STOCHASTIC MODELING OF VEHICLE TRAJECTORY DURING LANE-CHANGING

Yoshihiro Nishiwaki, Chiyomi Miyajima, Hidenori Kitaoka, Kazuya Takeda,

Department of Media Science, Graduate School of Nagoya University, Nagoya 465-8603, Japan

ABSTRACT

A signal processing approach for modeling vehicle trajectory during lane changing driving is discussed. Because individual driving habits are not a deterministic process, we developed a stochastic method. The proposed model consists of two parts: a dynamic system represented by a hidden Markov model and a cognitive distance space derived from the range distance distribution. The first part models the local dynamics of vehicular movements and generates a set of probable trajectories. The second part selects an optimal trajectory by stochastically evaluating the distances from surrounding vehicles. From experimental evaluation, we show that the model can predict the vehicle trajectory at given traffic conditions with 17.6 m prediction error for two different drivers.

***Index Terms*—** Driving Behavior, Dynamic System, hidden Markov model, Sampling

1. INTRODUCTION

Driving safety and efficiency in vehicle driving are central issues in modern societies. Even though the fatality rate has apparently peaked in Japan, traffic accidents were still responsible for approximately 6,000 fatalities in 2007 [1]. Recent energy problems are also a serious threat to modern society. Such technologies as pre-crash safety and hybrid energy have contributed to solving these problems [2]-[4]. On the other hand, such technologies concerning drivers as driver monitoring and in-vehicle interfaces are still not commonly utilized. Studies that model human driving behavior are insufficient, although vehicular behavior has been widely studied from the viewpoint of control theory. Since human behaviors are not deterministic, research that models driving behavior from the stochastic signal processing viewpoint is important. In this paper, we propose a stochastic method of predicting vehicle trajectories during lane changing (LC). In our proposed method, a trajectory model can be fully trained by a set of collected data based on the maximum likelihood principle without predetermined parameters. In addition, using a hidden Markov model (HMM), our proposed method can model the multi-state behavior of lane changing without explicit knowledge about the state transitions or predetermined parameters.

Various approaches have predicted vehicular behaviors. Danielsson et al. [5] generated vehicle trajectories of a surrounding vehicle for a few seconds. However, driver characteristics were not considered and the method was not evaluated quantitatively using an actual signal. Althoff et al. [6] stochastically modeled the presence of trucks, cars, and pedestrians in traffic for a few seconds. However, driver characteristics were not considered, either.

The most important contribution of this study to the above previous studies is developing a model that can predict vehicle behavior of about a 20-second period based on stochastic signal processing. Such long-term prediction is not discussed in the previous works based on a control theory assuming that sensing data are updated every short period. Also since the models used in the approach are fully trainable, driver-dependent trajectory prediction can be easily implemented.

The proposed method consists of two parts. The first uses a hidden Markov model to characterize the stochastic dynamic properties of the vehicular movements that originate from the driver's habitual characteristics. Since lane change activity consists of multiple states, i.e., examining the safety of traffic environments, moving into the next lane and adjusting to its traffic flow, a single dynamic system cannot model the trajectory. In addition, the boundaries between states cannot be observed from the trajectory. HMM models such a stochastic state transition system, and the EM algorithm can train an HMM without explicit information of the state boundaries [7]. Furthermore, once the joint probability of a signal and its time derivative, i.e., $z[n]$ and $\Delta z[n]$, is trained, the most probable signal sequence, $\{z[n]\}_{n=1,\cdots,N}$ can be calculated for the given state transition pattern [8]. Therefore, this part can be used for generating trajectory hypotheses or bottom-up processing.

The second part is a cognitive hazard map calculated from the car following distance distributions of the training data. Here, the driver's sensitivity of the range distance to a near-by vehicle in a particular location is modeled. Such sensitivities to surrounding vehicles are then integrated into a hazard map in a probability domain. Therefore, this function can be used for the trajectory selection. Finally, the two process are combined into a trajectory predicting algorithm that first generates a set of probable trajectories by sampling the HMM and then selects the optimal trajectory based on the cognitive hazard map of the surrounding traffic.

