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GENERATION OF PEDAL OPERATION PATTERNS OF INDIVIDUAL DRIVERS IN CAR-FOLLOWING FOR PERSONALIZED CRUISE CONTROL

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Abstract— **This paper presents a method to generate car-following patterns for individual drivers. We assume that driving is a recursive process. A driver recognizes a road environment such as velocity and following distance and adjusts gas and brake pedal positions. A vehicle status changes according to the driver's operation and the road environment changes according to the vehicle status. Driving patterns of each driver are modeled with a Gaussian mixture model (GMM), which is trained as a joint probability distribution of following distance, velocity, pedal position signals and their dynamics. Gas and brake pedal operation patterns are generated from the GMMs in a maximum likelihood criterion so that the conditional probability is maximized for a given environment i.e., following distance and velocity. Experimental results for a driving simulator show that car-following patterns generated from GMMs for three different drivers maintain their individual driving characteristics.**

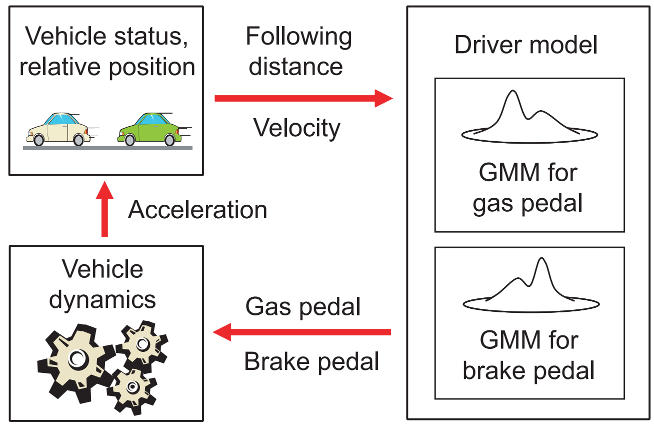

Fig. 1. Cyclic process of driving signal generator.

I. INTRODUCTION

The number of driver's license holders and car owners is increasing each year, and the car has obviously become indispensable for our daily life. To improve safety and road traffic efficiency, intelligent transportation system (ITS) technologies, including adaptive cruise control (ACC), lane-keeping assist systems (LKAS) and driver warning system have been developed over the last several years [1]–[5]. Many of these conventional methods directly estimated the acceleration or throttle angle and resulted in successful estimation accuracy. However, these conventional driver assist systems do not always suit all drivers. To improve driving comfort, they need to be intelligently personalized based on individual driving styles.

In this paper, we propose a method to generate car-following patterns for individual drivers to personalize headway control. Gas and brake pedal operation patterns of the target driver are modeled using Gaussian mixture models (GMMs) [6], and car-following patterns are generated from the statistical driver model of the target driver. Given velocity and following distance, pedal operation patterns are estimated in a maximum likelihood criterion from the GMMs. Contrary to the conventional methods which directly estimate the acceleration or throttle angle, our method estimates the pedal operation signals from the driver models iteratively given only initial conditions of velocity and the patterns of lead vehicle. The driving pattern generation method is evaluated using driving signals collected in a simulator for three different drivers.

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II. DRIVING SIGNALS

Observable driving signals can be categorized into three groups:

i) Driving behavior signals
(e.g., gas pedal operation, brake pedal operation, and steering angle)
ii) Vehicle status signals
(e.g., velocity, acceleration, and engine speed)
iii) Vehicle position signals
(e.g., following distance, relative lane position, and yaw angle).

Among these signals, we focused on the driving behavior signals, especially drivers' characteristics with respect to gas and brake pedal operation.

III. GENERATION OF DRIVING BEHAVIOR SIGNALS

A cyclic process of the driving signal generator is shown in Fig. 1. The generator is composed of the following three parts.

- Driver model based on GMM
- Vehicle dynamics
- Vehicle status and relative position

First, gas and brake pedal operation signals are generated from a driver model on the basis of vehicle status and positions. The acceleration degree of the vehicle is calculated

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based on the velocity dynamics using the generated pedal patterns. Vehicle status and the relative positions change on the basis of vehicle behavior. Gas and brake pedal patterns are regenerated from the driver model.

A. Driver Model

The driver model consists of two GMMs trained using gas and brake pedal operation signals for the target driver. Gas and brake pedal patterns are generated from the driver model on the basis of vehicle status and relative position to other vehicles.

