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MODELING AND PREDICTION OF DRIVING BEHAVIOR

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1. INTRODUCTION

Driving assistance systems that adapt to an individual driver are essential for avoiding traffic accidents because there are individual differences in the way of driving. To realize such systems, it is necessary to take account of not only observable physical quantities, but also information inferred from observation. For example, a collision avoidance system warns a driver according to an estimated probability of a future collision.

Several probabilistic inference methods have been applied to modeling and recognition of driving behavior. Sakaguchi et al. inferred a probabilistic distribution of brake onset time by a static Bayesian network from various evidence, such as weather condition, methodical driving style scores, accelerator pedal release timing, and so on [1]. Dynamic Bayesian networks, including well-known hidden Markov models, have also attracted many researchers. Forbes et al. provided a decision-making model for an autonomous vehicle of a simple simulation environment [2]. Oliver et al. used a hidden Markov model for modeling and recognizing driving maneuvers at a tactical level [3]. Pentland et al. applied a switching Kalman filter for modeling and recognizing simulated driving behavior [4].

Nevertheless, only a few studies have proposed a method for predicting future driving behavior. Sakaguchi et al. designed a predictor through a Bayesian network. However, their static model was not appropriate for a time series prediction of dynamic behavior.

We propose a predictive method for driving behavior in the near future using a simple dynamic Bayesian network. The proposed method shows good performance in a stop probability prediction problem [5]. In this study, we applied the proposed method to future speed prediction. Especially, we compared two simple dynamic Bayesian networks: a hidden Markov model (HMM) and a switching linear dynamic system (SLDS).

2. DRIVING BEHAVIOR MODEL

We assumed that human driving behavior has the following characteristics. First, it consists of various behavior elements (e.g., accelerating, turning at an intersection). Observable behavior (e.g., pedal strokes) depends on the current element. We cannot ascertain directly what is a current element from observation since there is no one to one relationship. Second, drivers' intentions and environmental factors cause transitions between elements. It is essentially impossible to exactly observe drivers' intentions and environmental factors.

We adopted model structures shown in Fig. 1 considering the above. Behavior elements are described by a hidden variable – the *internal state*. The current internal state depends on the previous internal state. Observable behavior depends on the current internal state (and the previous observable behavior in the left model).

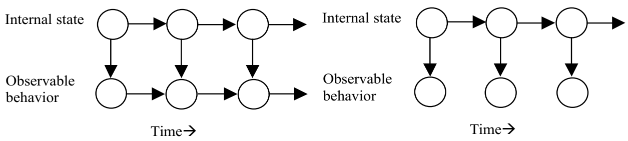

Fig. 1. Models of driving behavior

We formulated a mathematical model as

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

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. $\Pr(s(t)=i) = \delta_i(t)$;
$a_{i,j}$ 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.

When we assume that $f_i(\bullet) \sim \mathrm{N}(\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i)$, (1) is a well-known Gaussian HMM (Fig. 1, right). 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 (SLDS; Fig. 1, left).

These models do not specifically address the driver's intention and environmental factors that cause state transitions. Effects of these factors are acquired into the state transition table $a_{i,j}$ as stochastic incidents.

3. PREDICTION ALGORITHM

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

$$\bar{\mathbf{y}}_i(T)=\mathbf{y}(T) \qquad \delta_j(T+n)=\sum_i a_{i,j}\delta_i(T+n-1)$$

$$\bar{\mathbf{y}}_i(T+n)\sim\frac{\sum_j a_{j,i}\delta_j(T+n-1)\,\mathrm{N}\left(\boldsymbol{\mu}_i+\mathbf{w}_i\bar{\mathbf{y}}_j(T+n-1),\boldsymbol{\Sigma}_i\right)}{\sum_j a_{j,i}\delta_j(T+n-1)}$$

$$\tilde{\mathbf{y}}(T+n)\sim\sum_i \delta_i(T+n)\bar{\mathbf{y}}_i(T+n) \qquad \{n=1\ldots\} \tag{3}$$

In this study, we approximate the above (3) because (3) is intractable for SLDSs.

