Modeling and Prediction of Driving Behaviors Using a Nonparametric Bayesian Method with AR Models

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***Abstract*—To develop a new generation ADAS that avoids a dangerous condition in advance, we need to predict driving behaviors. Since a nonparametric Bayesian method with a two-level structure successfully predicted the symbolized behaviors only, we applied a nonparametric Bayesian method with linear dynamical systems to predict the driving behavior. The method called the beta process autoregressive hidden Markov model (BP-AR-HMM) segments driving behaviors into states each of which corresponds to an AR model and it predicts future behaviors using the estimated future state sequence and the dynamical systems therein. Here, the segmentation as well as the parameters of the dynamical systems are determined using given training data in an unsupervised way. We carried out experiments with real driving data and found that the BP-AR-HMM predicted driving behaviors better than other methods.**

***Index Terms*—Bayesian nonparametrics, driving behavior modeling, autoregressive hidden Markov model.**

I. Introduction

RECENT advanced driver assistance systems (ADASs) such as automatic braking system [1], [2], adaptive cruise control or lane-keeping system [3]–[5] and pedestrian protection [6]–[8] have reduced the number of traffic accidents [9]. These systems detect a dangerous condition and warn the driver of the condition. This means that the driver falls into the dangerous condition once, which should be avoided in advance.

To prevent a car from a dangerous condition, the future movement of the car must be estimated, which results in the prediction of driving behaviors since the car is operated by a driver (Fig. 1). Some systems have successfully predicted specific behaviors, for example, braking behaviors [10], "approaching a traffic light" behaviors [11], lane departure behaviors [12], and behaviors at intersections [13], [14]. Although they successfully predict specific behaviors in a short time scale, few systems have achieved to predict general behaviors in a longer time scale.

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To treat general behaviors, a prediction system must divide a sequence of behaviors into segments and extract sequences of segments. Taniguchi et al. [15] formulated this problem as a two-level structure and solved it based on an analogy with language (letters/words) by a nonparametric Bayesian method called the nested Pitman-Yor language model (NPYLM) [16]. They modeled driving behaviors by the NPYLM and predicted sequences of segments that corresponded to more than eight seconds. However, they predicted only symbolized behaviors, not driving behaviors themselves, that are necessary to predict the future movement of the car.

Inspired by the success of the NPYLM in predicting driving behaviors, in this paper, we proposed to apply a nonparametric Bayesian method with dynamical systems to predicting driving behaviors, not the sequence of symbols. Driving behaviors are well modeled by a set of linear dynamical systems called a hybrid dynamical system (HDS), wherein the dynamics switches from one to another [17], [18]. The HDSs have some variants depending on the switching method and the dynamical systems therein such as the Markov dynamic model [18], the switching linear dynamical systems [19] and the autoregressive hidden Markov model (AR-HMM) [20]. In this study, the AR-HMM was employed because it is a simplest model to express dynamics although more complicated models were employed in the literature [21], [22]. The AR-HMM must determine the number of AR models (the number of kinds of behaviors in driving) in advance. To avoid this difficulty, we incorporated the nonparametric Bayesian technique into the AR-HMM, which was proposed as the beta process autoregressive hidden Markov model (BP-AR-HMM) [23].

The BP-AR-HMM divides a sequence of behaviors into segments (called driving letters in [15]) in an unsupervised way and assigns an AR dynamical system to each segment. When given a sequence, the BP-AR-HMM is trained by alternatively carrying out the segmentation of the sequence according to the estimated dynamical systems and the identification of the dynamical system in each segment. After trained, the BP-AR-HMM predicts a sequence of segments (driving letters) using the state transition probability of the HMM and then predicts the behaviors using the AR model in each segment.

In the following, we show the soundness of the BP-AR-HMM for prediction of driving behaviors using the real driving data obtained by the authors' group. Note that a part of behavior prediction of Dataset 1 (Sec. III. B) was reported

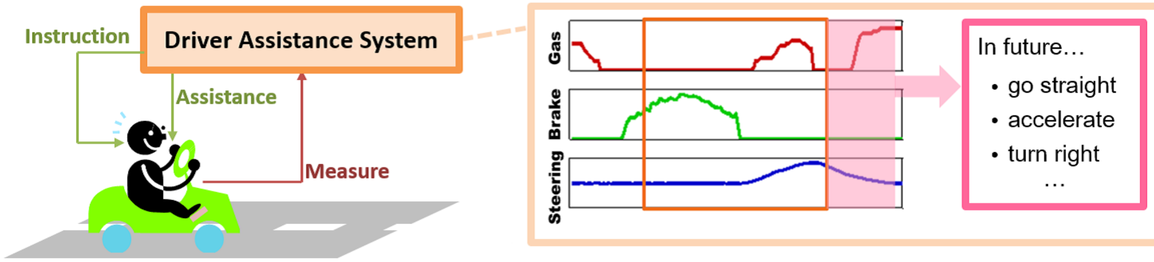


Fig. 1: Typical application of driver assistance system.

in a conference [24].