1) Features Modeled by GMMs: GMMs model feature $\boldsymbol{x}$ consisting of velocity V_t, following distance F_t with their first and second-order dynamics ΔV_t, ΔF_t, $\Delta^2 V_t$Cand $\Delta^2 F_t$ and gas or brake pedal pattern G_t or B_t with their first-order dynamics ΔG_t or ΔB_t:

$$\boldsymbol{x} = (V_t, F_t, \Delta V_t, \Delta F_t, \Delta^2 V_t, \Delta^2 F_t, \Delta G_t, G_t)^T. \quad (1)$$

The dynamic features are calculated differently for velocity/following distance and pedal patterns because pedal patterns are the features we estimate. Hence, the dynamic features of the pedal operation patterns include the signal at time $t+1$. We calculate the first-order dynamic features of velocity and following distance as follows:

$$\Delta x(t) = x(t) - \frac{\sum_{k=1}^{T-2} kx(t-k-1)}{\sum_{k=1}^{T-2} k}, \quad (2)$$

where $x(t)$ is the velocity or following distance at time t. The second-order dynamic feature is calculated from the first-order dynamic feature based on the same equation. The first-order dynamic features of pedal patterns are calculated using signals at time $t+1$:

$$\begin{aligned} \Delta x(t) &= x(t+1) - \frac{\sum_{k=1}^{T-2} kx(t-k)}{\sum_{k=1}^{T-2} k} \\ &= x(t+1) + C(t). \end{aligned} \quad (3)$$

The calculation of Eqs.(2) and (3) are shown in Figs. 2 and 3, respectively. Dynamic features are calculated as the weighted difference between the current or future signal and the past signals. The weights for $x(t)$ or $x(t+1)$ and the past $T-2$ signals are equal. In the generation of driving behavior signals, driving signals up to time t are known. We define $C(t)$ using the known signals as follows.

$$C(t) = \frac{-\sum_{k=1}^{T-2} kx(t-k)}{\sum_{k=1}^{T-2} k}. \quad (4)$$

2) Estimation of Gas and Brake Pedal Patterns: We estimate the pedal patterns using GMMs based on the assumption that a driver determines the gas and brake pedal patterns from the velocity and following distance. We estimate the gas and brake pedal patterns from the joint probability distribution of the features so that the conditional probability is maximized. This is a problem of maximization of the conditional probability. The generator finds the suboptimal maximum point of the GMM by a hill-climbing search starting from the chosen point and generates next driving

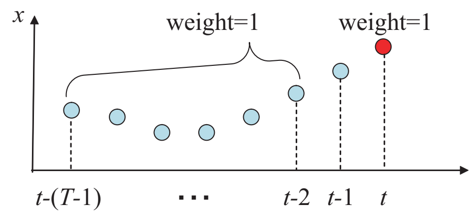

Fig. 2. Calculation of dynamic features for velocity and following distance using Eq.(2).

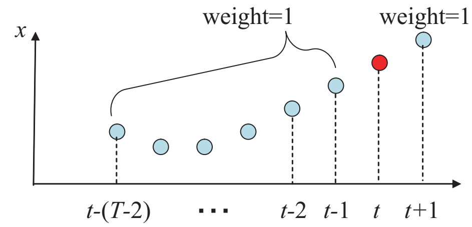

Fig. 3. Calculation of dynamic features for pedal operation signals using Eq.(3).

signals. As an example, consider the generation of gas pedal pattern. The value of gas pedal pattern $\hat{G}_{t+1}$ is estimated based on the following equation.

$$\hat{G}_{t+1} = \arg\max_{G_{t+1}} p(\boldsymbol{x}' \mid \boldsymbol{\theta}_m), \quad (5)$$

where $\boldsymbol{x}' = (V_t, F_t, \Delta V_t, \Delta F_t, \Delta^2 V_t, \Delta^2 F_t, \Delta G_t, G_{t+1})^T$ is the feature set used in estimation. Note that $\boldsymbol{x}'$ includes the cumulative estimation error. $\boldsymbol{\theta}_m = \{w_m, \boldsymbol{\mu}_m, \boldsymbol{\Sigma}_m\}$ is the mixture weight, mean vector, and covariance matrix of the chosen m-th mixture component. $p(\boldsymbol{x}' \mid \boldsymbol{\theta})$ is a weighted Gaussian given as follows.

$$p(\boldsymbol{x}' \mid \boldsymbol{\theta}_m) = \frac{w_m}{\sqrt{(2\pi)^D |\boldsymbol{\Sigma}_m|}} \cdot \exp\left\{-\frac{1}{2}(\boldsymbol{x}' - \boldsymbol{\mu}_m)^T \boldsymbol{\Sigma}_m^{-1} (\boldsymbol{x}' - \boldsymbol{\mu}_m)\right\} \quad (6)$$