Without losing generality, we can rewrite $\bar{\mathbf{y}}_i(T+n)$ in (3) as (4) because the probability distribution of $\bar{\mathbf{y}}_i(T+n)$ is always a normalized summation of normal distributions.

$$\bar{\mathbf{y}}_i(T+n)\sim\sum_{j=1} q_j(T+n)\,\mathrm{N}\left(\bar{\boldsymbol{\mu}}_{i,j}(T+n),\bar{\boldsymbol{\Sigma}}_{i,j}(T+n)\right) \tag{4}$$

$$q_1(T+n)>q_2(T+n)>\ldots.$$

We approximated (4) to (5) by neglecting minor terms.

$$\hat{\mathbf{y}}_i(T+n)\sim\sum_{j=1}^{K} q_j(T+n)\,\mathrm{N}\left(\bar{\boldsymbol{\mu}}_{i,j}(T+n),\bar{\boldsymbol{\Sigma}}_{i,j}(T+n)\right) \tag{5}$$

When K=1, (5) is identical to the approximation proposed in a previous work [5].

4. DATA PREPARATION

We prepared the actual data in the real road environment to evaluate the predictors. We developed a vehicle equipped with sensing devices to collect data [1]. The sampling rate was 30 Hz for sensor signals. One test subject drove the vehicle. 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 City, Japan. We extracted those parts of records that were taken at 20 [Km/h] or lower speed. The vehicle stopped once or twice in 16 of 33 cases because the roadway beyond was blocked with traffic or a traffic signal. In other cases, the vehicle passed the intersection without a stop. The following analysis used vehicle speed and brake and accelerator pedal strokes as observable behavior. We used 16 of 33 records to train behavior models with the Baum-Welch algorithm. The remaining 17 records were assumed to be test data.

5. PREDICTION OF DRIVING BEHAVIOR

Fig. 3 shows examples of time series prediction of probability distribution of the vehicle's speed at the approach to the intersection. Results differ greatly between the SLDS and the HMM. Results predicted through the SLDS show two ridges that clearly predict two types of behavior: stopping at the intersection (vehicle's speed is nearly 0, about 4[s]), and passing the intersection without a stop (the vehicle decreases its speed for turning at the intersection but does not stop). Through the HMM, we cannot clearly know these characteristics of future behavior. The SLDS was also superior to the HMM in prediction errors of speed through test data. SLDSs shows smoother and more precise distribution than HMMs. The predicted distribution through HMMs is not smooth because of the model limitation.

6. CONCLUSION

SLDSs give us more precise information than HMMs, as shown in Fig. 3. To achieve sophisticated driving assistance, SLDSs could be superior to HMMs. On the other hand, HMMs are still useful tools because they require less computational power than SLDSs. In this study, we did not include the driver's intention and environmental factors in behavior models because of the difficulty of observing them. Future work may offer improved performance of predictors by integrating uncertain information about them.

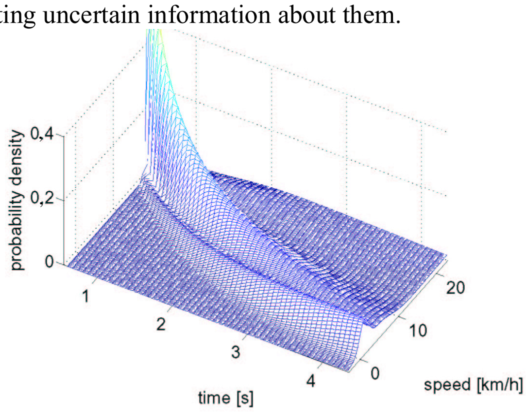

Fig. 2 Prediction through the SLDS model

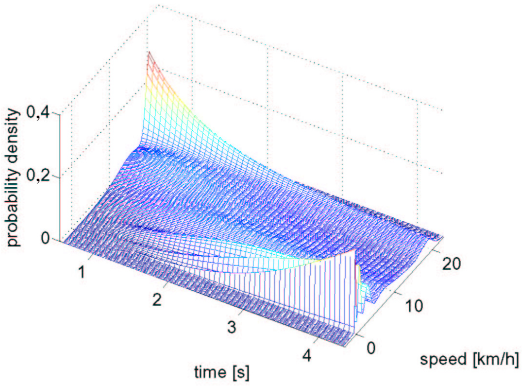

Fig. 3 Prediction through the HMM model

REFERENCES

[1] Y. Sakaguchi, et al., Measuring and modelling of driver for detecting unusual behavior, *18th ICESV*, 2003.
[2] J. Forbes, et al., The BATmobile: Towards a Bayesian Automated Taxi, *The 1995 ICJAI*, 1995.
[3] N. Oliver, et al., Graphical Models for Driver Behavior Recognition in a Smart Car, *IEEE ICIV*, 2000.
[4] A. Pentland, et al., Modeling and Prediction of Human Behavior, *Neural computation*, 11, pp.229–242, 1999.
[5] T. Kumagai, et al., Prediction of Driving Behavior through Probabilistic Inference, *EANN'03,* pp.117–123, 2003.

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