A comparative study of time series modeling for driving behavior towards prediction

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***Abstract*—Prediction of driving behaviors is an important problem in developing a next-generation driving support system. In order to take diverse driving situations into account, it is necessary to model multiple driving operation time series data. In this study we modeled multiple driving operation time series with four modeling methods including beta process autoregressive hidden Markov model (BP-AR-HMM), which we used in our previous study. We quantitatively compared the modeling methods with respect to prediction accuracies, and concluded that BP-AR-HMM excelled the other modeling methods in modeling multiple driving operation time series and predicting unknown driving operations. The result suggests that BP-AR-HMM estimated behaviors of a driver and transition probabilities between the behaviors more successfully than the other methods, because BP-AR-HMM can deal with commonalities and differences among multiple time series, but the others cannot. Therefore BP-AR-HMM may help us to predict driver behaviors in real environment and to develop the next-generation driving support system.**

I. Introduction

Constantly high level of traffic accident occurrence is one of the most serious social problems in Japan. Statistics of Japanese police agency shows that approximately 690,000 per year of traffic accidents still occur, although the number of accidents develops a trend to decrease [1]. Therefore it is imperative to strive to prevent accidents furthermore, by supporting drivers to operate cars carefully and in a human-friendly way. Practically, some researchers enthusiastically have developed the indices of the risk of collision and the automatic emergency brake system for automotive vehicle, to reduce traffic accidents [2], [3]. These researches mainly aim to prevent traffic accidents only immediately before the accident would occur. Recently researchers turn to think about the estimation of driving scenes and the prediction of behaviors of drivers in order to realize novel driving support systems [4]–[8], not just to prevent collisions. If we can estimate driving scenes or driver behaviors, it is possible to utilize the driving support system like the collision preventing system according to present driving scene, which is effective to prevent accidents beforehand.

When driver behaviors are modeled in order to estimate driving scenes or predict driving behaviors, hidden Markov model (HMM) [3]–[5] that treats time series data, or its extension such as autoregressive hidden Markov model (AR-HMM) [6], [7] are often used. If multiple time series data can be assumed to have the identical set of states, transition probabilities and output processes, they can be modeled jointly with HMM or AR-HMM. When a dataset does not satisfy the assumption, however, it must be modeled separately. In practice it is not easy to judge whether we can model a set of time series data jointly or not. In order to model driving behaviors under diverse driving scenes, it is necessary to utilize the novel method that can solve the problem to deal with not only common features but also different features across multiple time series data. Also HMM or AR-HMM have the difficulty in model selection. If we model time series dataset with HMM or AR-HMM we need to consider fixed number of states, which corresponds to the number of behaviors, although appropriate number of the states is unknown beforehand.

Fox et al. proposed novel efficient modeling method, beta process autoregressive hidden Markov model (BP-AR-HMM) that utilizes beta process prior and enables to model multiple time series data considering common or different features across a set of data, and to determine the number of the features automatically [9]. They identified not only the common behaviors across multiple time series, but also the specific behavior exhibited in a specific time series using multiple time series of motion capture data. In a previous study we utilized BP-AR-HMM to model multiple driving operation time series, and could predict driving operations in unknown data successfully [10].

Our purpose of this study is to compare prediction abilities of driving operations among four time series modeling methods, that is, HMM, AR-HMM, BP-AR-HMM, and hierarchical Dirichlet process autoregressive hidden Markov model (HDP-AR-HMM), which can determine the number of features automatically as well as BP-AR-HMM [11]. In this paper we applied the four methods to the driving behavior dataset to model driving behaviors, and compare the prediction abilities of BP-AR-HMM with those of HMM, AR-HMM, and HDP-AR-HMM.

II. Driving Behavior Modeling

To model whole driving operation time series dataset, we used HMM, AR-HMM, HDP-AR-HMM and BP-AR-HMM. This section in particular describes an outline of BP-AR-HMM with reference to HMM and its extension.

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A. HMM and its model extension

To model time series data, hidden Markov model (HMM) and autoregressive hidden Markov model (AR-HMM) are widely used. In HMM each time point of time series has its latent state, and the latent state generates observable variables to model time series. And each latent state is subject to the Markov process, so its transition to a succeeding state is controlled by the transition matrix that describes the probabilities of transition from a state to all probable states. In AR-HMM, which is an extension of HMM, observable variables are subject to the identical vector-autoregressive (VAR) process as long as latent states belong to the identical state. According to this property we can expect that AR-HMM will give more promising result than HMM, when we apply it to data that exhibit its dynamical behavior contiguously. If we adopt either HMM or AR-HMM, however, it is necessary to determine the number of states using the cross-validation or according to the information criterion.

