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Prediction of Driving Behavior through Probabilistic Inference

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Abstract: Driving assistance systems are essential technologies to avoid traffic accidents, reduce traffic jams, and solve environmental problems. Not only observable behavioral data, but also unobservable inferred values should be considered to realize advanced driving assistance systems that are adaptable to individual drivers and situations. For this purpose, Bayesian networks, which are the most consistent inference approach, have been applied for estimation of unobservable physical values and internal states introduced for convenience's sake. Nevertheless, only a few reports have addressed prediction of future states of driving behavior. This paper proposes predicting driving behavior in the near future through a simple dynamic Bayesian network, which is a hidden Markov model or a switching linear dynamic system. The proposed predictors were examined with real data. We focused on prediction of the future stop probability at an intersection because it is one of the most important maneuvers for safety to avoid collision with other traffic elements (i.e. other vehicles and pedestrians) at an intersection. Both the HMM and the switching linear dynamic system worked well as stop probability predictors. The HMM represented the temporal structure of human driving behavior.

Keywords: dynamic Bayesian network, hidden Markov model, switching linear dynamic system, driving behavior prediction, driving assistance system, multi-step ahead prediction

1. Introduction

Driving assistance systems are essential technologies for avoiding traffic accidents, reducing traffic jams, and solving environmental problems. These assistance systems, whose typical feature is a warning system, produce a decision based on physical parameters such as headway distance and vehicle speed. However, individual driving behavior depends on myriad variables including individual driving characteristics, environmental conditions, driving intention, and so on. Additionally, some physical parameters might not be measured accurately. Not only observable behavioral data, but also unobservable inferred values should be considered to realize advanced driving assistance systems that can adapt to individual drivers and situations. For this purpose, Bayesian networks, which are the most consistent inferential approaches, have been applied for estimation of unobservable physical values and internal states introduced for convenience sake.

For example, one study [1] inferred a probabilistic distribution of brake onset time to cross line from various evidence, such as weather condition, methodical driving style scores, accelerator pedal release timing, and so on. Dynamic Bayesian networks, which include well-known hidden Markov models, have also attracted many researchers. The model used in another study [2] provided a decision-making model for an autonomous vehicle of a simple simulation environment through a dynamic probabilistic network. Another study [3] used a hidden Markov model for modeling and recognizing driving maneuvers at a tactical level. Dynamic Bayesian networks have also been applied for general behavior modeling: one study [4] applied a switching linear dynamic system for modeling and recognizing human locomotion. Another [5] applied a switching Kalman filter for modeling and recognizing simulated driving behavior.

Nevertheless, only a few investigations have addressed prediction of future states of driving behavior. Most dynamic Bayesian network applications have recognized temporal information or inferred current states, but have not predicted future states. Although one [1] estimated probabilistic distributions of future events, it was based on the static relation between predefined variables: it used no temporal information.

This study is intended to predict driving behavior in the near future through a simple dynamic Bayesian network, which is a hidden Markov model or a switching linear dynamic system. The proposed predictors were examined with real data. We focused on the prediction of the stop probability at an intersection during a driver's side turn because that is a very important maneuver for safety. It avoids collision with other traffic elements (i.e., other vehicles and pedestrians) at an intersection.

The remainder of this paper will be organized as follows. Section 2 introduces dynamic Bayesian networks and prediction algorithms. Section 3 describes measurement of actual vehicle data in the real road environment. Section 4 describes the learning procedure of dynamic Bayesian networks. Section 5 explains stop-probability prediction. Finally, Section 6 concludes with a discussion of the method used in this paper.

2. Dynamic Bayesian networks

2.1 Model structure

In this study, we denoted dynamic Bayesian networks as

$$\begin{aligned} \delta_j(t+1) &= \sum_i a_{i,j}(t)\delta_i(t) \\ \mathbf{y}(t) &= f_{s(t)}(\mathbf{y}(t-1)) \end{aligned}, \qquad (1)$$

where

t is discrete time,

$s(t)$ is the discrete state at time t,

$\delta_j(t)$ is the probability of state j at time t, i.e. $\Pr(s(t)=i)=\delta(i)$,

$a_{i,j}$ is the state transition probability from state i to j,

$\mathbf{y}(t)$ is the observable value vector at time t

and $f_i(\bullet)$ is the function that decides observation values at state i.

When we assume that $f_i(\bullet) \sim \mathrm{N}(\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i)$, (1) is a Gaussian hidden Markov model.

When we assume that $f_i(\bullet) \sim \mathrm{N}(\boldsymbol{\mu}_i + \mathbf{w}_i\mathbf{y}(t-1), \boldsymbol{\Sigma}_i)$, (1) is a switching linear dynamic system.