We focus on the exponent and rewrite $\boldsymbol{x}' - \boldsymbol{\mu}_m$ as follows.

$$\boldsymbol{x}' - \boldsymbol{\mu}_m = \begin{pmatrix} V_t - \mu_{m,1} \\ F_t - \mu_{m,2} \\ \Delta V_t - \mu_{m,3} \\ \Delta F_t - \mu_{m,4} \\ \Delta^2 V_t - \mu_{m,5} \\ \Delta^2 F_t - \mu_{m,6} \\ \Delta G_t - \mu_{m,7} \\ G_{t+1} - \mu_{m,8} \end{pmatrix} = \begin{pmatrix} V_t - \mu_{m,1} \\ F_t - \mu_{m,2} \\ \Delta V_t - \mu_{m,3} \\ \Delta F_t - \mu_{m,4} \\ \Delta^2 V_t - \mu_{m,5} \\ \Delta^2 F_t - \mu_{m,6} \\ G_{t+1} + C_t - \mu_{m,7} \\ G_{t+1} - \mu_{m,8} \end{pmatrix} \quad (7)$$

Then, we separate it into constant and variable terms as follows.

$$\boldsymbol{x}' - \boldsymbol{\mu}_m = \begin{pmatrix} V_t - \mu_{m,1} \\ F_t - \mu_{m,2} \\ \Delta V_t - \mu_{m,3} \\ \Delta F_t - \mu_{m,4} \\ \Delta^2 V_t - \mu_{m,5} \\ \Delta^2 F_t - \mu_{m,6} \\ C_t - \mu_{m,7} \\ -\mu_{m,8} \end{pmatrix} + G_{t+1} \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 1 \end{pmatrix}$$

$$= \quad \boldsymbol{a} + G_{t+1}\boldsymbol{g} \tag{8}$$

The exponential part of Eq.(6) becomes

$$\begin{aligned} & -\frac{1}{2}(\boldsymbol{x}^{'} - \boldsymbol{\mu}_m)^T \boldsymbol{\Sigma}_m^{-1} (\boldsymbol{x}^{'} - \boldsymbol{\mu}_m) \\ &= \quad -\frac{1}{2}(\boldsymbol{a} + G_{t+1}\boldsymbol{g})^T \boldsymbol{\Sigma}_m^{-1} (\boldsymbol{a} + G_{t+1}\boldsymbol{g}) \\ &= \quad -\frac{1}{2}(\boldsymbol{g}^T \boldsymbol{\Sigma}_m^{-1} \boldsymbol{g} G_{t+1}^2 + 2\boldsymbol{a}^T \boldsymbol{\Sigma}_m^{-1} \boldsymbol{g} G_{t+1} + \boldsymbol{a}^T \boldsymbol{\Sigma}_m^{-1} \boldsymbol{a}) \\ &= \quad p_m G_{t+1}^2 + q_m G_{t+1} + r_m, \end{aligned} \tag{9}$$

where p_m, q_m, and r_m are defined as follows.

$$p_m \quad = \quad -\frac{1}{2}\boldsymbol{g}^T \boldsymbol{\Sigma}_m^{-1} \boldsymbol{g} \tag{10}$$

$$q_m \quad = \quad -\boldsymbol{a}^T \boldsymbol{\Sigma}_m^{-1} \boldsymbol{g} \tag{11}$$

$$r_m \quad = \quad -\frac{1}{2}\boldsymbol{a}^T \boldsymbol{\Sigma}_m^{-1} \boldsymbol{a}. \tag{12}$$

The estimate of gas pedal pattern $\hat{G}_{t+1}$ that maximizes Eq.(6) is given as follows.

$$\hat{G}_{t+1} = -\frac{q_m}{2p_m} \tag{13}$$

Then, the suboptimal maximum value is found by a hill-climbing search starting from the maximum point among the estimates calculated by the above equations or intersection points of mixture components. The intersection points are obtained by solving the following equation with respect to G_{t+1}:

$$\begin{aligned} & \frac{w_i}{\sqrt{(2\pi)^D |\Sigma_i|}} \exp(p_i G_{t+1}^2 + q_i G_{t+1} + r_i) \\ & \qquad = \frac{w_j}{\sqrt{(2\pi)^D |\Sigma_j|}} \exp(p_j G_{t+1}^2 + q_j G_{t+1} + r_j), \end{aligned} \tag{14}$$

where i and j represent the i-th and j-th mixture components, respectively. Then, the logarithm of Eq.(14) becomes

$$\begin{aligned} & (p_i - p_j)G_{t+1}^2 + (q_i - q_j)G_{t+1} + \\ & \qquad r_i - r_j + \log\left(\frac{w_i |\Sigma_j|^{\frac{1}{2}}}{w_j |\Sigma_i|^{\frac{1}{2}}}\right) = 0. \end{aligned} \tag{15}$$

This is a quadratic function. So we can easily calculate the intersection points.

