EUSIPCO 2013 1569744787

APPLYING BAYESIAN NONPARAMETRICS TO NON-HOMOGENEOUS DRIVING OPERATION DATA TOWARDS PREDICTION

Ryunosuke Hamada[†] *Takatomi Kubo*[†] *Kazushi Ikeda*[†] *Zujie Zhang*[†] *Tomohiro Shibata*[†]
Takashi Bando[‡] *Masumi Egawa*[‡]

[†] Nara Institute of Science and Technology, Japan [‡] DENSO CORPORATION, Japan

ABSTRACT

Prediction of driving behaviors is important problem in developing the next-generation driving support system. In order to take account of diverse driving situations, it is necessary to deal with multiple time series data considering commonalities and differences among them. In this study we utilize the beta process autoregressive hidden Markov model (BP-AR-HMM) that can model multiple time series considering common and different features among them using the beta process as a prior distribution. We apply BP-AR-HMM to actual driving operation data to estimate vector-autoregressive process parameters that represent the segmental driving behaviors, and with the estimated parameters we predict the driving behaviors of unknown test data. Prediction accuracy of test data using BP-AR-HMM is compared with that of using classical HMM. The results suggest that it is possible to identify the dynamical behaviors of driving operations using BP-AR-HMM, and with BP-AR-HMM we can predict driving behaviors better in actual environment than with HMM.

***Index Terms*—** driving behavior prediction, Bayesian nonparametric approach, beta process autoregressive hidden Markov model, beta process

1. 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]. 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 utilized. Takano et al. used HMM to model driving behaviors and concluded that their prediction method did not give enough accurate prediction of subject's driving operation for automated driving systems [5]. Other researchers used AR-HMM whose output vector under a state is subject to its own vector-autoregressive (VAR) process [6, 7]. Although it is possible to model time series dataset that could be assumed to have the same set of states, transition probabilities and output processes jointly with HMM or AR-HMM, a dataset that does not satisfy the assumption 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 [9]. In previous study, we used BP-AR-HMM to model multiple driving operation time series, and confirmed that we could predict unknown driving operations with BP-AR-HMM [10].

Our purposes of this study is to compare prediction accuracies of driving operations with HMM and BP-AR-HMM. In this paper we applied both HMM and BP-AR-HMM to the driving behavior dataset to model driving behaviors, and predicted unknown driving operation sequences with behaviors estimated by HMM and BP-AR-HMM. We then compare the prediction ability of BP-AR-HMM with that of HMM, and discuss differences between modeling of driving behaviors with HMM and BP-AR-HMM.

2. DRIVING BEHAVIOR MODELING

To model whole driving operation time series dataset, we utilized BP-AR-HMM that is an extension of HMM and AR-HMM. This section describes an outline of BP-AR-HMM with reference to HMM and its extension.

2.1. HMM and its model extension

To model time series data, hidden Markov model (HMM) and autoregressive hidden Markov model (AR-HMM) are widely utilized. 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, sticky hierarchical Dirichlet process hidden Markov model (sHDP-HMM) [11]. The sHDP-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]. Taniguchi et al. utilized sHDP-HMM to model driving behaviors, and succeeded to segment driving time series [8]. In contrast, we used BP-AR-HMM that is an extension of AR-HMM as a Bayesian nonparametric approach. BP-AR-HMM can take into account either common or different features across multiple time series data, modeling them jointly with the prior probability distributions generated by beta process [9].

2.2. 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 sHDP-HMM, it allows the number of states to be countably infinite in theory, and the number 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 shows the graphical model of BP-AR-HMM.

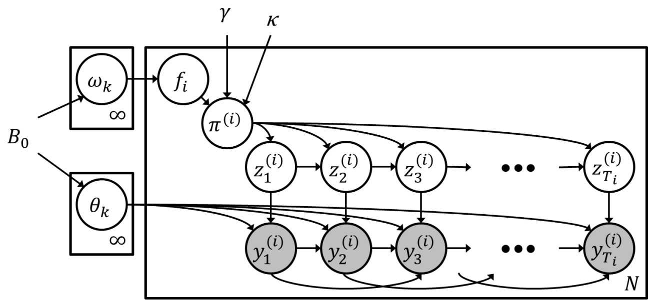

Fig. 1. Graphical model of BP-AR-HMM.

