LETTER

Prediction of Human Driving Behavior Using Dynamic Bayesian Networks

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SUMMARY This paper presents a method of predicting future human driving behavior under the condition that its resultant behavior and past observations are given. The proposed method makes use of a dynamic Bayesian network and the junction tree algorithm for probabilistic inference. The method is applied to behavior prediction for a vehicle assumed to stop at an intersection. Such a predictive system would facilitate warning and assistance to prevent dangerous activities, such as red-light violations, by allowing detection of a deviation from normal behavior.

key words: *dynamic Bayesian network, switching linear dynamic system, collision warning system, collision avoidance system, driving behavior prediction*

1. Introduction

Collision warning and avoidance systems (CWS/CAS) help prevent traffic accidents by giving assistance to drivers when they are about to come into collision [1]–[4]. Timing of the resultant warning or assistance is critical to their effective performance. Conventional CWS/CAS give assistance with reference to a *critical distance*, a distance required to avoid collisions while maintaining a safety margin. For example, a CWS/CAS for rear-end collisions gives assistance when the headway distance becomes less than a critical distance, which is determined using a function of physical quantities such as relative distance, vehicle velocity, and relative velocity [5]. A defect of that method is not to estimate the risk of collisions. It merely detects that a driver does not maintain the safety margin. For that reason, a system designed to avoid collisions by keeping a large safety margin often gives false alarms and interferes with normal driving maneuvers [1], [5]. CWS/CAS systems that assist drivers with more appropriate timing could be established if some probability estimation of future collisions were available. Prediction of human driving behavior is important to develop such an advanced CWS/CAS.

Bayesian approaches have been applied for inference of driving behavior that depends on uncertainty and/or unobservable variables including individual driving characteristics, environmental conditions, driving intention, and so on. Especially, dynamic Bayesian networks (DBN) are considered to be appropriate for modeling and inference regarding the dynamics of driving behavior. In one study [6], a DBN served as a decision-making model for an autonomous vehicle. Another study [7] used a hidden Markov model, a simple DBN, for modeling and recognition of driving behavior at a tactical level. A switching Kalman filter was also applied for the same purpose [8]. Nevertheless, few investigations have addressed prediction of driving behavior. Most dynamic Bayesian network applications have provided methods for recognition, but not for estimation of future behavior. Some studies have applied static Bayesian networks to estimate future braking timing [9]. However, the range of static networks' application is limited because static networks are inappropriate for modeling and inference with regard to dynamic behavior such as driving maneuvers.

We have studied inference algorithms to predict human driving behavior in the near future through a simple DBN. Previous works have examined algorithms for cases in which past observations are given [10], [11]. This paper presents an algorithm through a switching linear dynamic system (SLDS) for a case in which the result of the behavior is also given as a time series. Using assumptions regarding the behavior result, the proposed algorithm is applicable to behavior prediction for a vehicle that is assumed to stop because of a red light, an on-coming vehicle, or for some other reason. This estimation would be useful for testing a hypothesis that the vehicle is going to stop, and allow detection of red-light violations.

2. Structure of the Driving Behavior Model

Considering driving behavior characteristics, this study adopts the behavior model shown in Fig. 1 [10], [11]. In this model, the current internal state depends on the preceding internal state. Observable behavior depends on the current internal state and the previous observable behavior. A mathematical model of driving behavior is formulated as

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

where t is discrete time; $s(t)$ is the discrete internal state at

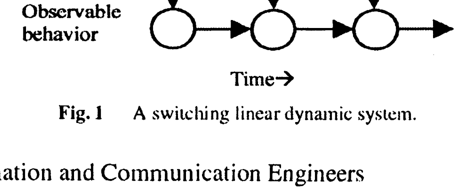

Fig. 1 A switching linear dynamic system.

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time t; $\delta_j(t)$ is the probability of internal state j at time t, i.e. $\Pr(s(t) = j) = \delta_j(t)$; $a_{i,j}$ is the internal state transition probability from internal state i to j; $y(t)$ is the observable values at time t; and $f_i(y(t))$ is the function that determines observable values from internal state i and the preceding observable values. We assume that

$$f_i(y(t)) \sim N(\boldsymbol{\mu}_i + \boldsymbol{w}_i \boldsymbol{y}(t), \boldsymbol{\Sigma}_i), \tag{2}$$

where $N(\boldsymbol{\mu}_i + \boldsymbol{w}_i \boldsymbol{y}(t), \boldsymbol{\Sigma}_i)$ is a multivariate normal distribution whose mean is $\boldsymbol{\mu}_i + \boldsymbol{w}_i \boldsymbol{y}(t)$ and covariance is $\boldsymbol{\Sigma}_i$. The above model is termed an SLDS or autoregressive hidden Markov model [12]. Learning and inference algorithms of SLDS are given as the extension of those of hidden Markov models (HMM).