In the rest of this paper, we discuss and evaluate our proposed method as follows. In Sections 2 and 3, a HMM-based generation model and a cognitive hazard map are discussed, respectively. The experimental evaluation of the method is given in Section 4, and Section 5 summarizes the results and future works.

2. MODELING TRAJECTORIES BY HMM

2.1. Trajectory data

A set of vehicle movement observations was measured using a driving simulator. Relative longitudinal and lateral distances from the vehicle's position when starting the lane change, $x_i[n]$, $y_i[n]$, and the velocity of the vehicles, $\dot{x}_i[n]$, $\dot{y}_i[n]$, were recorded every 160 ms. Here $i = 1, 2, 3$ is an index for the location of surrounding vehicles (Figure 1), and $(x_0[n], y_0[n])$ represents the position of the target (ego) vehicle.

The time period of lane changing activity, $n = 1, \cdots, N$, starts when V0 (ego vehicle) and V2 are at the same longitudinal location and ends when the V0's lateral location reaches the local minimum as shown in Figure 1.

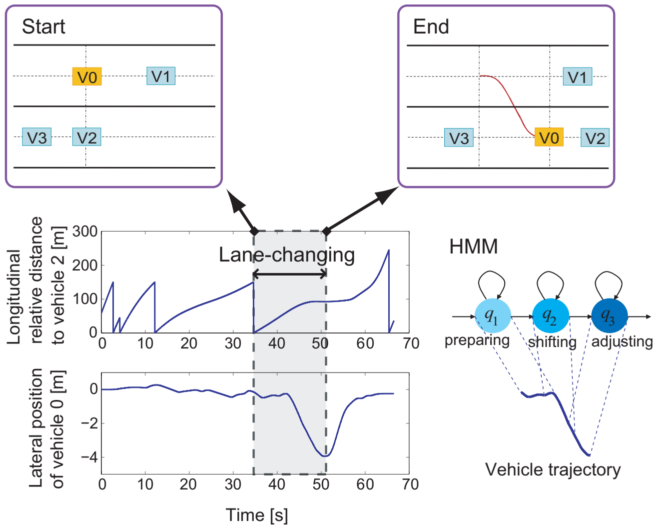

Fig. 1. Lane change trajectory and geometric positions of surrounding vehicles. V0 is the vehicle changing lanes.

2.2. Hidden Markov Model

We used a three-state HMM to describe the three different stages during a lane change: preparation, shifting, and adjusting. In the proposed model, each state is characterized by a joint distribution of eight variables:

$$\mathbf{v} = [\dot{x_0}, \dot{x_1}, \dot{x_2}, y_0, \Delta\dot{x_0}, \Delta y_0, \Delta^2\dot{x_0}, \Delta^2 y_0]^t. \quad (1)$$

Note that hereafter we omit time index $[n]$ from the variables. In general, longitudinal distance, x_0, monotonically increases in time and cannot be modeled by an i.i.d. process. Therefore, we use longitudinal speed $\dot{x_0}$, as a base (static) variable to characterize the trajectory. We calculated higher order time derivatives by delta operation given by

$$\Delta c[n] = \frac{\sum_{k=-K}^{K} k \cdot c[n-k]}{\sum_{k=-K}^{K} k^2} \quad (2)$$

because it is robust to noise contamination.

Finally, after training the HMM by a set of recorded trajectories, mean vector μ_j and covariance matrix Σ_j of the trajectory variable $\mathbf{v}$ are estimated for each state $j = 1, 2, 3$. Meanwhile the distribution of time length N is modeled by a Gaussian distribution.

2.3. Trajectory Generation from a hidden Markov model

As shown in the later experiments, the trajectory's shape is governed by the HMM and the duration of the LC activity. When the driver performs LC in a shorter time, the sharper trajectory is used. We generate a set of probable LC trajectories by determining state durations $\{d_j\}$ by sampling the corresponding pdfs as follows.