II. Materials and Methods

A. Generative model

We used the BP-AR-HMM to model driving behaviors [23]. This is an extension of the AR-HMM to a nonparametric Bayesian method with beta processes and the AR-HMM is a combination of the HMM and autoregressive processes. The HMM assigns a hidden state at each time point according to the state-transition probability and generates observable variables from a certain (usually Gaussian) distribution associated with the hidden state. The AR-HMM assigns a hidden state in the same way but generates observable variables by using a vector-autoregressive (VAR) model associated with the hidden state. The VAR model with the hidden state z_t produces the observable variables $\boldsymbol{y}_t^{(i)}$ at time t of the ith time series according to

$$\boldsymbol{y}_t^{(i)} = A_{z_t}\boldsymbol{y}_{t-1}^{(i)} + \epsilon_t, \tag{1}$$

where A_{z_t} is the VAR coefficient matrix and ϵ_t is the Gaussian noise at time t.

The BP-AR-HMM assigns a hidden state (VAR model) in the same way as the AR-HMM. Differently from the AR-HMM, the BP-AR-HMM makes a new state not assigned so far in a certain probability according to a beta process. Thus, the beta process generates a prior probability of emergence ω_k of state k according to

$$B = \sum_{k=1}^{\infty} \omega_k \delta_{\theta_k}, \tag{2}$$

where B is a draw of the beta process, δ_{θ_k} is a Dirac measure at state k, and θ_k is a VAR parameter including the VAR coefficients A_k. The AR coefficients are chosen according to a predefined base measure B_0, which is typically a matrix Gaussian distribution (Fig. 2) [23]. Accoridng to the formulation above, the posterior probability given the N time series is expressed as

$$B \mid \boldsymbol{y}_{1:T_1}^{(1)}, \boldsymbol{y}_{1:T_2}^{(2)}, \ldots, \boldsymbol{y}_{1:T_N}^{(N)}, B_0, c \sim \mathrm{BP}\left(c+N,\ \sum_{k=1}^{\infty} \frac{m_k}{c+N}\delta_{\theta_k} + \frac{c}{c+N}B_0\right), \tag{3}$$

where m_k is the count that the state k emerges in N time series and c is a positive constant that controls the probability a new state appears. This model can produce an infinite number of states in principle and determines the total number of states according to the intrinsic complexity of given data.

The behavior vector $\boldsymbol{y}_t^{(i)}$ in this paper consisted of the accelerator opening rate, the brake pressure and the steering angle (Fig. 3).

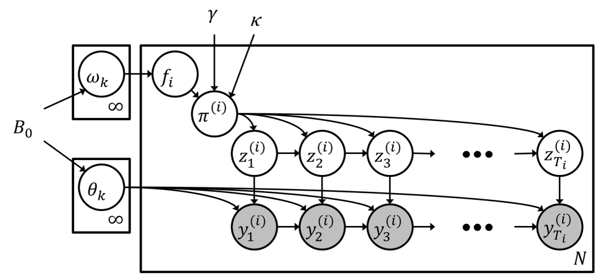


Fig. 2: Graphical model of BP-AR-HMM. $\boldsymbol{y}_t^{(i)}$, observable variable; $z_t^{(i)}$, hidden state at time point t in time series i; θ_k, VAR parameters of state k; $\pi^{(i)}$, state transition probabilities; f_i, emergence of the states in time series i; κ, γ, hyper-parameters; B_0, base measure [23].

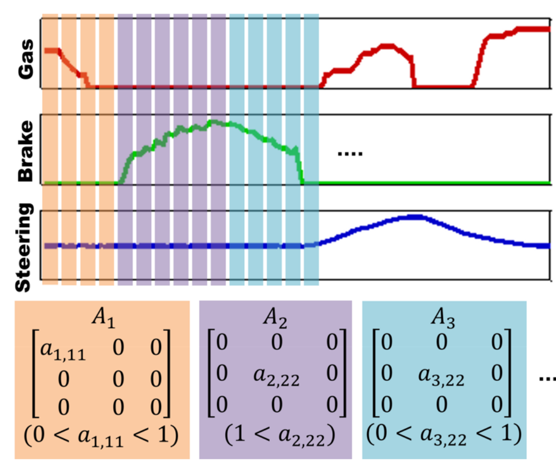


Fig. 3: A typical example of BP-AR-HMM applied to driving behaviors.