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:

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

where mass ω_k is a mass of an atom in a draw B that is generated by beta process conjugate to Bernoulli process, which is represented by base measure B_0, ω_k and θ_k:

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

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

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:

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

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:

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

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

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

where dynamical behavior θ_k consists of $\theta_k = \{\mathbf{A}_k, \boldsymbol{\Sigma}_k\}$, and VAR coefficient matrix $\mathbf{A}_k = [\mathbf{A}_{1k}, \mathbf{A}_{2k}, ..., \mathbf{A}_{rk}]$. They applied matrix-normal inverse-Wishart distribution (MNIW) to $\{\mathbf{A}_k, \boldsymbol{\Sigma}_k\}$ as prior distribution. The MNIW is consists of a matrix-normal distribution $\mathcal{MN}(\mathbf{A}_k; \mathbf{M}, \boldsymbol{\Sigma}_k, \mathbf{K})$ given $\boldsymbol{\Sigma}_k$, and inverse-Wishart distribution $\mathcal{IW}(\mathbf{S}_0, n_0)$, where $\mathbf{M}, \boldsymbol{\Sigma}_k, \mathbf{K}^{-1}$ denote mean matrix, covariance matrices for column and row of $\mathbf{A}_k$, and $n_0, \mathbf{S}_0$ denote degree of freedom and scale matrix in inverse-Wishart distribution.

In this study we assumed that the order of VAR process r is 1, and the other parameters are same as our previous study, as well as method of parameter estimation [10]. The code of BP-AR-HMM developed by Fox is available on [14].

2.3. 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 gas pedal opening rate, brake pressure and steering angle of the car. We measured these three driving operations with sampling rate 10Hz, 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]. Fig. 3 shows the state sequences drawn on the course 2.

2.4. 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 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.

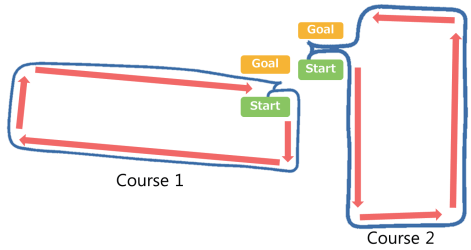

Fig. 2. Course 1 and 2. The subject was instructed to drive the car clockwise on course 1, and counterclockwise on course 2.

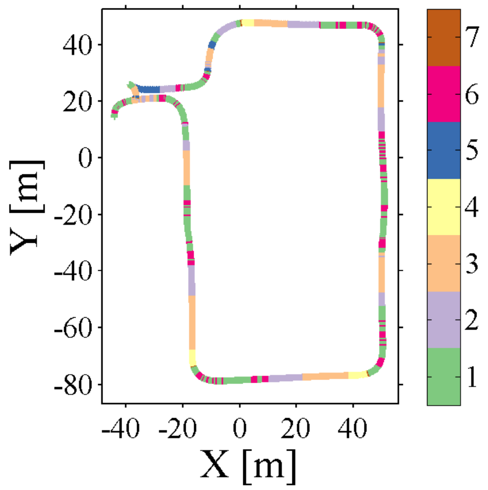

Fig. 3. Course 2 with estimated state sequences using BP-AR-HMM.

3. 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 course, as well as seven VAR process parameters $\theta_k = \{\mathbf{A}_k, \boldsymbol{\Sigma}_k\}\,(k = 1, 2, \ldots, 7)$. Fig. 3 shows the relationship between the state sequence during a lap of course 2 (Fig. 3). We focus our attentions on the locations just facing left corners of the course 2, which reveal the reproducible representation of state sequence across laps. 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 corner of the course 2. The reason why upper right corner did not reveal such state sequence pattern, which is probably because the subject stopped the car in front of the upper right corner and did not stop in front of the other corners, so it is probable that driving operations of the former and the latter might differ from each other. BP-AR-HMM succeeded to capture such difference of driving operations.

The VAR process coefficient matrices of state 4 and 7, $\mathbf{A}_4$

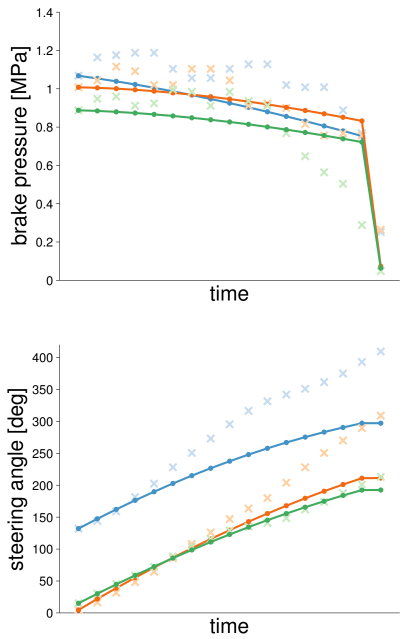

Fig. 4. Prediction of driving operations. *cross*: actual observations of driving operations, *solid line*: predicted driving operations. Orange, blue and green represent those on the course 2 at lower left, lower right and upper left corners of turning left, respectively.