First determine LC time N by sampling its trained distribution. Then determine state durations d_j by also uniformly sampling the state duration distribution by

$$d_j = \left\lceil \frac{\xi_j N}{\sum_{k=1}^{K} \xi_k} \right\rceil. \quad (3)$$

Where ξ_j is a random variable that follows a uniform distribution between 0 and 1. Once a set of state durations is determined, the maximum likelihood HMM signal synthesis algorithm[8] generates the most probable trajectory. Simply repeating this process will produce a set of probable vehicle trajectories characterized for a trained driver.

3. TRAJECTORY SELECTION

Although various natural driving trajectories may exist, due to the surrounding vehicle conditions, the number of LC trajectories that can be realized under the given traffic circumstances is limited. Furthermore, the selection criteria of the trajectory based on the traffic context differ among drivers, e.g., more sensitive to the front vehicle than the side vehicle etc. Therefore, we model the selection criterion of each driver by a scoring function for LC trajectories based on vehicular contexts, i.e., relative distances from the surrounding vehicles.

In the proposed method, a hazard map $\mathcal{M}(x_i, y_i)$ is built in a stochastic domain based on the histograms of the relative positions to surrounding vehicles $\mathbf{r}_i = [x_i - x_0, y_i - y_0]^t$. Again, note that we omit time index $[n]$.

To model the sensitivity, we calculated covariance matrix $\mathbf{R}_i$ of each of three distances, $\mathbf{r}_i, i = 1, 2, 3$, from the training data. Since the distance varies more widely in less sensitive distance, we use the quadrature form of inverse covariance matrices $\mathbf{R}_i^{-1}$ as a metric of the cognitive distance. Then calculate hazard map $\mathcal{M}(x_0, y_0, x_i, y_i)$ for surrounding vehicle Vi by

$$\mathcal{M}(\mathbf{r}_i) = \frac{1}{1 + \exp\left\{\alpha_i \left(\mathbf{r}_i^t \mathbf{R}_i^{-1} \mathbf{r}_i - \beta_i\right)\right\}}. \quad (4)$$

Where α_i is a parameter for the minimum safe distance defined so that the minimum value of cognitive distance $\mathbf{r}^t\mathbf{R}^{-1}\mathbf{r}$ of the training data corresponds to the lower 5 % distribution values. β_i is the mean value of $\mathbf{r}^t\mathbf{R}^{-1}\mathbf{r}$.

$$\alpha_i = \frac{\log(0.05) - \log(0.95)}{min\{\mathbf{r}_i^t \mathbf{R}_i^{-1} \mathbf{r}_i\} - \overline{\mathbf{r}_i^t \mathbf{R}_i^{-1} \mathbf{r}_i}} \quad (5)$$

$$\beta_i = \overline{\mathbf{r}_i^t \mathbf{R}_i^{-1} \mathbf{r}_i} \quad (6)$$

Harzard map $\mathcal{M}$ can be regarded as an *a posteriori* probability of being in the safe driving condition under range distances $\Pr\{\text{safe}|\mathbf{r}\}$, when the likelihood is given as a exponential quadrature form, i.e.,

$$\Pr\{\mathbf{r}|\text{safe/unsafe}\} \propto \exp\left\{-\frac{1}{2}\mathbf{r}^t\mathbf{A}\mathbf{r}\right\}. \quad (7)$$

Therefore, integrating the harzard maps for three surrounding vehicles can be simply done by interpolating three probabilities with weights λ_i into an integrated map,

$$\mathcal{M}' = \sum_i \frac{\lambda_i}{1 + \exp\left\{\alpha_i \left(\mathbf{r}_i^t \mathbf{R}_i^{-1} \mathbf{r}_i - \beta_i\right)\right\}}. \quad (8)$$

Once the geometrical positions of the surrounding vehicles at time point n, $\mathbf{r}_i[n]$ are given, $\mathcal{M}'$ can be calculated for each time point, and averaging the value over the LC time can compare the possible trajectories. Then the optimal trajectory which has the lowest value is selected among the possible trajectories.