B. Training and prediction

When sequences of behaviors were given, the unknown variables are the state (AR model) at each time step and the AR coefficients of the AR model. To estimate them from the given sequence, the BP-AR-HMM assigns a state to each time step using the current criterion for assignment and updates the estimates of the AR coefficients in the states and the state transition probability using the assigned data, and iterates this procedure until the estimates satisfy a certain condition [23].

The BP-AR-HMM code in [25] was used in our experiments, where the parameters were estimated using a Markov chain Monte Carlo (MCMC) sampling with a sum-product algorithm [26] and reversible jump MCMC [27]. Their hyper-parameters, γ and κ, were assumed to have gamma-distribution priors and the other parameters were set as follows: The order of the VAR processes, one; the prior distribution of observation noises, Gaussian with mean zero where the variance was the covariance of the observed data multiplied by 0.75. In the experiments for Dataset 2 (See the next subsection), the parameters were estimated using the Viterbi algorithm [28] according to the past driving behaviors to reduce the computational complexity.

The BP-AR-HMM can predict how the states and the behaviors change in the future. First, the trained BP-AR-HMM made a sequence of states according to the estimated state transition probability. Since each state expressed a VAR process, behaviors in the future were predicted using the VAR process of the state at each time point.

For the prediction of the state sequences, we took two different methods. The first method chose the most probable state as the predicted state (Fig. 4(a)). This method is easy to implement with less computational complexity. The second method predicted the states successively according to the Bayesian inference, using the Viterbi algorithm with the state transition probability, the AR coefficients, and a batch of past behaviors (Fig. 4(b)). The Viterbi algorithm calculates the maximum joint probability of the state sequence for state $k = 1, 2, \ldots, K$,

$$\psi_t^{(i)}(k) = \max_{z_{t-l}^{(i)},\ldots,z_{t-1}^{(i)}} p(z_{t-l}^{(i)}, \ldots, z_{t-1}^{(i)}, z_t^{(i)} = k \mid \boldsymbol{y}_{t-l}^{(i)}, \ldots, \boldsymbol{y}_t^{(i)}), \quad (4)$$

by using the recursive equation

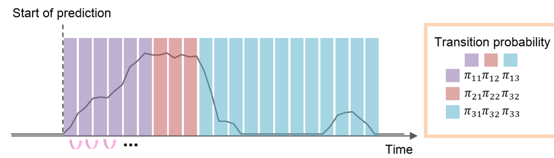
$$\psi_t^{(i)}(k) = \max_j \psi_{t-1}^{(i)}(j)\, \pi_{jk}\, p(\boldsymbol{y}_t^{(i)} | A_k \boldsymbol{y}_{t-1}^{(i)}), \quad (5)$$

where l is a length of time window, and give the estimate as

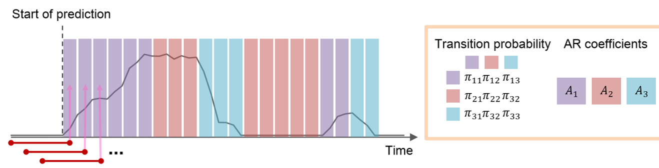
$$z_t^{(i)} = \operatorname*{argmax}_k \psi_t^{(i)}(k). \quad (6)$$

C. Datasets

We used two datasets. Dataset 1 was the same dataset as Driving Data in Factory Course in [15], where one participant drove our experimental car along two courses in a factory five laps for each (Fig. 5). Dataset 2 was the same dataset as Driving Data on Public Road also in [15], where one participant drove our experimental car along a course in a public road in Japan for nine roundtrips (Fig. 15 in [15]). The eighteen runs took 42.9 minutes in average with standard deviation 6.6 minutes. During the experiments, the accelerator opening rate, the brake pressure, the steering angle, and the speed of the car were measured through control area network (CAN) at a sampling rate of 10 Hz.



(a) Naive prediction



(b) Prediction with Viterbi

Fig. 4: Overview of state sequence prediction.

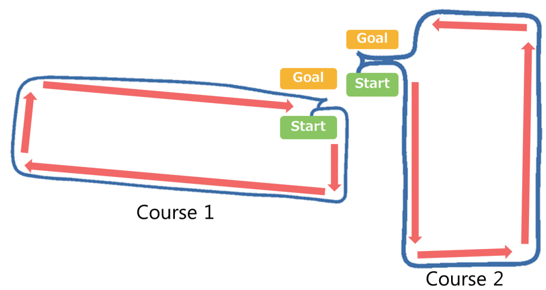


Fig. 5: Courses 1 and 2 of a short track experiment. Subject was instructed to drive car clockwise along course 1, and counterclockwise along course 2.