3. Prediction Algorithm

A prediction algorithm that incorporates only past observations [11] is shown first. Given past observation $\boldsymbol{y}_p = \{\ldots, \boldsymbol{y}(T-1), \boldsymbol{y}(T)\}$, the estimation of future behavior $\boldsymbol{y}(T+1), \boldsymbol{y}(T+2), \ldots$ is performed in the following straightforward manner.

$$p(\boldsymbol{y}(t) \mid \boldsymbol{y}_p) = \sum_i \rho_{\delta,i}(t) p(\rho_{y,i}(t)), \quad t = T+1, T+2, \ldots$$

$$\rho_{\delta,i}(t) \stackrel{def}{=} (\delta_i(t) \mid \boldsymbol{y}_p), \ \rho_{y,i}(t) \stackrel{def}{=} (\boldsymbol{y}(t) \mid \boldsymbol{y}_p, \rho_{\delta,i}(t) = 1) \tag{3}$$

$$\rho_{y,i}(T) = \boldsymbol{y}(T), \ \rho_{\delta,i}(T) = \delta_i(T) \mid \boldsymbol{y}_p \tag{4}$$

$$\rho_{y,i}(t) \sim \frac{\sum_j a_{j,i} \rho_{\delta,j}(t-1) N(\boldsymbol{\mu}_i + \boldsymbol{w}_i \rho_{y,j}(t-1), \boldsymbol{\Sigma}_i)}{\sum_j a_{j,i} \rho_{\delta,j}(t-1)} \tag{5}$$

$$\rho_{\delta,j}(t) = \sum_i a_{i,j} \rho_{\delta,i}(t-1) \tag{6}$$

We approximated (5) above as follows because (5) is computationally intractable. Without losing generality, we can rewrite $\rho_{y,i}(t)$ in (5) as (7) because the probability distribution of $\rho_{y,i}(t)$ is always a normalized summation of normal distributions:

$$\rho_{y,i}(t) \sim \sum_{j=1} q_j(t) N\left(\overline{\boldsymbol{\mu}}_{i,j}(t-1), \overline{\boldsymbol{\Sigma}}_{i,j}(t-1)\right) \tag{7}$$

where q_j is a scalar and $q_1(t) > q_2(t) > \ldots$

We approximate (7) to (8) by neglecting minor terms whose index j is greater than K.

$$\rho_{y,i}(t) \sim \sum_{j=1}^{K} q_j(T+n) N\left(\overline{\boldsymbol{\mu}}_{i,j}(T+n), \overline{\boldsymbol{\Sigma}}_{i,j}(T+n)\right) \tag{8}$$

Given past observations $\boldsymbol{y}_p = \{\ldots, \boldsymbol{y}(0), \boldsymbol{y}(1)\}$ and the result of future behavior $\boldsymbol{y}_r = \{\boldsymbol{y}(T), \boldsymbol{y}(T+1), \ldots\}$, the estimation of future behavior $\boldsymbol{y}(2), \boldsymbol{y}(3), \ldots, \boldsymbol{y}(T-1)$ is performed through the junction tree algorithm. The following *inference* algorithm is derived through message passing with the junction tree shown in Fig. 2.

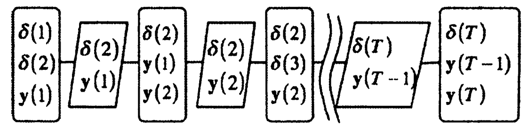

Fig. 2 A junction tree for SLDS.

$$p(\boldsymbol{y}(t) \mid \boldsymbol{y}_p, \boldsymbol{y}_r) \propto p(\boldsymbol{y}(t) \mid \boldsymbol{y}_p) p(\boldsymbol{y}_r \mid \boldsymbol{y}(t)), \quad t = 2, 3, \ldots, T-1 \tag{9}$$

$$p(\boldsymbol{y}(t) \mid \boldsymbol{y}_p) = \sum_i \rho_{\delta,i}(t) p(\rho_{y,i}(t))$$

$$\rho_{\delta,i}(t) \stackrel{def}{=} (\delta_i(t) \mid \boldsymbol{y}_p), \ \rho_{y,i}(t) \stackrel{def}{=} (\boldsymbol{y}(t) \mid \boldsymbol{y}_p, \rho_{\delta,i}(t) = 1) \tag{10}$$

$$p(\boldsymbol{y}_r \mid \boldsymbol{y}(t)) = \sum_i \lambda_{\delta,i}(t) p(\lambda_{y,i}(t))$$

