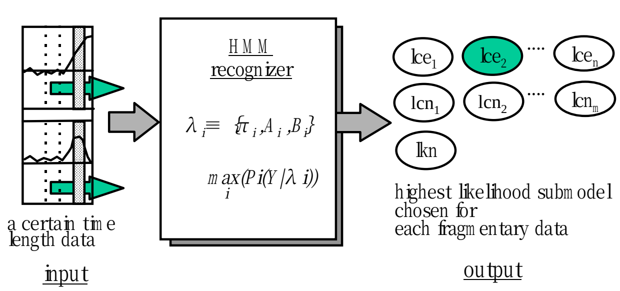
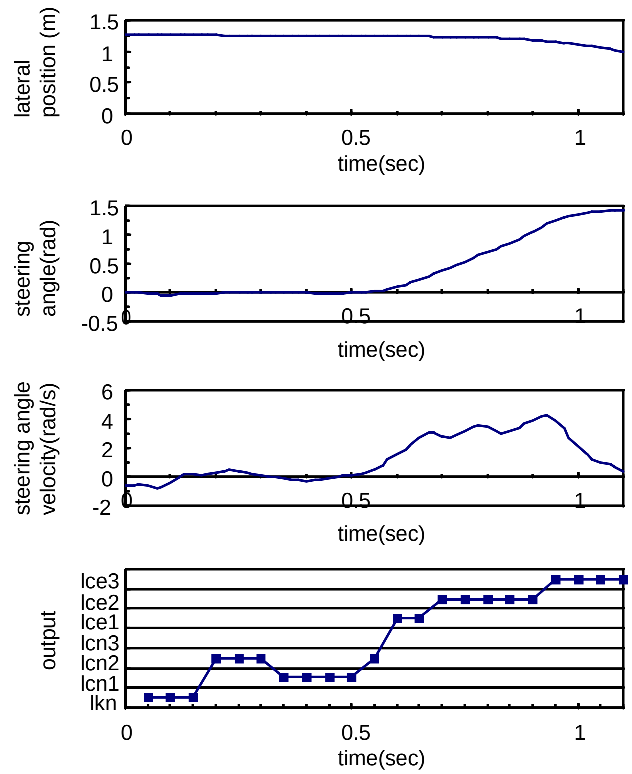
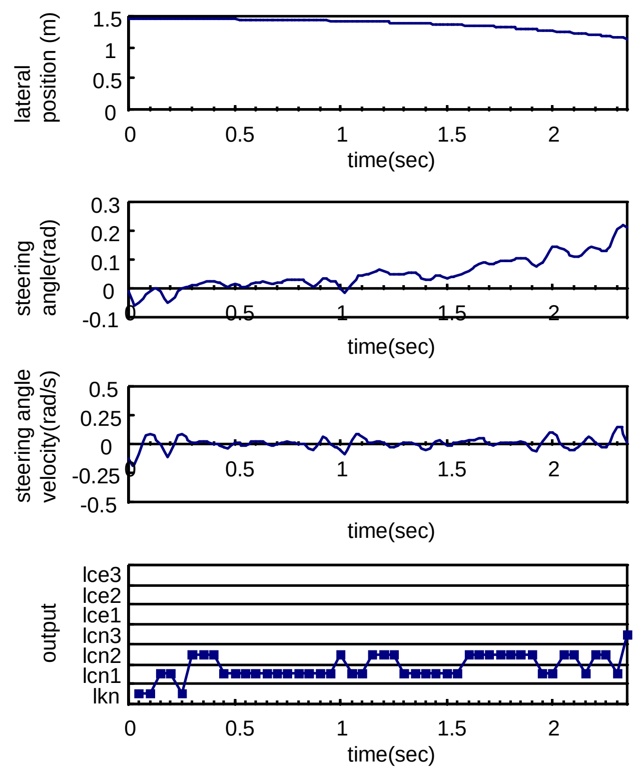