Brake pedal pattern can be estimated in the same way as gas pedal pattern. Although pedal pattern signals can be estimated without dynamic features, we use dynamic features to retain continuity in generated signals.

The driving signal generator has two driver models for gas and brake pedal patterns. Generated pedal signals can have both positive values because they generate gas and brake pedal signals independently. However, it is very rare that a driver hits gas and brake pedals simultaneously. To avoid such situations, we use the gas pedal signal preferentially and set the brake pedal signal to zero.

The driver model is trained for representing the relationship of velocity, following distance, and pedal patterns of the training data. However, the training data does not involve following distance data of more than 100 m or less than 1 m. Therefore, when the model encounters situations that are not included in the training data, it cannot adequately estimate pedal patterns. As a result, the vehicle can be too far away from the lead vehicle or bump into the rear of the lead vehicle. To avoid this situation, we used forced control of gas and brake pedals. If $B_{t+1} < B_{\text{force}}$ and $F_t < F_{\text{close}}$ we set $\hat{B}_{t+1}$ to B_{force}. If $\hat{G}_{t+1} < G_{\text{force}}$ and $F_t > F_{\text{far}}$ we set $\hat{G}_{t+1}$ to G_{force}. Otherwise, we used the estimated values from the driver models.

B. Vehicle Dynamics

The vehicle dynamics calculation part estimates the acceleration degree, $a(t)$, using gas pedal pattern $G(t+1)$, brake pedal pattern $B(t+1)$, and velocity $V(t)$ at time t. The vehicle dynamics calculation module was implemented based on the internal model of the driving simulator.

C. Vehicle Environment

The vehicle status and relative position, including velocity and following distance, change on the basis of vehicle acceleration. The velocity and the following distance at time $t+1$ are calculated as follows.

$$V(t+1) \quad = \quad V(t) + a(t) \cdot T \tag{16}$$

$$\begin{aligned} F(t+1) \quad &= \quad d_{\text{front}}(t+1) \\ &- \quad (d_{\text{mycar}}(t) + V(t+1) \cdot T), \end{aligned} \tag{17}$$

where $a(t)$ is the acceleration degree obtained from the vehicle dynamics module, and $d_{\text{front}}(t)$ and $d_{\text{mycar}}(t)$ are the total travel distances from the start point of the lead vehicle and ego-vehicle, respectively. The system estimates the signals every $T = 0.1$ second.

IV. Experiment

We evaluated the individual characteristics of the generated car-following patterns from the driver models trained for three different drivers (drier A, B, and C). Driver A was a tailgater who followed very close to the lead vehicle, and the other two drivers were conservative drivers who tended to keep a safe distance from the lead vehicle.

A. Data Collection

We recorded observable driving signals using a driving simulator for the training of GMMs. The course was straight. We used two velocity patterns of the lead vehicle, as shown in Fig. 4. The upper velocity pattern was recorded on an express way in the same simulator, and the lower pattern is an artificial velocity pattern aimed at obtaining all velocity ranges. We recorded the observable driving signals for two different velocity patterns of the lead vehicle four times, i.e., eight times in total. The gas pedal pattern was digitized linearly from 0 to 10000, and brake pedal pattern from 0 to 5000.

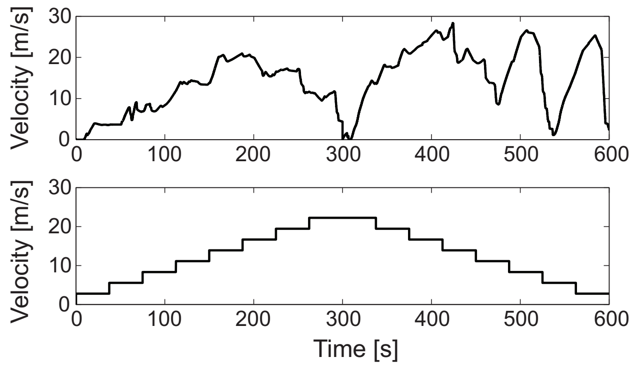

Fig. 4. Velocity patterns of lead vehicle.

