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Forward Collision Avoidance Systems Considering Driver's Driving Behavior Recognized by Gaussian Mixture Model

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Abstract—**Although it is well known that driver's intention and driving behavior have great influence on the performance of the advanced driver assistance systems (ADAS), little consideration has been taken in the design of the existing systems. To improve the system performance, in particular, the acceptance and adaption of ADAS to human drivers, it is important to understand human drivers' intention and driving behavior that makes the systems more human-like or personalized for forward collision avoidance (FCA) and autonomous emergency braking (AEB). The research presented in this paper proposed a method to recognize driver's intention and driving behavior based on Gaussian Mixture Model (GMM). A typical testing scenarios of longitudinal braking case was created under a real-time driving simulator with both PanoSim-RT® and dSPACE®. The samples with 36 drivers were used for the testing, and the driving data were collected, analyzed and further employed in driving behavior recognition via a Gaussian mixture model. An optimization method was taken in model parameter identification. The parameters were used in the control design of FCA systems. Compared with existing FCA systems, the proposed personalized systems have demonstrated advantages in both performance and human acceptance.**

I. Introduction

A Forward Collision Avoidance (FCA) system is a system aimed to mitigate or avoid potential front collision proactively by detecting safety hazard ahead via sensor fusion of multiple sensing devices and by performing appropriate actions accordingly if imminent danger is determined, such as giving warnings to the drivers or braking autonomously [1].

Forward Collision Avoidance or similar systems were developed since 1990s and have gained great popularity in recent years as driving safety has become increasingly concerns and issues worldwide. Although many factors have been taken into consideration in algorithm design aimed to optimize the system performance to avoid potential collisions, such as coefficient of tire-road adhesion, sensing accuracy and reliability, drivers' adaptation and acceptance, however, have been little studied and improved. Cautious drivers are more inclined to early but gentle braking for longer braking distance with larger TTC and smaller but smooth deceleration when safety threat is detected ahead. Reckless drivers, on the other hand, are apt to late but sharp braking which often leads to shorter braking distance with smaller TTC and large but abrupt deceleration. Many other drivers, however, may behave more or less in between. Therefore, it is necessary to understand the differences and variations among drivers in terms of their driving intention and behavior in developing human-like or personalized forward collision avoidance systems.

Some studies on drivers' driving behavior were found from literature in the design of adaptive cruise control (ACC) systems. Zhao et al from Chinese Academy of Science [2] proposed a supervised adaptive dynamic programming (SADP) algorithm for a full-range ACC system via online learning drivers' behavior on vehicle follow up before the system starts. Fancher et al from University of Michigan proposed an ACC system by comparing it with human driving in order to learn and determine the follow-up parameters, such as TG and TTC to ensure queue stability of the ACC systems [3]. Moon et al from Seoul National University [4] proposed an algorithm for pitch control when braking aimed to provide natural follow-up performance similar to real drivers by analyzing real human driving data and extracting human driving characteristic parameters.

Despite progresses being made in achieving human-like vehicle controls for active safety by taking into consideration of human drivers' driving behavior, many algorithms are either too complicated for real-time implementation, or lack of accuracy in reflecting drivers' true characteristics. Neural network algorithm is an example that was widely adopted in the prior research. Since it identifies different types of driving behavior from a large number of data, the quality of the characteristic parameters greatly influences the accuracy of the neural network model. However, the characteristic parameters can only be adjusted subjectively based on the simulation results.

The contribution of this paper was in proposing a Gaussian mixture model (GMM) based method [5] to identify drivers' driving behavior in the algorithm design of forward collision avoidance systems with the advantages of model adaptation and capability in generating probability densities of arbitrary shapes. Besides, Gaussian mixture model has the advantages of both real-time implementation and high accuracy. First an accurate recognition model of driver's driving behavior was established and verified under a real-time driving simulator with 36 drivers as samples. A forward collision avoidance algorithm was then designed with classified alarm and braking execution strategy based on the recognition results on driver's driving behavior. Finally simulation and experiment were conducted which demonstrated the proposed GMM-based method to be more accurate and more efficient compared with other algorithms in the prior art.