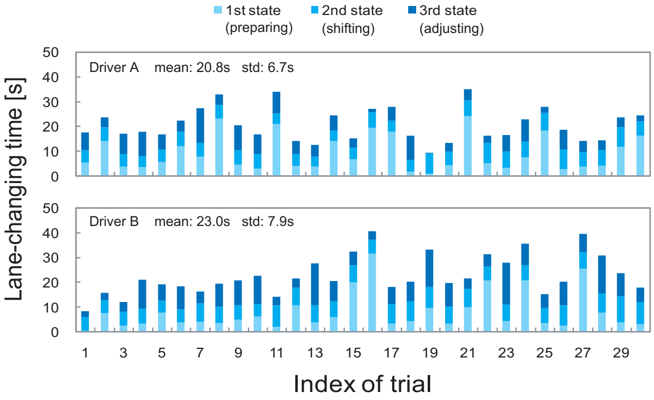

Fig. 2. LC time and its most probable state distribution calculated by the trained HMM.

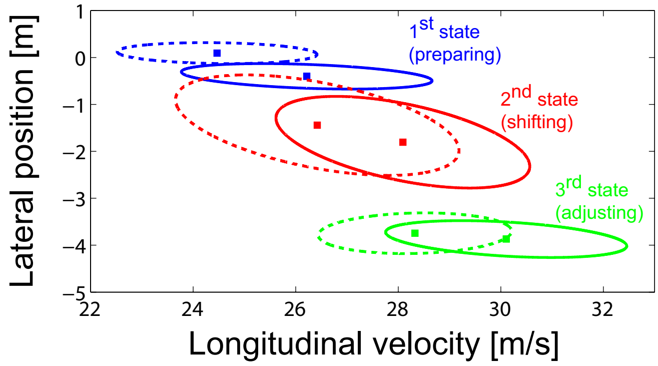

Fig. 3. Joint pdfs of trajectory variables trained for each state of two drivers(solid:driver A, dotted:driver B). (only plotted for $\dot{x}$ and y.) The square shows the mean and the contour represents the 'one sigma' boundary.

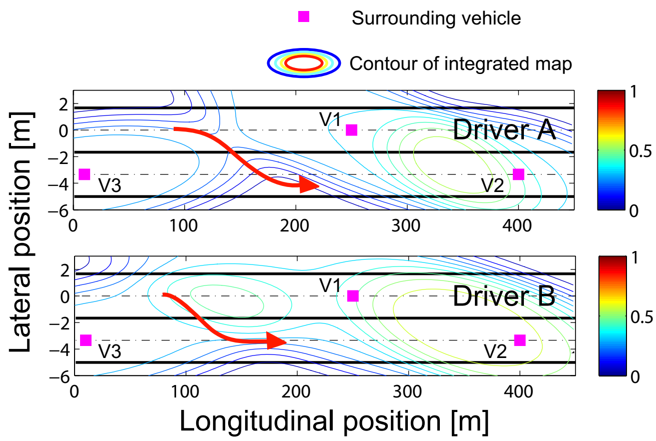

Fig. 4. Trained hazard maps of two drivers when the same geometric positions of surrounding vehicles are given.

4. EVALUATION

4.1. Data collection and set up

Thirty LC drivings were recorded for two drivers using a driving simulator under simulated urban highway conditions where the traffic was moderatory dense. The drivers were instructed to pass the preceding car when possible. Figure 2 shows the distribution of the LC time and its most probable state distribution. The state distribution characterizes the driving behavior in LC activity. For example, on average, driver B required more time than A to complete a LC. Thirty trials were used for 3-fold cross validation tests: twenty for training and ten for tests. Each state of an HMM is characterized by a joint Gaussian pdf of trajectory variables and trained using a HTK[9] HMM toolkit.