B. Training of GMM

We trained GMMs using the expectation maximization (EM) algorithm [6] for each driver to fit the drivers' individual characteristics. The feature vector $\boldsymbol{x}$ modeled by GMMs includes velocity V, following distance F, their first and second dynamic features ΔV, ΔF, $\Delta^2 V$, $\Delta^2 F$, gas pedal pattern G, and its first dynamic feature ΔG as shown in Eq.(1). Driver models for the brake pedal patterns were trained in the same way. We used full covariance matrices for the GMMs to represent correlations among the features. Experimental conditions are summarized in Table I.

TABLE I

EXPERIMENTAL CONDITIONS.

# of drivers	3
Sampling frequency	10 Hz
Training data length	30 min. (Pattern 1)
	40 min. (Pattern 2)
Test data length	10 min. (Pattern 1)
Features	$V\ \Delta V\ \Delta^2 V\ F\ \Delta F\ \Delta^2 F\ G\ \Delta G$
	$V\ \Delta V\ \Delta^2 V\ F\ \Delta F\ \Delta^2 F\ B\ \Delta B$
Δwindow length	0.8 sec
# of GMM mixture components	1, 2, 4, 8
GMM covariance matrix	Full covariance matrix
$(G_{\text{force}}, B_{\text{force}}, F_{\text{close}}, F_{\text{far}})$	(5000, 500, 5m, 80m)

C. Experimental Results

We compared the generated data with the real data of the target driver. To objectively evaluate how well the driver models could represent driver characteristics in car-following, signal to deviation ratios (SDRs) to driving signals are calculated. The SDR is defined as follows:

$$\text{SDR} = 10 \log_{10} \frac{\sum_{n=1}^{N} x^2(n)}{\sum_{n=1}^{N} (x(n) - \hat{x}(n))^2} \quad [\text{dB}] \qquad (18)$$

where N is the length of signals, $x(n)$ is the real signal, and $\hat{x}(n)$ is the generated signal.

The SDRs of the gas pedal pattern for three drivers are shown in Fig. 5 and those of the brake pedal pattern and the following distance are shown in Figs. 6 and 7, respectively. Higher SDRs were obtained for all drivers when modeling with one or two mixture component GMMs. Drivers' characteristics could be represented with only one or two mixture components. The experimental result for the tailgater (Driver A) is shown in Fig. 8 and for conservative drivers (Drivers B and C) who tended to be far from the lead vehicle is in Figs. 9 and 10. The resulting following distance sometimes becomes too small or 0 m. This is attributed to the fact that the training data for GMMs did not include the data for such uncommon situations as too small following distance, and estimation errors were accumulated by the ad-hoc forced control applied to brake pedal signals under the situations beyond the system control. It is also because the proposed driver model did not include the internal vehicle state, e.g., gear position, and engine speed. However, we can see that the generated gas pedal patterns follow the outlines of their original pedal patterns. The resulting following distances also maintained their characteristics in the driving behavior in car following in the face of the cumulative estimation error.

V. CONCLUSION

We generated pedal operation patterns in car following for each driver. We confirmed that GMM driver models could generate driving signals that maintained the driver individualities in car-following patterns. We plan to use longer-term dynamics of driving signals and hidden Markov models for modeling the signals. We also plan to evaluate the generated signals both subjectively and objectively.

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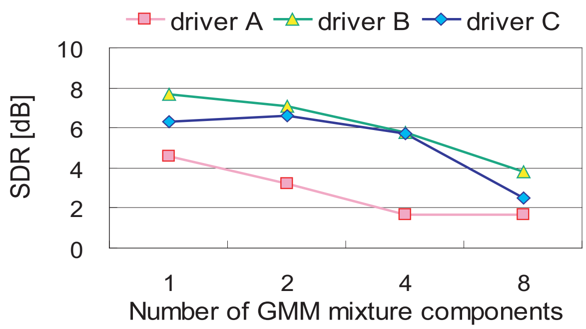

Fig. 5. SDR for gas pedal pattern.