Figure 10. Configuration of a Continuous HMM Recognizer



(a) LCE



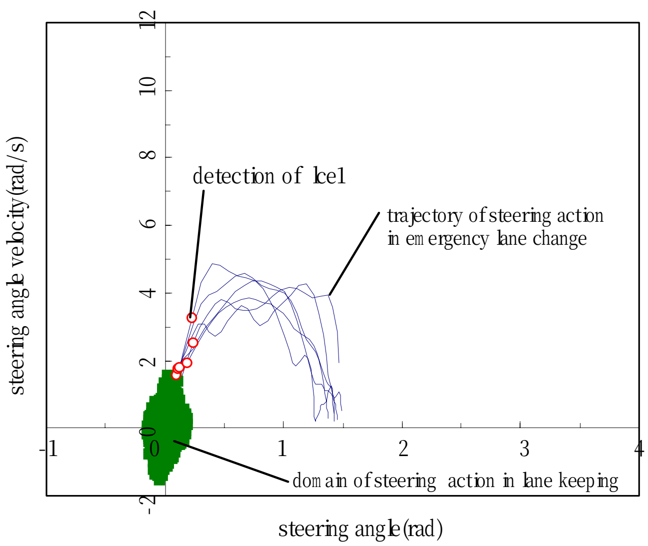
(b) LCN

Figure 11. Result in Continuous Recognition

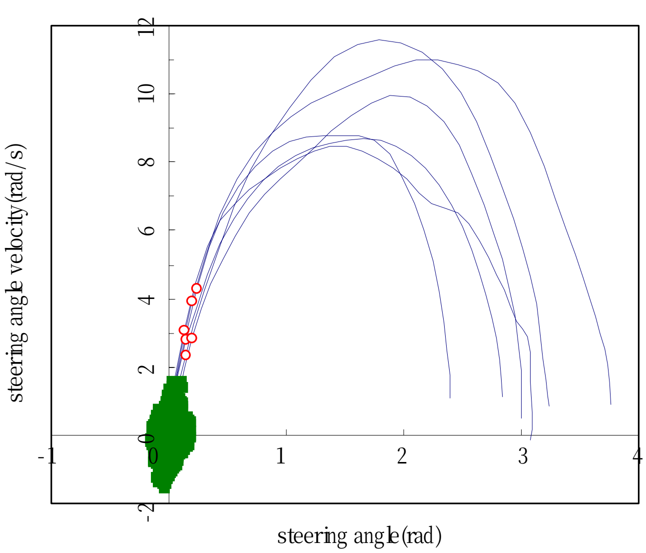
were eliminated so that one of the sub HMMs, that is, either lkn, lcn1 to lcnn, or lce1 to lcem, would be output as the recognition result. The steering angle and steering angle velocity were used for observation data, and the recognition period was set to 50 msec. The configuration of the HMM recognizer is shown in Figure 10.

RECOGNITION RESULTS

As an example of the recognition results, steering data and the recognition result sequence in LCE and LCN are shown in Figure 11. In the figure, time 0 indicates the time of command presentation and lateral position stands for the distance from the edge of the left and right lanes. For LCE, it is observed that lce1 appeared almost simultaneously with the initiation of steering, followed by lce2 and lce3 in regular order, indicating that recognition in the steering time portion was performed correctly. The recognition rate was 98.3% when the sequential output of lce1, lce2, and lce3 after the start of steering is regarded as correct recognition. The rate at which lces were recognized for LCN and LKN data by mistake was 0% for LCN and 0.29% for LKN respectively.



(a) female subject



(b) male subject

Figure 12. Trajectories of Steering Action in Emergency Lane Change

Trajectories of the steering angle and steering angle velocity in LCE for a male and a female subject are shown in Figure 12. It is obvious that lane changes were recognized just after both subjects initiated steering action, although the profiles of the two subjects differ considerably. The distribution of the time to generate lce1 after command presentation in cases where LCE were correctly recognized is shown in Figure 13. The timing of lce1 recognition was concentrated in the region between 0.5 and 0.7 sec., which corresponds to the general reaction time for the initiation of evasive steering action. These recognition results suggest the possibility of continuous HMM recognition and detection of an emergency lane change at an early stage of an evasive steering maneuver. It should be noted that lcn in addition to lkn are recognized as actions that the driver performs during the reaction time period thus indicating that the individual sub-HMMs of LKN and LCN overlap significantly in terms of the measurement sequence that they can generate with high likelihood. The recognition results for LCN show the same tendency as that seen in the reaction time domain of LCE. The decline in the recognition rate of LCN and LKN as a result of eliminating the grammar is thought to suggest the importance of context, i.e., the sequence in the time domain, in driver behavior. To achieve continuous recognition of normal lane changes and lane keeping, it will be necessary to use an HMM that takes into account contextual dependence, such as through improvement of the time length or grammar.

Furthermore, toward the application to driver assistance

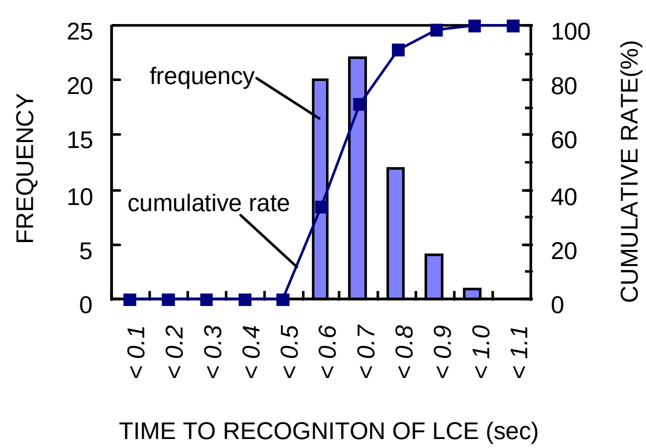


Figure 13. Frequency for time to Recognize LCE

systems, it is imperative to enhance the model to cope with more realistic situation. One of those issues is a problem of road environment such as exit or merge at interchanges on highways or curved road, for instance. An attempt to expand current recognition system by simply increasing recognition categories seems to be impractical, because it is supposed to easily cause explosion of the number of categories. Substantially, we should consider a framework to generalize current recognition system. The limit of the current system would be noticed from the fact not treating information for external environment, but only using steering action data. Accordingly, incorporating those information into the model seems to be helpful. A method of implementation is that we build a recognition system which firstly identify running situation by using data from image processing, navigation, or communication system between road and vehicle, just like pruning procedure, then execute recognition for focused candidates. For curved road, a method identifying of curvature by above mentioned way, then have recognition apply steering data eliminated the component of curvature would be promising. These ideas described here are aimed at taking into account driver behavior strategy which is involved in strong interaction between environment, which also well correspond to the concept of IDM.

CONCLUSION

Using driver behavior data measured with a driving simulator, an HMM-based driver behavior recognition model in lane changes was developed that takes into account the characteristics of the driver model within the driver model framework, and its fundamental performance was analyzed. Primary conclusions are as follows.

1) The results suggest that HMMs can be used to model driver behavior and build a system for recognizing driver behavior in lane changes. Further, HMMs have the potential to detect a lane change in the very early stage of steering.

2) An analysis conducted with the HMM-based model indicated the formularity and importance of context in driver behavior. A modeling approach for improving early recognition of lane changes was also found.

3) To apply HMM-based driver behavior recognition to driver assistance systems, it will be necessary to develop general models and assure robustness corresponding to actual driving situations, in addition to improving recognition performance by resolving the above-mentioned issues.

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