Fox et al. proposed an extensional model that can determine the number of states according to training data automatically, HDP-AR-HMM [11]. Fig. 1(a) shows the graphical model of HDP-AR-HMM. The HDP-AR-HMM is a kind of methods referred to as Bayesian nonparametric approaches that are developed actively by researchers recently. The methodology of Bayesian nonparametrics is one of the method of Bayesian statistics, attempting to learn the model complexity automatically according to training data [12]. Another property of HDP-AR-HMM is that multiple time series can share the identical set of states and transition probabilities between the states, applying hierarchical Dirichlet process prior to AR-HMM. So we can identify a certain state that reveals in certain time series with one that reveals in another time series.

B. BP-AR-HMM

Fox et al. proposed BP-AR-HMM as a Bayesian nonparametric approach that can model multiple related time series data taking into account commonalities and differences among them. Each state has its dynamical behavior, and each dynamical behavior is represented by a specific VAR process. As is for HDP-AR-HMM, the number of states is determined according to the intrinsic complexity of a training dataset. Transition from a state to its succeeding state is subject to the Markov process as well as AR-HMM, but transition probabilities are determined for each time series respectively. Fig. 1(b) shows the graphical model of BP-AR-HMM.

Authors assume that there exists N time series data and they share common dynamical behaviors $\theta_1, \theta_2, \ldots$. Binary indicator variable $\mathbf{f}_i = [f_{i1}, f_{i2}, \ldots]$ represents which dynamical behaviors time series i exhibits. When time series i exhibits dynamical behavior k , it is represented as $f_{ik} = 1$, and f_{ik} can be defined by Bernoulli process and represented as:

$$f_{ik} | \omega_k \sim Bernoulli\left(\omega_k\right) \tag{1}$$

where mass ω_k is a mass of an atom in a draw B that is generated by beta process conjugate to Bernoulli process,

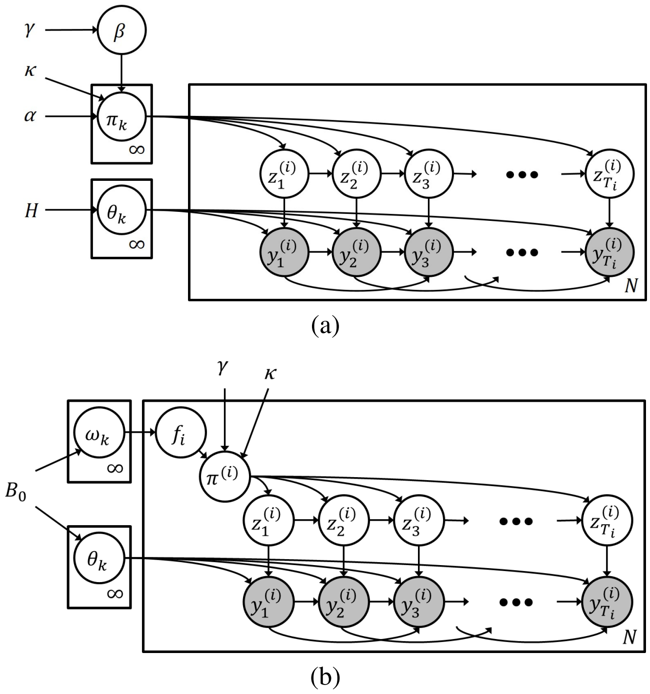

Fig. 1. Graphical model of (a) HDP-AR-HMM and (b) BP-AR-HMM.

which is represented by base measure B_0, ω_k and θ_k:

$$B | B_0 \sim BP\left(c, B_0\right) \tag{2}$$

$$B = \sum_{k=1}^{\infty} \omega_k \delta_{\theta_k} \tag{3}$$

where δ_{θ_k} represents measure concentrated at θ_k, referred to as an atom at θ_k. The total mass of a base measure B_0 is $B_0(\Theta) = \alpha$ where Θ is a probability space. In this study, a concentration parameter c of beta process is set to 1. Beta process is conjugate to Bernoulli process, and marginalizing it along B results to gain predictive distributions known as Indian buffet process (IBP) [13]. In time series i , transition from a state to its succeeding state is subject to Dirichlet distribution:

$$\pi_j^{(i)} | \mathbf{f}_i, \gamma, \kappa \sim Dir\left(\left[\gamma, \ldots \gamma, \gamma + \kappa, \gamma, \ldots\right] \otimes \mathbf{f}_i\right) \tag{4}$$

where $\otimes$ denotes the element-wise vector product, and κ is a hyperparameter that adds additional mass to self-transition probability. Let $\boldsymbol{y}_t^{(i)}$ denote observable variable of time series i at time t , and $z_t^{(i)}$ latent state. If we assume each dynamical behavior is r-order VAR process, the relation between a state and a corresponding observation can be formulated as follow:

$$z_t^{(i)} \sim \pi^{(i)}_{z_{t-1}^{(i)}} \tag{5}$$

$$\boldsymbol{y}_t^{(i)} = \sum_{m=1}^{r} \mathbf{A}_{m, z_t^{(i)}} \boldsymbol{y}_{t-m}^{(i)} + \boldsymbol{e}_t^{(i)}\left(z_t^{(i)}\right) \tag{6}$$

$$\boldsymbol{e}_t^{(i)}\left(k\right) \sim \mathcal{N}\left(\mathbf{0}, \boldsymbol{\Sigma}_k\right) \tag{7}$$

where dynamical behavior θ_k consists of $\theta_k = \{\mathbf{A}_k, \boldsymbol{\Sigma}_k\}$, and VAR coefficient matrix $\mathbf{A}_k = [\mathbf{A}_{1k}, \mathbf{A}_{2k}, ..., \mathbf{A}_{rk}]$.

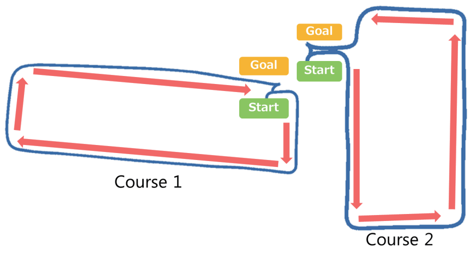

Fig. 2. Course 1 and 2. The subject was instructed to drive the car clockwise on course 1, and counterclockwise on course 2.

They applied matrix-normal inverse-Wishart distribution (MNIW) to $\{\mathbf{A}_k, \mathbf{\Sigma}_k\}$ as prior distribution. In this study, we assumed that the order of VAR process r is 1. Assigned parameters and estimation method are the same as our previous study [10]. The code of BP-AR-HMM developed by Fox is available on [14].

C. Measurement of driving behavior data

In this study, we measured data in a real road environment. A subject was a 35 year-old eyesight-corrected male who drove on a daily basis, and had neither any disease nor disability of vision nor motor. We instructed him to drive our experimental car along the two courses (Fig. 2), and to make a stop after every lap he went around the course. The total number of laps are five for each course respectively. During the experiment there are other cars than ours around and people occasionally walked across the road. We attached sensors to the experimental car, so we could measure accelerator opening rate, brake pressure and steering angle of the car. We measured these three driving operations with sampling rate 10Hz that is enough to model driving behaviors, and concatenated them into the observation column vector $\boldsymbol{y}_t^{(i)}$. We have already confirmed the correspondence between the estimated state sequences obtained from applying BP-AR-HMM to our time series data and the locations of the car on the courses, which is consistent across laps [15].

D. Evaluation methods of prediction accuracy

Finally we evaluate prediction accuracies of an unknown time series with learned models. Takano et al. evaluated the prediction accuracy of their proposed method according to the mean absolute error (MAE) [5]. We follow the evaluation of the study and evaluate the prediction accuracies of HMM, AR-HMM, HDP-AR-HMM and BP-AR-HMM. Another way to evaluate the prediction accuracies of models is to calculate the root mean squared error (RMSE), which is equivalent to biased estimation of the standard deviation of residual error. We also use RMSE to evaluate the prediction accuracies.

III. Result

We first applied BP-AR-HMM to training time series data that are consist of four laps for each course, sum up to eight time series. And we obtained four estimated state sequences and transition matrices of states for each

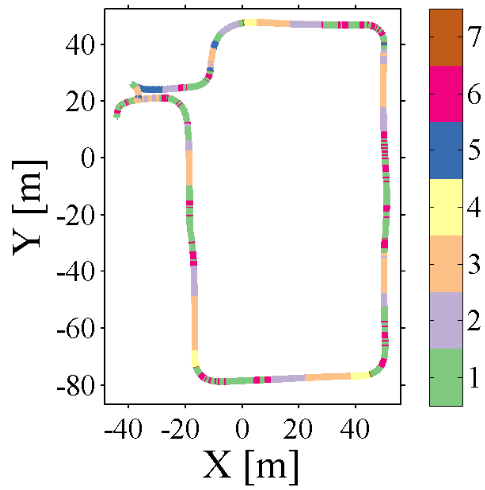

Fig. 3. Course 2 with estimated state sequence using BP-AR-HMM.