2.2 Prediction algorithm

Given observation $\mathbf{y}(t)$ $\{t = 1...T\}$ and inferred $\delta_i(T)$, the prediction is performed in the following straightforward ways:

(1) Hidden Markov model

$$\begin{aligned} \delta_j(T+n) &= \sum_i a_{i,j}\delta_i(T+n-1) \qquad \{n = 1...\} \\ \mathbf{y}(T+n) &\sim \sum_i \delta_i(T+n)\mathrm{N}(\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i) \qquad ;\text{ and} \end{aligned} \qquad (2)$$

(2) Switching linear dynamic system

$$\begin{aligned} \delta_j(T+n) &= \sum_i a_{i,j}\delta_i(T+n-1) \qquad \{n = 1...\} \\ \mathbf{y}(T+n) &\sim \sum_i \delta_i(T+n)\mathrm{N}(\boldsymbol{\mu}_i + \mathbf{w}_i\mathbf{y}(T+n-1), \boldsymbol{\Sigma}_i) \end{aligned}. \qquad (3)$$

In this study, we approximate (3) to (4) because (3) is computationally expensive.

$$
\begin{aligned}
&\delta_j(T+n) = \sum_i a_{i,j}\delta_i(T+n-1) \qquad \{n = 1\ldots\} \\
&\mathbf{y}(T+n) \sim \sum_i \delta_i(T+n)\,\mathrm{N}\big(\boldsymbol{\mu}_i + \mathbf{w}_i\tilde{\mathbf{y}}_i(T+n-1), \boldsymbol{\Sigma}_i\big) \\
&\tilde{\mathbf{y}}_i(T+n) \sim \mathrm{N}\Big(\boldsymbol{\mu}_i + \mathbf{w}_i\tilde{\mathbf{y}}_{J_i(T+n-1)}(T+n-1), \boldsymbol{\Sigma}_i\Big) \\
&J_i(T+n-1) = \arg\max_j a_{j,i}\delta_j(T+n-1) \\
&\tilde{\mathbf{y}}_i(T) = \mathbf{y}(T)
\end{aligned}
\tag{4}
$$

Note that $\tilde{\mathbf{y}}_i(T+n)$ $\{n = 1\ldots\}$ is always a normal distribution.

3. Data preparation

We evaluated the proposed predictor using actual data in a real road environment**.** We developed a vehicle equipped with sensing devices to measure driving behavior [6]. Sensing devices included those for driver's operational behavior, such as steering wheel operation, and those for the vehicle condition, such as vehicle speed. This study used vehicle speed and pedal strokes of the acceleration and brake pedals. Pedal sensors attached to the pedals detected the pedal strokes. The speed signal was obtained from the front wheel speed sensor. We resampled the data at 15 Hz after measurements; the sampling rate was 30 Hz for sensor signals.

We measured the driver's side turn behavior (i.e., right turn behavior in Japan) 33 times at an intersection in a suburb of Tsukuba, Japan (Fig. 1). One testee drove the car. We removed portions of 20 [Km/h] or higher speeds from records. The car stopped once or twice in 16 of 33 cases because the roadway beyond was blocked with traffic or the traffic signal (see the top row of Figs. 4 and 7). In other cases, the car passed the intersection without stopping. We assumed 16 of 33 records to be learning data. The remaining 17 records were assumed to be test data.

4. Learning and inference

The Baum-Welch algorithm and the Viterbi algorithm are the most widely used learning and inference algorithms for HMMs. Learning and inference algorithms for switching linear dynamic systems are given as the extension of those of HMMs [9]. In this study, we used "The Bayes Net Toolbox for Matlab" [10] for learning and inference.

We gave the speed of the vehicle and the pedal stroke to a dynamic Bayesian network as observable data. The pedal stroke was given as the subtraction of the stroke of the brake pedal from the stroke of the accelerator pedal (hereafter called the pedal stroke). Sizes of the HMM and the switching linear dynamic system were determined by the number of states, Q. The increase of Q contributed to improvement of the stop-prediction accuracy. However, performance was not so sensitive to Q when Q was somewhat larger. In this study, we chose Q = 15 for the HMM and Q = 11 for the switching linear dynamic system.

Figure 2 shows topology of the trained HMM. Each $f_i(\bullet)$ was plotted on the plane of the speed and the pedal stroke. An ellipse shows $\boldsymbol{\Sigma}_i$. Arrows show major state transitions and their directions. The process of decelerating, stopping and accelerating was clearly obtained in the model.