Four hundred possible trajectories were generated from an HMM. First, by sampling the distribution of the LC duration twenty times and then for each LC duration N, twenty sets of state durations $\{d_j\}$ were hypothesized by also sampling the uniform distribution by (3). For selecting the optimal trajectory, we integrated three hazard maps into a single hazard map with equal weights, i.e., $\lambda_{1,2,3} = 0.33$, which is represented by equation (8). We have assumed that surrounding vehicle speed $\dot{x}_i$ and $\dot{y}_i$ are constant throughout the LC activity.

4.2. Results

The trained joint pdfs of the trajectory variables were plotted for each HMM state of the two drivers in Figure 3. We confirmed that the habitual difference in LC driving behavior can be modeled in HMM parameters. The trained hazard maps $\mathcal{M}'$ for the two drivers shown in 4 also depict the differences in sensitivities to the surrounding vehicles. The possible generated trajectories, the selected optimal trajectory, and the actual trajectory recorded for the condition are shown in figure 5. Although this model tries to predict the vehicular trajectory over a 20-second period, the proposed method can generate a reasonable prediction for each driver. The trajectories of the two drivers are clearly different.

For further quantitative evaluation, we calculated the difference of the predicted and actual trajectories based on dynamic time warping (DTW) using the normalized square difference as a local distance:

$$D(i,j) = \min \begin{cases} D(i-1,j) \\ D(i-1,j-1) \\ D(i,j-1) \end{cases} + \frac{1}{I+J-1}\left(\frac{(x_0[i]-\hat{x}_0[j])^2}{\sum_{n=1}^{I} x_0^2[n]} + \frac{(y_0[i]-\hat{y}_0[j])^2}{\sum_{n=1}^{I} y_0^2[n]}\right), \quad (9)$$

where I and J are the length of the actual and predicted trajectories, and the DTW recursion proceeds from $D(0,0) = 0$ to $D(I,J)$. We used $10\log(D)$ as a signal-to-deviation (SDR) index for the prediction. This is because the length of the actual and predicted trajectories are different.

The average SDR value for 60 tests was -26.1 dB. We also tested our method for the correct LC time, i.e., $I = J$. When the correct LC time is given, the root mean square error (RMSE) between the predicted and actual trajectories can be calculated. The average RMSE for 60 tests was 17.6m.

The effectiveness of the proposed method in predicting a long period of trajectory is confirmed.

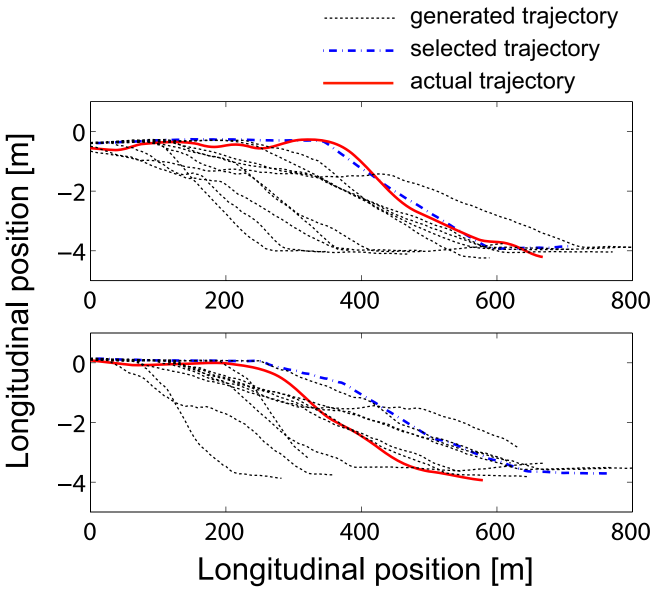

Fig. 5. Examples of the generated (dotted lines) and the selected (a broken line) trajectories. The actual trajectory observed under the given condition is also plotted by a solid line.