D. Evaluation

We compared the prediction performance of our model, the BP-AR-HMM, with the simple HMM, the sticky hierarchical Dirichlet process HMMs (HDP-HMMs), the AR-HMM and the HDP-AR-HMM to see the effectiveness of introducing AR models and beta processes. The evaluation was done in two ways using the five-fold (Dataset 1) or nine-fold (Dataset 2) cross validation method. The one is the correspondence ratio of states between the predicted and the reference sequences as in [15], where the reference sequence was determined by another BP-AR-HMM trained using all data. The other is the accuracy of the behaviors, that is, the accelerator opening rate, the brake pressure and the steering angle, by calculating the mean absolute error (MAE) between the measured and predicted driving behaviors.

III. Results

A. State sequence prediction

1) Dataset 1: Given the whole data with Courses 1 and 2 in Dataset 1, the BP-AR-HMM produced seven states (AR models) and assigned one of them to each time point (Fig. 6). Although several disturbances occurred such as a pedestrian crossing a road and another vehicle in front of the experimental car, the assignment of the states was consistent and 76.9% of the states at the same position were coincident in three or more laps among five (Fig. 7). Moreover, the same state sequence frequently appeared in the same situations. For example, when the driver turned left, the sequence of states, 3-7-1, appeared in Course 2, which was analyzed hereafter.

To evaluate the prediction ability of our model, the BP-AR-HMM predicted the state sequence of a lap in the cross validation procedure. The model trained with the rest correctly predicted the state sequence of a lap for 23.4 time points (2.34 seconds) on average (Fig. 8).

2) Dataset 2: Given the whole data (nine go-runs and nine return-runs) in Dataset 2, the BP-AR-HMM produced eight states (AR models) and assigned one of them to each time point (Fig. 9). Here, we concentrated the driving behaviors at the left-turns in an intersection because the driving behaviors in other situations widely diverged. For example, the driver changed the lane in some runs and did not in others.

For Dataset 2, the state sequences are not consistent as the case for Dataset 1. However, they seem to be classified to four classes (Fig. 9, leftmost) and the class depends on the vehicle's speed of the car. Note that the state sequences were estimated using the Viterbi algorithm because the estimation of driving states is not so easy task compared with a short track case.

B. Behavior prediction

1) Dataset 1: Using the predicted states and the corresponding AR models, the BP-AR-HMM predicted the behaviors of the driver (the brake pressure and the steering angle) during left-turn corners in Course 2 in Dataset (Fig. 6), where the initial state was set to State 3 since the sequence of states, 3-7-1, frequently appeared in left-turn corners.

The BP-AR-HMM had a smaller mean absolute error (MAE) in the brake pressure than the other models but did not have a significantly smaller MAE in the steering angle (Fig. 10), where the accelerator opening rates were omitted because they almost always took the value of 0% during the corners. This is because the BP-AR-HMM predicted the sudden decrease in brake pressures in four laps in the five although it did not predict the gradual increase in steering angles except for one lap (Fig. 11). Note that the HMM without AR models could not predict any of the above.

2) Dataset 2: Since the driving behaviors were strongly affected by the vehicle's speed, we included the vehicle's speed to the state variables, that is, each state consisted of the accelerator opening rate, the brake pressure, the steering angle and the vehicle's speed. The HMM with AR models, i.e., AR-HMM, HDP-AR-HMM and BP- AR-HMM, had smaller MAE in predicting the vehicle's speed but they didn't have significant difference in the driving behaviors (Fig. 12). Here, the numbers of states of HMM and AR-HMM were selected so that their MAEs took minimum. This means that nonparametric Bayesian methods were comparative in performance without model selection.

IV. Discussion

In our experiments using real driving data, the BP-AR-HMM successfully predicted not only states but also driving behaviors themselves for Dataset 1.

The duration time successfully predicted was shorter than the double articulation analyzer [15] (Fig. 8). This is because the BP-AR-HMM did not treat the states as sequences explicitly as the language model does [15], [16]. Nonetheless, it could predict the sequences of states by virtue of the dynamics (AR model) in each state and this implies the soundness of introducing AR models to HMM models.

The prediction accuracies of the modeling methods for driving behaviors were compared in terms of MAE and the BP-AR-HMM outperformed the other models that do not have dynamics such as the HMM and the HDP-HMM (Fig. 10). In addition, the BP-AR-HMM showed a little smaller MAE than the AR-HMM and the HDP-AR-HMM that include AR models. The HDP-AR-HMM is a nonparametric Bayesian method of the AR-HMM as the BP-AR-HMM. One property of the HDP-AR-HMM is to share a state transition probability among sequences [29] although the BP-AR HMM assigns a different one to each state. This may be the reason why the BP-AR-HMM would work better since the driving behaviors were not homogeneous but heterogeneous due to the variety of road conditions.