Figure 3 shows the topology of the trained switching linear dynamic system. Each $f_i(\bullet)$ was plotted on the plane of w_{11} and w_{12}. Here, w_{11} is the weight between the speed at time t and time $(t-1)$; w_{12} is the weight between the speed at time t and the pedal stroke at time $(t-1)$. Arrows show major state transitions and their directions. It is difficult to interpret topology of the switching linear dynamic system because nodes have many variables and output values depend on input values. However, it was at least readily plausible that w_{12} is greater than 0 and w_{11} is nearly equal to 1.

5. Stop probability prediction

We applied the above HMM to estimate the future stop-probability. We used the following function to estimate the stop probability.

$$\begin{aligned} stop_T(T_p) &= \Pr(speed(T_p) < Const_{speed} \mid \mathbf{y}(t)\ \{t = 1..T\}) \\ &\cdot \Pr(pedal\_stroke(T_p) < Const_{pedal} \mid \mathbf{y}(t)\ \{t = 1..T\}) \end{aligned} \tag{5}$$

Here, $stop_T(T_p)$ is the stop probability at time T_p predicted at a prediction point T. We chose $Const_{speed} = 0.5$ and $Const_{pedal} = -5$.

Figure 4 shows an example of the stop probability prediction at some prediction point. We denoted the actual stop time as T_{stop}. The vehicle stopped at around time 7 s: $T_{stop} \approx 7[s]$. Prediction of the stop probability at the actual stop time, $stop_T(T_{stop})$, approached 1 as the prediction point approached the actual stop time (see also Fig. 6). At around prediction time 21 s, the predicted stop probability of the near future rose without an actual stop because the speed was sufficiently low and the deceleration rate was high. At time 22 s, the brake pedal was released and the accelerator pedal was depressed. Thereby the stop probability decreased to zero. The predicted stop did not actually occur when it was canceled in mid-course: detecting the change in the pedal stroke, the predictor signaled the canceling of the stop maneuver.

Figure 5 shows the relationship between the predicted stop probability, $stop_T(T_p)$, and the actual stop rate. In an ideal predictor, a predicted stop probability is equal to an actual stop rate. Figure 5 shows that the stop probability was nearly equal to the actual stop rate even though predicted values were somewhat larger than actual rates.

Figure 6 shows the average value of $stop_T(T_{stop})$ at every time to the stop, $(T_{stop} - T)$. This figure shows again that the stop probability approached 1 when prediction point T approached actual stop time T_{stop}. This fact corresponds to intuition.

Along with the HMM, the switching linear dynamic system also worked well to predict the stop probability. Figures 7– 9 show the prediction results. In addition to the stop probability prediction, fig. 7 shows the mean value of predicted vehicle speed.

6. Discussion

The proposed predictor produced the future stop probability given current and past observable data. Both the HMM and the switching linear dynamic system worked well. In almost all cases, the proposed system predicted the possibility of a future stop several seconds before its occurrence, as shown in Figs. 4–9; the vehicle did not stop when the predictor did not predict it, as seen in Figs. 5 and 8. This result is very significant to consider the application of the proposed system to driving assistance systems.

The predicted stop-probability considered changes of the driver's intention. The probability was smaller than 1 even during the typical stop maneuver (see Figs. 6 and 9) because the driver might change the intention and cancel the maneuver before the predicted stop. Therefore, the predicted stop-probability was nearly equal to the actual stop rate, as seen in Figs. 5 and 8. Various factors cause changes of the driver's intention. They were modeled in the state transition probabilities.

In this study, prediction was done by sequential inference through dynamic Bayesian networks. In contrast, many conventional studies have used dynamic Bayesian networks as a classifier. A textbook example is a strategy that prepares HMMs of the same number as recognition objects and then recognizes them by comparing their likelihoods. This strategy is applicable when only a part of a recognition object is observable. Given current and past data, HMMs could recognize ongoing behavior. However, for a recognition problem of behavior, it might be difficult to prepare a categorized learning data set for supervised learning of such dynamic Bayesian networks. Classifying human behavior into discrete categories is complicated because behavior is dependent on individuals and situations. Moreover, it is impossible to determine when an action starts and ends. These engender the difficulty of behavior definition. This study avoided this problem by replacing the definition of the whole sequence of behavior with behavior results as defined in (5).

The easiest way to construct a stop-probability predictor is to prepare a static table that describes the relationship between observable data and the frequency of future stops. However, several reasons recommend the dynamic approach. For example, the static approach requires more training data because of long-range predictions. In the preliminary study of the stop prediction problem of this paper, a simple probabilistic table could not work well in some cases; i.e. it could not determine the probability because of the lack of learning data.