Figure 6 shows the resultant SDRs when driver A's model is used for predicting driver B's trajectory and vice versa. SDR increased by more than 8.4 % when the different driver's model was used for the prediction. From the results, the effectiveness of the proposed model for capturing LC activity characteristics is also confirmed.

5. SUMMARY AND FUTURE WORKS

In this paper, we proposed a stochastic framework for modeling driving behavior where driver habitual and cognitive characteristics are modeled by an HMM and geometrical probability function. By generating a set of probable trajectories using HMM and then selecting the optimal trajectory by the geometric function, in the proposed method, the trajectory of a lane change about 20 seconds long can be predicted only from the intial conditions. Since model parameters can be trained from the statistically motivated training criteria, the personality in driving can be easily characterized from training data.

From the preliminary experimental evaluations, we confirmed that the model can generate a reasonably accurate personalized trajectory. However, various future works are needed. First, more analytical and quantitative evaluation of the method is indispensable that uses larger amount of data. Also, the model should be tested using realistic driving data collected under actual traffic conditions. Integrating the generation and selection parts in a consistent criterion is also very challenging but important future work.

ACKNOWLEDEMENT

This work was partially supported by the Strategic Information and Communications R&D Promotion Program (SCOPE) of Ministry of Internal Affairs and Communications, Japan. We are grateful to project members for their discussions.

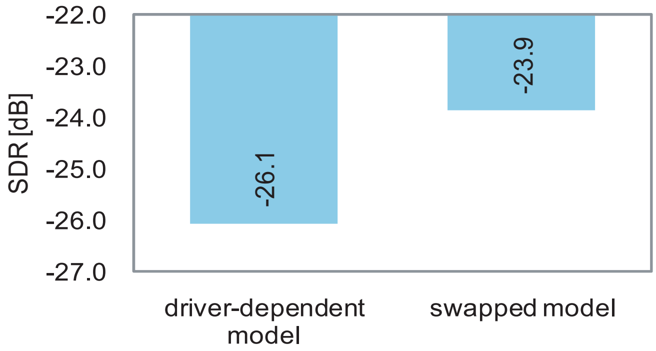

Fig. 6. Average SDR values of the predicted trajectory by the models of the same driver (left) and the different driver (right).

6. REFERENCES

[1] National Police Agency Traffic Bureau, "Road Traffic Accidents in 2008," http://www.npa.go.jp/toukei/koutuu48/Month.pdf

[2] P. E. An and C. J. Harris, "An intelligent driver warning system for vehicle collision avoidance," IEEE Trans. Syst., Man, Cybern. A, vol. 26, no. 2, Mar. 1996.

[3] R. Onken, "DAISY, an adaptive, knowledge-based driver monitoring and warning system," Proc. Vehicle Navigation and Information Systems Conference, pp.3–10, Aug. 1994.

[4] Q. Gong, Y. Li, and Z. R. Peng, "Computationally Efficient Optimal Power Management for Plug-in Hybrid Electric Vehicles Based on Spatial-Domain Two-Scale Dynamic Programming," 2008 IEEE International Conference on Vehicular Electronics and Safety (ICVES 2008), Columbus, Ohio, Sept. 2008.

[5] S. Danielsson, L. Petersson, and A. Eidehall, "Monte carlo based threat assessment: Analysis and improvements," Proc. of 2007 IEEE Intelligent Vehicles Symposium, pp.233–238, June 2007.

[6] M. Althoff, O. Stursberg, and M. Buss, "Stochastic reachable sets of interacting traffic participants," Proc. of 2008 IEEE Intelligent Vehicles Symposium, June 2008.

[7] L. R. Rabiner, "A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition," Proc. of the IEEE, pp. 257–286, Feb. 1989.

[8] K. Tokuda, T. Yoshimura, T. Masuko, T. Kobayashi, and T. Kitamura, "Speech parameter generation algorithms for HMM-based speech synthesis," Proc. of ICASSP, pp.1315–1318, June 2000.

[9] S. Young et. al., "The HTK Book," Entropic Labs and Cambridge University, 2001-2006.