and $\mathbf{A}_7$, are:

$$\mathbf{A}_4 = \begin{bmatrix} 0.1545 & -0.0082 & 0.0001 \\ 0.0061 & 0.9975 & -0.0001 \\ -0.6746 & 17.2974 & 0.9764 \end{bmatrix} \tag{8}$$

$$\mathbf{A}_7 = \begin{bmatrix} 1.0031 & 0.0272 & 0.0004 \\ -0.0694 & 0.5159 & -0.0001 \\ 12.5130 & 0.7974 & 1.0626 \end{bmatrix}. \tag{9}$$

Each element of the column vector $\boldsymbol{y}_t^{(i)}$ represents gas pedal opening, brake pressure and steering angle in order. When the car was in front and beyond the left-turn corner except upper right corner, gas pedal opening always kept 0%.And just when the state got to be fourth state, brake pressure and steering angle took positive values. As a result of these facts, when $\boldsymbol{y}_t^{(i)}$ was subject to VAR process of state 4 brake pressure attenuated gradually and steering angle increased progressively.

Next we show the result of predictions of driving operations of test data, fifth lap of course 2 (Fig. 4). Crosses and solid lines show actual observations and predicted driving operations respectively. The sampling rate is 0.1 second. We could predict the sudden decrease of brake pressure before turning left. Predicted driving operations almost trace the trends of actual observations, except the inherent fluctuation.

Fig. 5 shows the MAE and RMSE of HMM and BP-AR-HMM. We calculated MAE and RMSE for the brake pressure

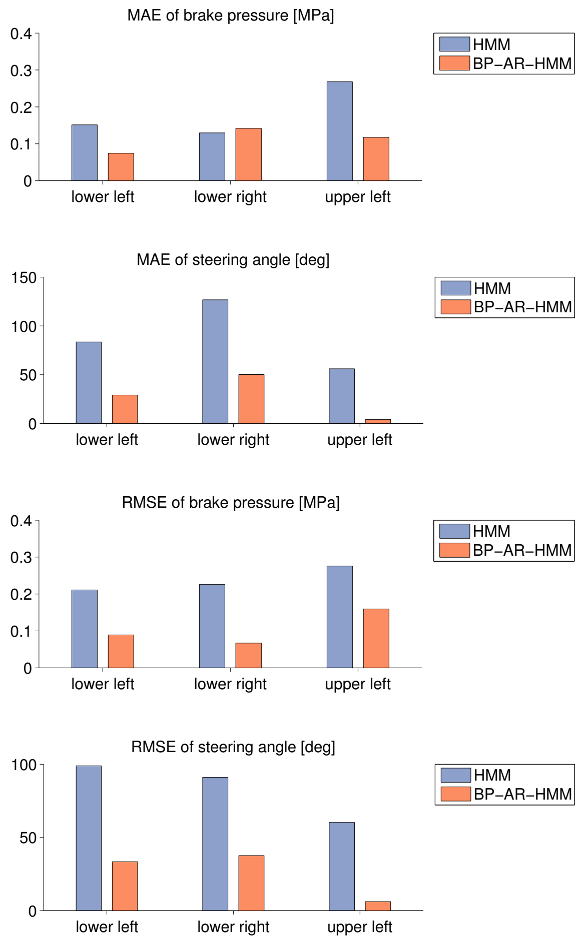

Fig. 5. Comparison of HMM and BP-AR-HMM with respect to MAE and RMSE. MAE and RMSE are calculated for the brake pressure and the steering angle on three intervals of prediction.

and the steering angle, because the prediction errors of the gas pedal opening are pretty small comparing with probable values of actual observation. We can see that BP-AR-HMM gave better prediction performances than HMM with respect to both MAE and RMSE.

4. DISCUSSION

In this paper, we modeled multiple time series of driving operation data with HMM and BP-AR-HMM, and compared prediction accuracies of unknown driving operations using estimated driving behaviors. As a result, HMM gave poor performance for predicting the dynamics of driving operations in the time interval of a certain length. This is because BP-AR-HMM has dynamical structure of observation vectors, which is represented by vector-autoregressive process with dynamical behavior, but HMM does not. In addition, it may affect the result that BP-AR-HMM can consider the difference of transition probabilities between driving behaviors in a non-homogeneous dataset that consist of multiple driving behavior data in different driving conditions, but HMM cannot.

As we saw in Fig. 3, 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 HDP-HMM, and analyzed them based on nested Pitman-Yor language model (NPYLM). They discovered same sequences of latent state labels in certain different positions on the experimental course. Inspecting whether some similar driving state patterns 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 a novel adaptive driving support system.

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