In general, it is difficult to forecast future states precisely through dynamic Bayesian networks because inference addresses time slices for which no observations have been given (e.g. [7],[8]). However, the predictor of the present study showed good performance for the specific temporal structure of human driving behavior as seen in Fig. 2. That is, the driver behaved according to certain habits while changing intention. This structure is also an important finding of this study.

The HMM and the switching linear dynamic system described behavior in a quite different manner. The HMM could be a good profiling tool of the driver's behavior because it visualizes behavior as seen in Fig. 2. On the other hand, the switching dynamic system could describe behavior with a smaller number of states than the HMM because a single linear dynamic system describes the relation of observable data between time t and $(t-1)$.

References

[1] Y. Sakaguchi, M. Okuwa, Ken'ichiro Takiguchi, and M. Akamatsu, Measuring and modeling of driver for detecting unusual behavior for driving assistance, (to appear in Proceedings of 18th International Conference on Enhanced Safety Vehicles, 2003)
[2] J. Forbes, T. Huang, K. Kanazawa, and S. Russell, The BATmobile: Towards a Bayesian Automated Taxi, The 1995 International Joint Conference on AI (1995).
[3] N. Oliver and A. Pentland, Graphical Models for Driver Behavior Recognition in a Smart Car, IEEE Intl. Conference on Intelligent Vehicles (2000).
[4] Vladimir Pavlovic, James M. Rehg, Tat-Jen Cham, and K. P. Murphy, A dynamical Bayesian Network Approach to Figure Tracking Using Learned Dynamic Models, International Conference on Computer Vision (1999).
[5] A. Pentland and A. Liu, Modeling and Prediction of Human Behavior, Neural Computation, 11, pp.229–242 (1999).
[6] M. Akamatsu, Measuring Driving Behavior, detecting unusual behavior for driving assistance, SICE Annual Conference in Osaka (2002).
[7] U. Kjærulff, A computational scheme for reasoning in dynamic probabilistic networks, Proceedings of the Eighth Conference on Uncertainty in Artificial Intelligence, Morgan Kaufmann Publishers, San Mateo, California, pp.121–129 (1992).
[8] P. Dagum, A. Galper, E. Horvitz and A. Seiver, Uncertain Reasoning and Forecasting, International Journal of Forecasting, 11, pp.73–87 (1995).
[9] K. P. Murphy, Dynamic Bayesian Networks: Representation, Inference and Learning, dissertation, PhD thesis, U.C. Berkeley, Dept. Comp. Sci. (2002).
[10] K. P. Murphy, The Bayes Net Toolbox for Matlab, Computing Science and Statistics: Proceedings of Interface, 33 (2001).