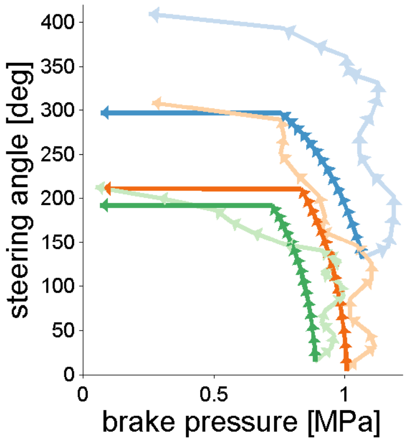

Fig. 4. Prediction of driving operations with BP-AR-HMM. *light-colored arrows*: actual observations of driving operations, *deep-colored arrows*: predicted driving operations. Orange, blue and green arrows are those on the course 2 at lower left, lower right and upper left corners of turning left, respectively.

course, as well as seven VAR process parameters $\theta_k = \{\mathbf{A}_k, \mathbf{\Sigma}_k\}\ (k = 1, 2, \ldots, 7)$. Fig. 3 shows the relationship between the state sequence during a lap of course 2. We focus our attentions on the locations just facing left-turn corners of the course 2, which reveal the reproducible representation of state sequence across laps as well as our previous study [10]. The driving state revealed state 4 (cream-color) followed by state 7 (brown) at the location just before turning left, lower left, lower right, and upper left corners of the course 2.

Next we show the result of predictions of driving operations of test data, fifth lap of course 2 (Fig. 4). Light-colored and deep-colored arrows show actual observations and predicted driving operations respectively. Each arrow represents the change of driving operations during the interval of 0.1 second. Predicted accelerator opening rates are not presented because their values keep around 0% during left-turn corners. We could predict the sudden decrease of brake pressure before turning

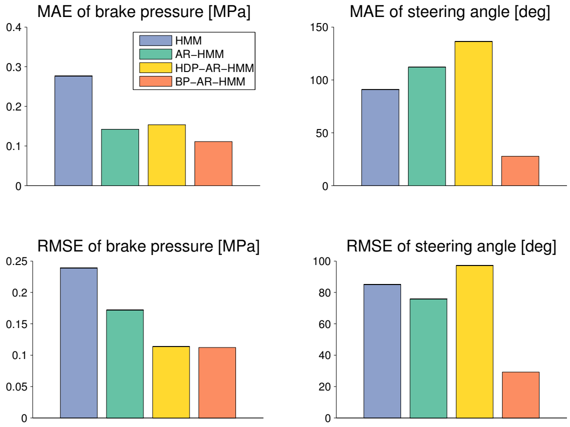

Fig. 5. Comparison of prediction accuracies among modeling methods with respect to MAE (top) and RMSE (bottom). MAE and RMSE are calculated for the brake pressure and the steering angle on left-turn corners.

left. Predicted driving operations almost trace the trends of actual observations, except the inherent fluctuation.

Fig. 5 shows the MAE and RMSE of HMM, AR-HMM, HDP-AR-HMM and BP-AR-HMM. We calculated MAE and RMSE for the brake pressure and the steering angle, because the prediction errors of the accelerator opening are pretty small comparing with probable values of actual observation. In HMM and AR-HMM, the numbers of states that perform best in terms of MAE are selected. We can see that BP-AR-HMM gave better prediction performances than the other methods with respect to both MAE and RMSE.

IV. Discussion

In the previous study, we confirmed that the driving operation sequence of unknown time series can be predicted with estimated dynamical behaviors by BP-AR-HMM [10]. In this paper, we applied four modeling methods including BP-AR-HMM to multiple time series of driving operation data in order to model driving behaviors. And we compared prediction accuracies among modeling methods in terms of MAE and RMSE, and found that BP-AR-HMM gave the best performance among them. BP-AR-HMM excelled AR-HMM and HDP-AR-HMM although each method has the vector-autoregressive property of driving operations. This may be because BP-AR-HMM can deal with commonalities and differences among multiple time series, but the others cannot. In addition, different parameter estimation schemes of these methods might affect the prediction abilities.