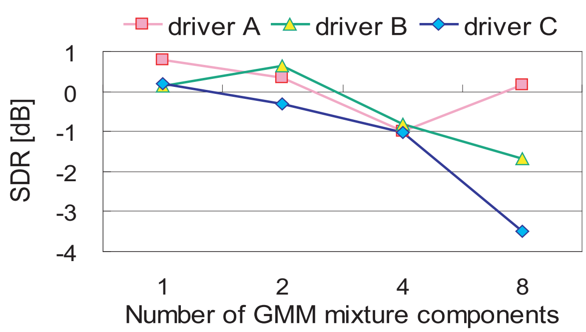

Fig. 6. SDR for brake pedal pattern.

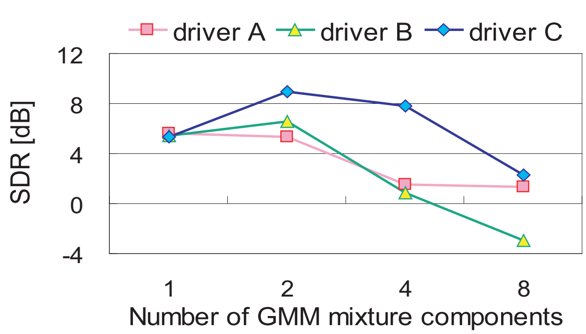

Fig. 7. SDR for following distance.

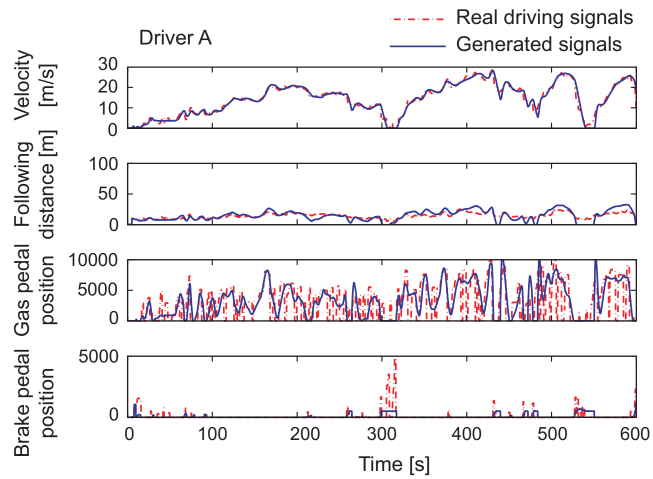

Fig. 8. Generated driving signals (Driver A).

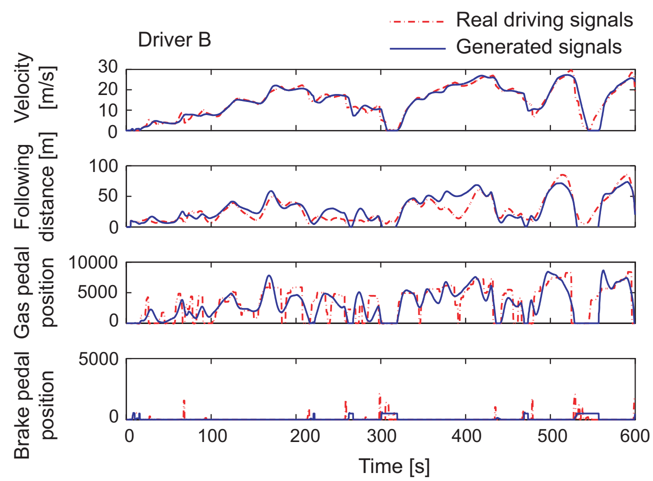

Fig. 9. Generated driving signals (Driver B).

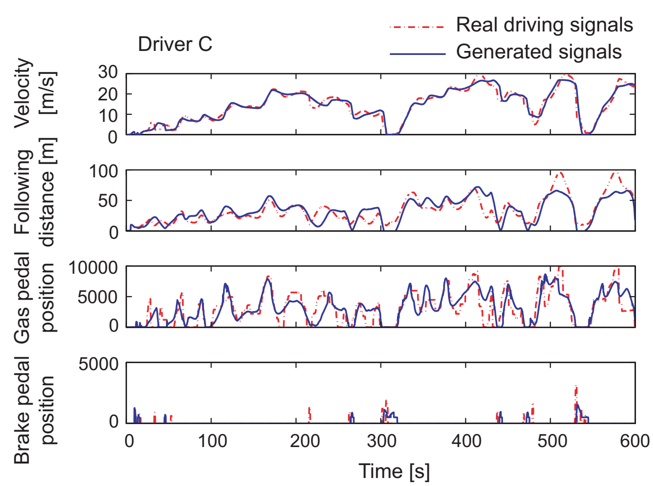

Fig. 10. Generated driving signals (Driver C).