$$\lambda_{\delta,i}(t) \stackrel{def}{=} (\delta_i(t) \mid \boldsymbol{y}_r), \ \lambda_{y,i}(t) \stackrel{def}{=} (\boldsymbol{y}(t) \mid \boldsymbol{y}_r, \lambda_{\delta,i}(t) = 1) \tag{11}$$

$$\rho_{y,i}(t) \sim \frac{\sum_j a_{j,i} \rho_{\delta,j}(t-1) N(\boldsymbol{\mu}_i + \boldsymbol{w}_i \rho_{y,j}(t-1), \boldsymbol{\Sigma}_i)}{\sum_j a_{j,i} \rho_{\delta,j}(t-1)} \tag{12}$$

$$\rho_{\delta,j}(t) = \sum_i a_{i,j} \rho_{\delta,i}(t-1), \ \rho_{y,i}(1) = \boldsymbol{y}(1), \quad \rho_{\delta,i}(1) = \delta_i(1) \mid \boldsymbol{y}_p \tag{13}$$

$$\lambda_{y,i}(t) \sim \frac{\sum_j a_{i,j} \lambda_{\delta,j}(t+1) N\left(\boldsymbol{w}_i^{-1}(\lambda_{y,j}(t+1) - \boldsymbol{\mu}_i), \boldsymbol{w}_i^{-1} \boldsymbol{\Sigma}_i \boldsymbol{w}_i^{T-1}\right)}{\sum_j a_{i,j} \lambda_{\delta,j}(t+1)} \tag{14}$$

$$\lambda_{\delta,j}(t) = \sum_i a_{j,i} \lambda_{\delta,i}(t+1), \ \lambda_{y,i}(T) = \boldsymbol{y}(T), \quad \lambda_{\delta,i}(T) = \delta_i(T) \mid \boldsymbol{y}_r \tag{15}$$

The same approximation technique is used in calculation of $\rho_{y,i}(t)$ and $\lambda_{y,i}(t)$ because (12) and (14) are the same type as (5).

The algorithms shown above are also applicable to HMM because HMM are special cases of SLDS.

4. Modeling of Driving Behavior

We prepared driving behavior data in a real road environment to evaluate the proposed method. We developed a vehicle equipped with sensing devices to collect data [9]. The sampling rate was 15 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 measured data that were taken at 20 km/h or lower speeds. The vehicle stopped once or twice in 16 of 33 cases because traffic or a traffic signal blocked the roadway beyond. In other cases, the vehicle passed through the

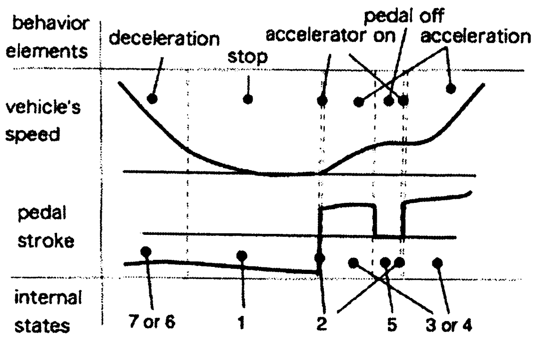

Fig. 3 Relation between internal states and observations.

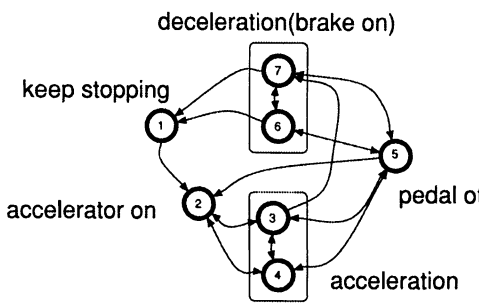

Fig. 4 Transition between internal states.

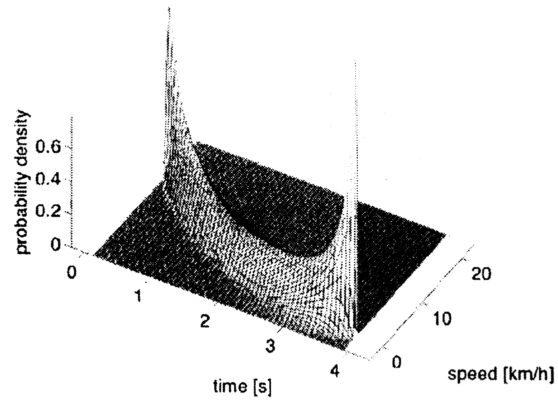

Fig. 5 An example of driving behavior prediction.