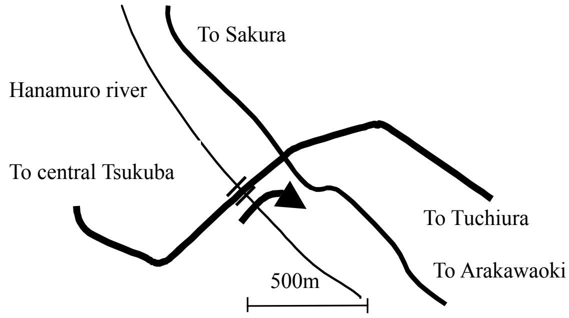

Fig. 1 An intersection in a Tsukuba suburb

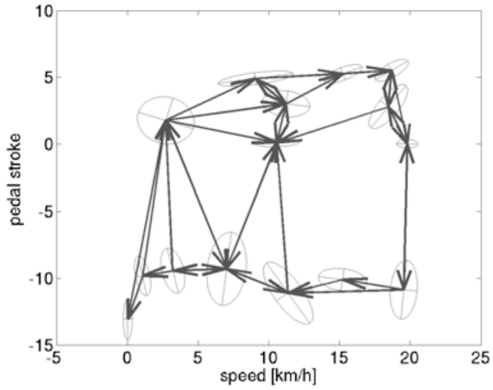

Fig. 2 Topology of the HMM

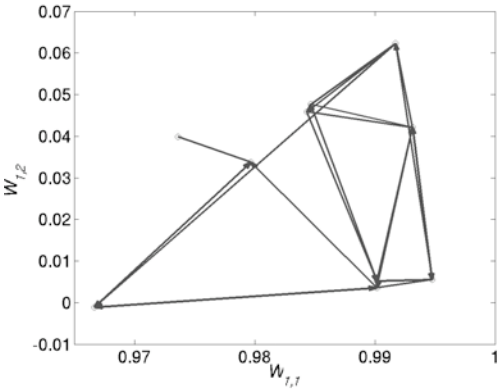

Fig. 3 Topology of the switching linear dynamic system

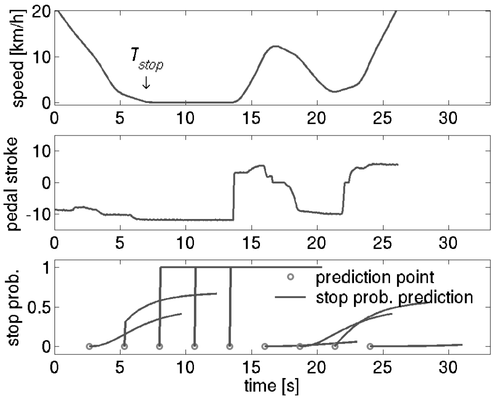

Fig. 4 Stop probability through the HMM

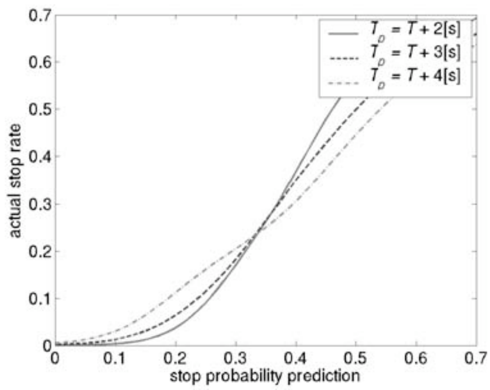

Fig. 5 Predicted stop probability through the HMM and the actual stop rate

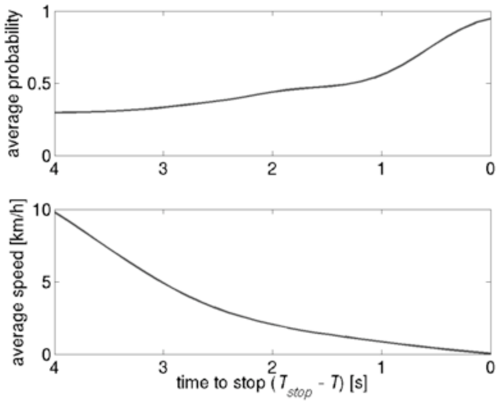

Fig. 6 Averaged predicted stop probability through the HMM

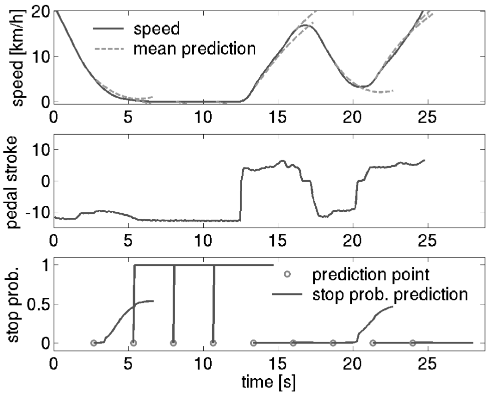

Fig. 7 Stop probability through
the switching linear dynamic system

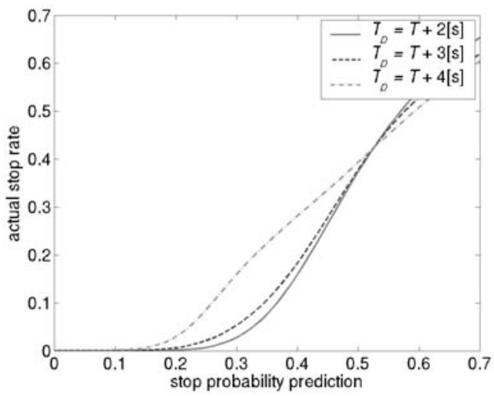

Fig. 8 Predicted stop probability through
the switching linear dynamic system and the
actual stop rate

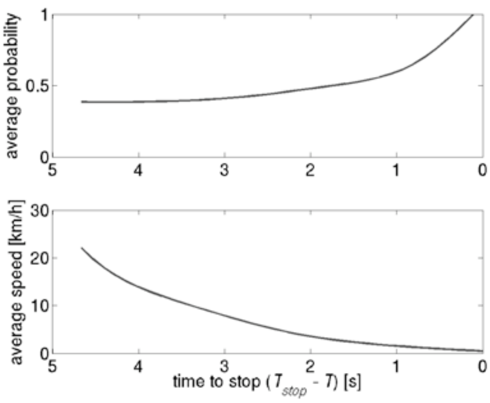

Fig. 9 Averaged predicted stop probability
through the switching linear dynamic system