For Dataset 2, however, the models had comparable MAE (Fig. 12). This may be because the driving behaviors at intersections are not the same (Fig. 9). Although we succeeded to predict the vehicle's speed by including the speed to the measurement, we need to study more to improve the behavior prediction.

V. Conclusion

We showed the BP-AR-HMM successfully predicted the driving behaviors. The BP-AR-HMM automatically segmented the past driving behaviors into discrete states each of which corresponded to an autoregressive dynamical model and predicted the state sequences as well as the driving behaviors better in our experiments. Although the BP-AR-HMM fails to predict in some cases, the AR models are found to be effective to predict the driving behaviors that might be useful for a new type of advanced driver assistance systems that predict dangerous conditions in advance.

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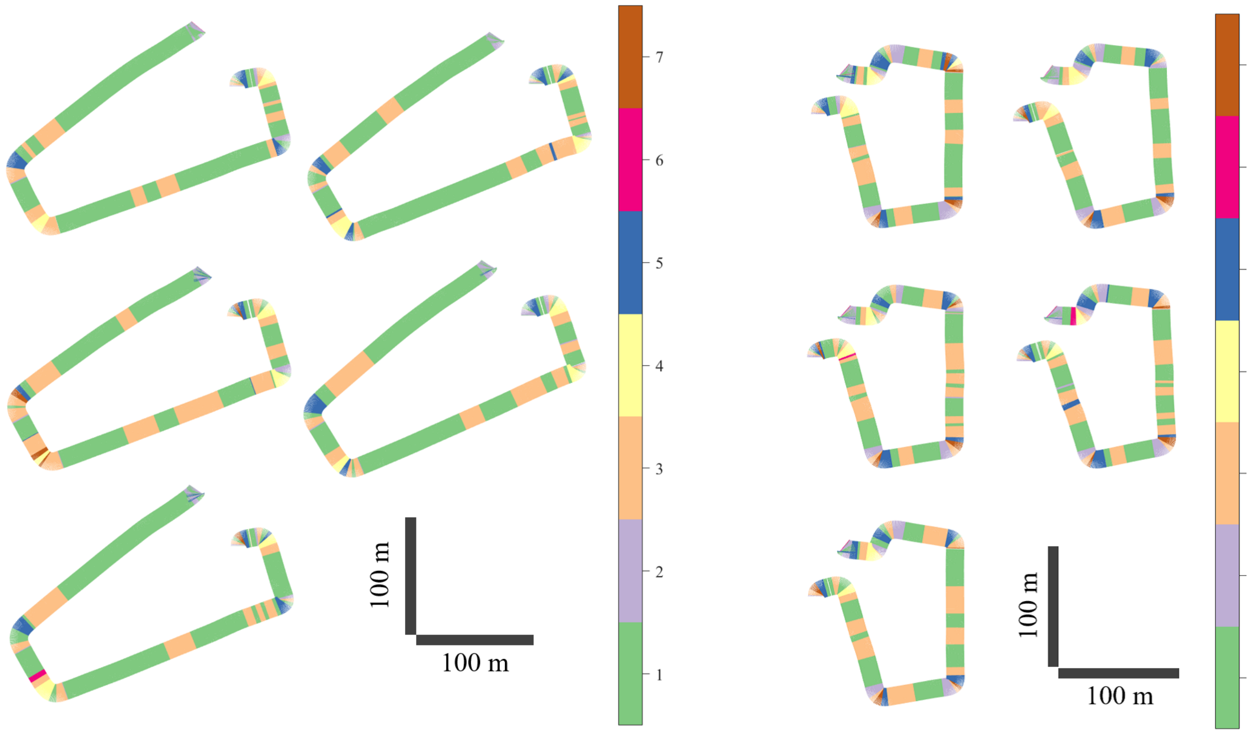

(a) Course 1

(b) Course 2

Fig. 6: Determined state sequences with our model. The five laps are shown.

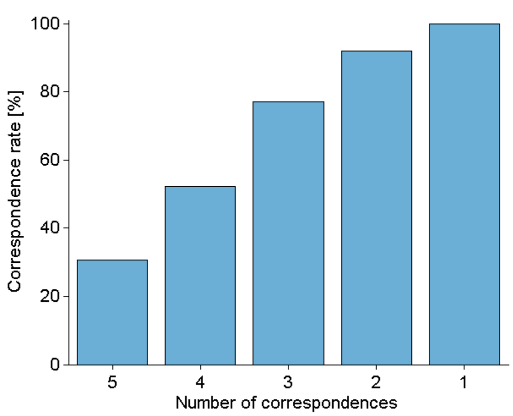

Fig. 7: Correspondence rate of the assigned states in five laps.