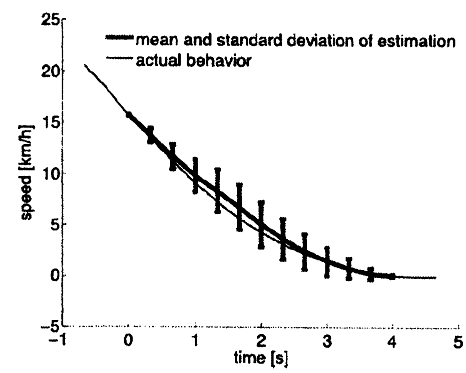

Fig. 6 An example of estimation and actual behavior. Observations of actual behavior before time 0 s and after time 4 s were given for the estimation of behavior from time 0 s to 4 s.

intersection without stopping. We used half the records as training data and the remainder as test data.

The vehicle's speed and the brake and accelerator pedal strokes were given to an SLDS as observable data. The pedal strokes were given as a combination variable: the subtraction of the stroke of brake pedal from that of the accelerator pedal (hereafter called the pedal stroke). We determined the number of internal states, Q, using cross-validation. The increase of Q contributed to improving the prediction accuracy, whereas performance was not so sensitive to Q and sensitive to initial values as Q was greater than about 7. We chose $Q = 11$ in this study.

We investigated the role of each internal state of SLDS to confirm the model's validity. Figure 3 shows a time course of vehicle's speed and internal states inferred by the inference algorithm [12], where we assume that $Q = 7$ to clarify and simplify our illustration of the role of internal states. Each internal state corresponded to each behavior element: *acceleration*, *stop*, *accelerator on*, *pedal off*, or *deceleration*. Each state represented the dynamics of each element. For instance, another examination demonstrated that a transient response in each internal state approximated that of corresponding behavior. Figure 4 shows the major transitions between these internal states. A sequence of behavior from deceleration, stop, accelerator on, then to acceleration, appeared clearly in the transition through internal states 7 to 1 or 6 to 1, 1 to 2, and 2 to 3 or 2 to 4. There were no physically impossible transitions, such as that from acceleration to stop, i.e. from internal state 2 to 1. The above results show that driving behavior was acquired in an efficient manner in the proposed model.

5. Estimation of Stop Behavior

We applied the proposed method for estimation of stop behavior for the last 4 s before stopping to demonstrate its effectiveness. Figures 5 and 6 show an example of results. Figure 5 shows the probability distribution of behavior as estimated by the proposed method. Here, the actual driving behavior data before time 0 s and the information that the vehicle stopped after 4 s were given. Figure 6 shows a time course of actual vehicle's speed and the mean and standard deviation of estimation. The error between the mean and actual speed was less than 2 km/h and less than a standard deviation. We conducted the same estimation through those parts of seven test data that consisted of stop maneuvers. Experiments showed that the error was less than 2 km/h at the maximum and the average of error was less than 1 km/h (Fig. 7). The proposed method provided a good estimation of stop behavior.

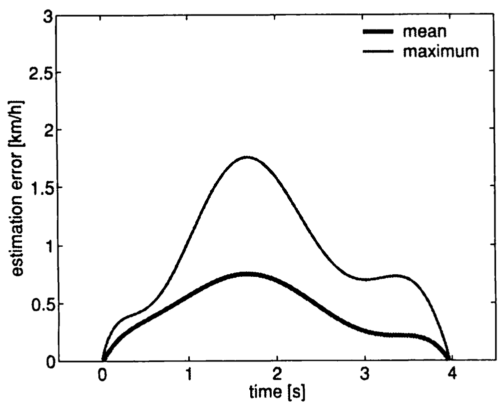

Fig. 7 Estimation error.

6. Discussion

This study presented a method of inferring future human driving behavior when its resultant behavior and past observations are given. The proposed method provided a good estimation of stop behavior under the condition that past driving behavior and information on a future stop were given. Only deterministic information was given in this study; however, the method is also applicable to more uncertain cases in which past and future information is given as probability distributions.

Estimation of stop behavior would allow early detection of "non stopping behavior" by testing a hypothesis that driving behavior is a stop behavior, and establishing CWS/CAS as an effective assistance. The proposed method would also be useful for mining data from a behavior database: extracting models of maneuvers whose results are assumed, such as stopping at a stop sign, acceleration in the acceleration lane and so on.

Obstacles remain to this method's application for CWS/CAS. First, estimation must be valid for a wide range of situations in addition to those of limited intersections, certain time periods, and so on. Moreover, it must be shown that the proposed method is effective for unspecified drivers. We have confirmed the effectiveness of this method for only a few subjects aside from the experiments explained herein. Second, the proposed method poses constraint conditions as a function of time. We posited that a vehicle would stop 4 s later. However, distance is more important than time in CWS/CAS applications. This method should accept a constraint condition on distance. That is, driving behavior must be explained as a function of distance, such as a dynamic Bayesian network whose sequence is indexed by distance instead of time.

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