As we saw in Fig. 3, the same driving state patterns revealed in front of left-turn corners on course 2 across laps. Taniguchi et al. [8] encoded driving behavior time series data into the sequence of hidden state labels of sticky hierarchical process hidden Markov model (sHDP-HMM), and analyzed them based on nested Pitman-Yor language model (NPYLM). They discovered the same sequences of latent state labels in certain different positions on the experimental course. Inspecting whether some similar patterns of state transition exist in driving operation time series is our future work. Our future work also includes (i) adding multiple subjects or diverse driving situations to training data, and (ii) enlarging the size of dataset. The inspections might give us profound knowledge in developing the novel adaptive driving support system.

References

[1] Traffic Bureau of Japanese National Police Agency, "Occurences of traffic accidents in 2011," http://www.e-stat.go.jp/SG1/estat/List.do?lid=000001086731, September accessed on Sep. 16, 2012, *in Japanese*.

[2] S. Kitajima, Y. Marumo, T. Hiraoka, and M. Itoh, "Comparison of evaluation indices for estimating driver's risk perception of rear-end collision," *JARI Research Journal*, vol. 30, pp. 495–498, 2008.

[3] H. Mima, K. Ikeda, T. Shibata, N. Fukaya, K. Hitomi, and T. Bando, "Estimation of driving phase by modeling brake pressure signals," in *Proc. of International Conference on Neural Information Processing*, 2009.

[4] K. Ikeda, H. Mima, Y. Inoue, T. Shibata, N. Fukaya, K. Hitomi, and T. Bando, "An adaptive real-end collision warning system for drivers that estimates driving phase and selects training data," *ISCIE Journal 'Systems, Control and Information'*, vol. 24-8, pp. 193–199, 2011, *in Japanese*.

[5] W. Takano, A. Matsushita, K. Iwao, and Y. Nakamura, "Recognition of human driving behaviors based on stochastic symbolization of time series signal," in *Proc. of IEEE/RSJ International Conference on Intelligent Robots and Systems*. IROS, 2008, pp. 167–172.

[6] A. Utsugi, S. Kato, and M. Akamatsu, "Modeling of driving behavior based on long distant driving behavior datasbase," in *Proc. of Conference on 'Systems, and Information'*. SICE, 2005, pp. 124–127, *in Japanese*.

[7] Y. Kishimoto and K. Oguri, "A modeling method for predicting driving behavior concerning with driver's past movements," in *Proc. of IEEE International Conference on Vehicular Electronics and Safety*, 2008, pp. 132–136.

[8] T. Taniguchi, S. Nagasaka, K. Hitomi, N.P. Chandrasiri, and T. Bando, "Semiotic prediction of driving behavior using unsupervised double articulation analyzer," in *Proc. of 2012 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2012, pp. 849–854.

[9] E.B. Fox, E.B. Sudderth, M.I. Jordan, and A.S. Willsky, "Sharing features among dynamical systems with beta processes," in *Proc. of Advances in Neural Information Processing Systems*. NIPS, 2009, vol. 22, pp. 549–557.

[10] R. Hamada, T. Kubo, K. Ikeda, Z. Zhang, T. Shibata, T. Bando, and M. Egawa, "Towards prediction of driving behavior via basic pattern discovery with BP-AR-HMM," in *Proc of 2012 IEEE International Conference on Acoustics, Speech and Signal Processing*. ICASSP, 2013.

[11] E.B. Fox, E.B. Sudderth, M.I. Jordan, and A.S. Willsky, "Bayesian nonparametric methods for learning Markov switching processes," *IEEE Signal Processing Magazine*, vol. 27-6, pp. 43–54, 2010.

[12] N. Hjort, C. Holmes, P. Müller, and S. Walker, *Bayesian nonparametrics*, Cambridge University Press, 2010.

[13] T.L. Griffiths and Z. Ghahramani, "Infinite latent feature models and the Indian buffet process," in *Proc of Advances in Neural Information Processing Systems*. NIPS, 2005, vol. 18, pp. 475–482.

[14] E.B. Fox, "Homepage of Emily B. Fox," http://stat.wharton.upenn.edu/~ebfox/software.html, accessed on Aug. 30, 2012.

[15] T. Kubo, K. Ikeda, Z. Zhang, T. Shibata, T. Bando, and M. Egawa, "Estimation of Driving Situation from Multiple Time Series Data with Beta Process Autoregressive Hidden Markov Model," in *Symposium of Systems and Information*. SICE, 2012, *in Japanese*.