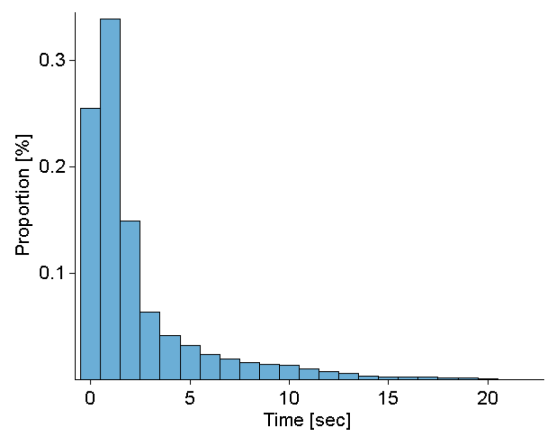

Fig. 8: Histogram of lengths the sequence prediction methods could predict.

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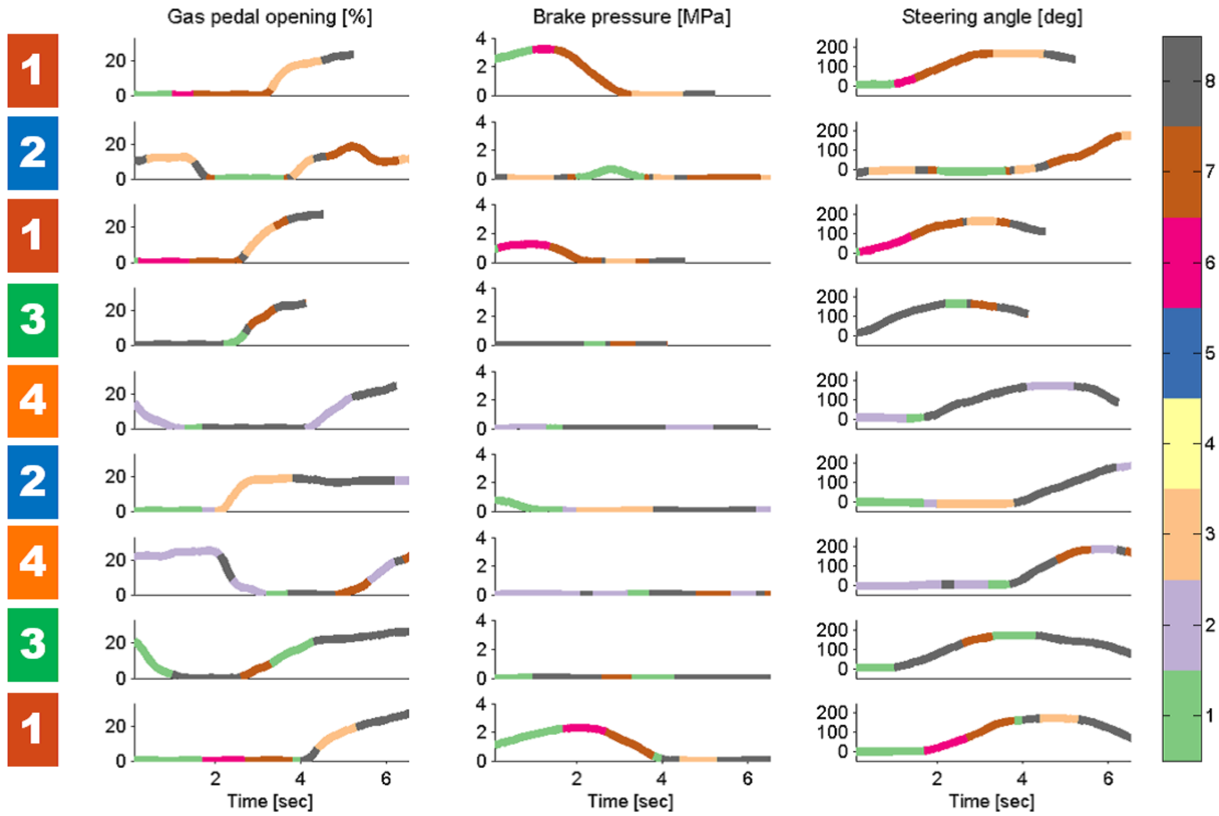

Fig. 9: Determined state sequences with our model. The nine return-runs are shown.

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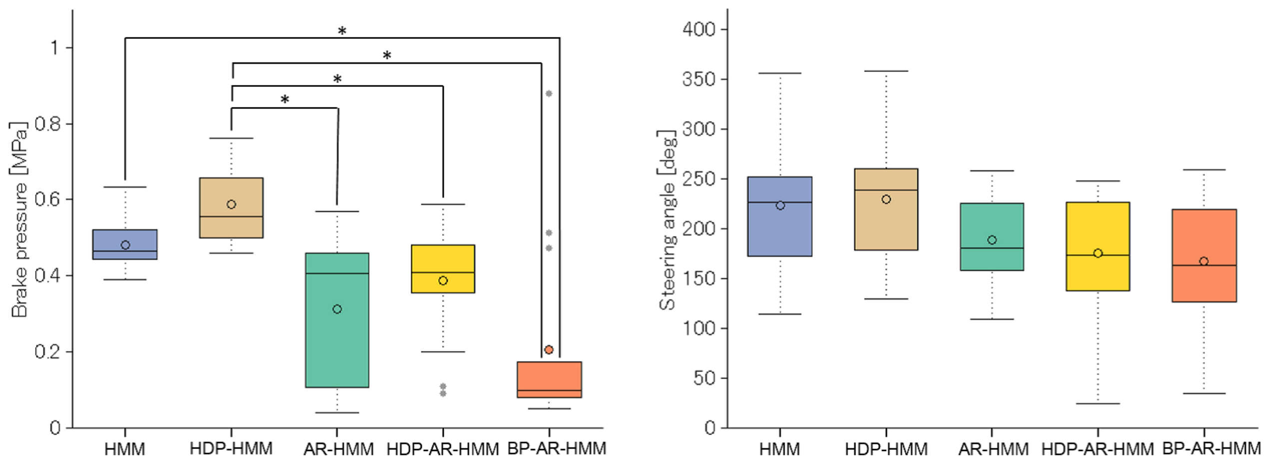
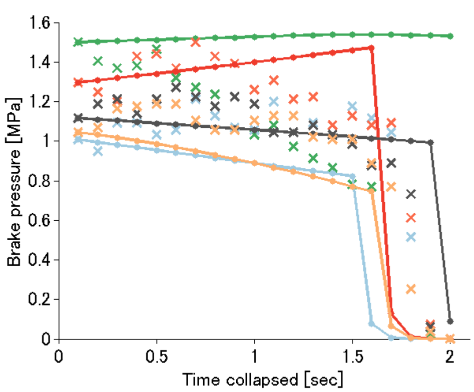
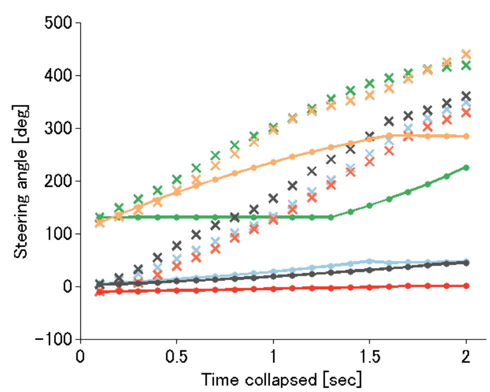


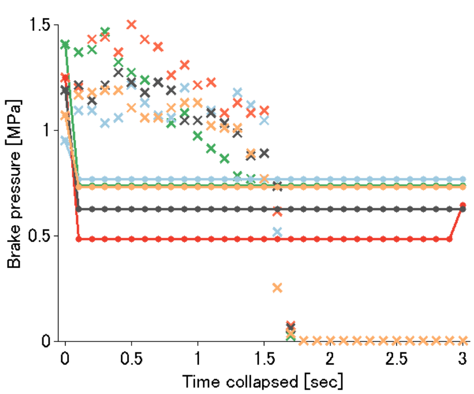
Fig. 10: MAEs of the models for brake pressures (left) and steering angles (right). Wilcoxon rank-sum test, Bonferroni corrected, $p \leq 0.05$.



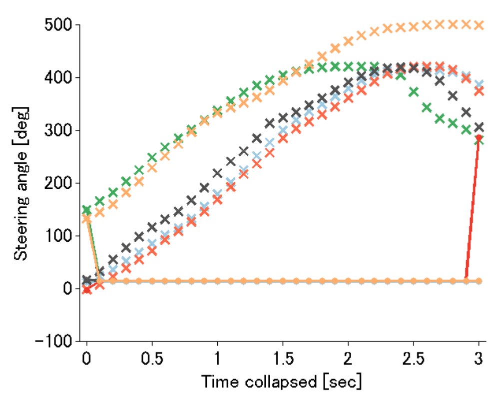
(a) Brake pressures, BP-AR-HMM.



(b) Steering angle, BP-AR-HMM.



(c) Brake pressures, HMM.



(d) Steering angle, HMM.

Fig. 11: Predicted and actual behaviors by the BP-AR-HMM and the HMM. x's, measured; lines, predicted; the same color shows the same run.

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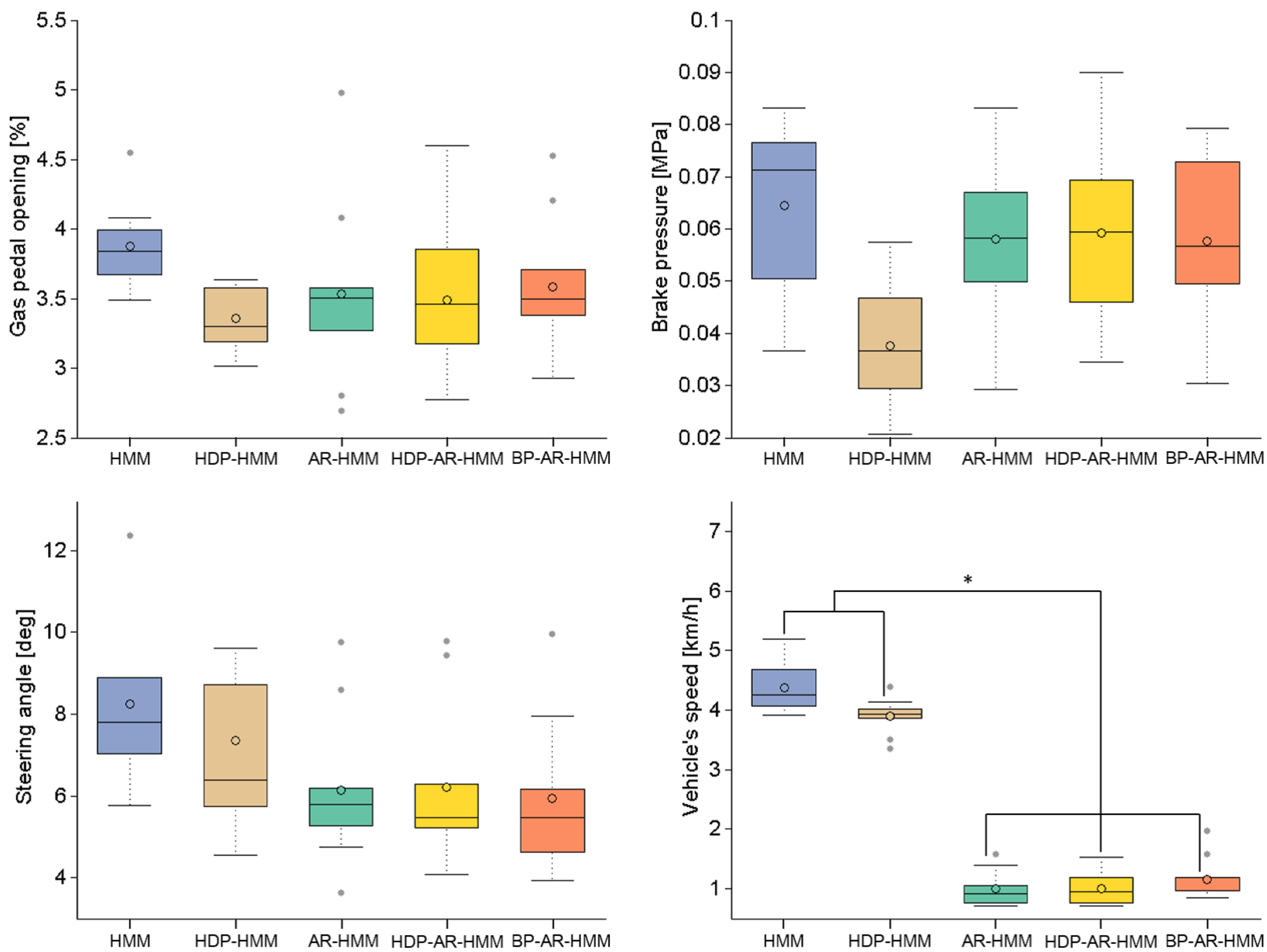

Fig. 12: MAEs of the models for the accelerator opening rate (upper right), the brake pressure (upper right), the steering angles (lower left) and the vehicle's speed (lower right). Wilcoxon rank-sum test, Bonferroni corrected, $p \leq 0.05$.

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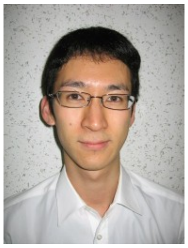

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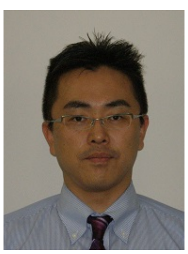

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