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The paper is organized as following: in Section II, the data acquisition system with a real-time driving simulator was designed and established to collect drivers' driving data. The GMM-based recognition method for drivers' driving behavior was created and discussed in Section III. The control strategy of FCA system was proposed in Section IV, followed by simulation and experimental verification in Section V. Finally some conclusive remarks were given in Section VI.

II. DESIGN OF DRIVING DATA ACQUISITION SYSTEM

In order to collect various drivers' driving data and analyze their driving behavior, a real-time driving simulator was employed.

A. Data Acquisition System

It is apparently unrealistic to collect all driving data with samples of 36 drivers purely based on road driving due to its high cost, long duration and often safety concerns in the cases of collision avoidance, in addition to other issues, such as variations of driving scenarios and environment, vehicle availability, etc. Driving simulator, on the other hand, has been widely regarded as an effective means in providing a safe and low-cost solution to simulate real road driving with various types of drivers under different yet flexible driving scenarios [6].

A high-fidelity and real-time driving simulator is proposed in this research not only as data acquisition system, but also for experimental verification on the proposed method. The system includes a full six degree of freedom based motion platform, a large curvy screen for display of driving environment, a dSPACE®-based real-time simulator, a PanoSim-RT®-based models with vehicles, traffic conditions, testing field, and even weather and light conditions, and with various types of environmental sensors, such as radar, camera, antenna for wireless communication, GPS, just to name a few [7]. The driver's inputs of steering, throttle and brake pedals were collected through ADC channels and were communicated via Ethernet cable connected to the simulators and controllers as shown in Fig. 1. The driving data acquisition system operates under PanoSim-RT® environment, an integrated driving simulation platform with virtual driving scene, which is run under an industrial personal computer(IPC) with a high-fidelity vehicle dynamics model and many other

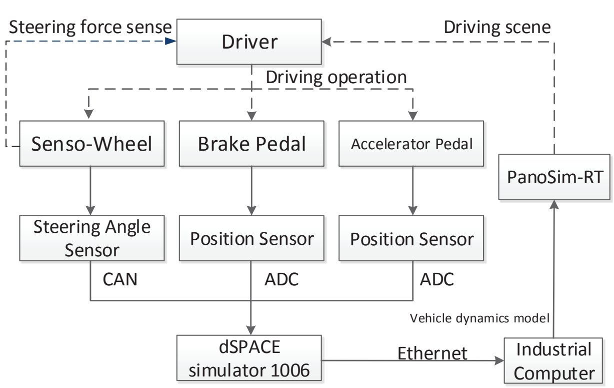

Figure 1. Schematic of Driving Data Acquisition System

Figure 2. Physical scene of driving data acquisition system

models of traffic, testing field and environmental sensors, etc. The IPC is connected via Ethernet to the dSPACE® simulator, which is equipped with a DS1006 board and several I/O boards. The driving simulator is also moved under a full-six degree of freedom motion base to emulate the dynamic motion feel with a large curvy display screen.

B. Design of Test Conditions

Thirty-six drivers were invited in this experiment including 24 males and 12 females. Since drivers' behaviors are their generic attributes, the differences of gender and age were not given much attention. Therefore, the drivers were selected at random basis. They were divided into three categories including cautious, general or reckless through questionnaires before. The drivers were trained before to get used to the operation of the driving simulator.

According to the test protocol of Euro NCAP about AEB systems, drivers are demanded to drive the host vehicle to 50km/h in a very short time, then maintain the uniform velocity for some time, brake the vehicle via their own judge to the front vehicle. The whole process and all the relevant data have been recorded. Through the data collected from the driving simulator, it's obvious that different drivers have different driving habits reflected in many aspects. However, in regard to forward collision avoidance systems, brake pedal opening is the most important factor affecting the performance of the systems which is shown in Fig. 3. The delay of the curve relative to cautious people was resulted from that the cautious driver accelerated slowly the first half of the experiment and took longer time.

III. DRIVING BEHAVIOR RECOGNITION BASED ON GMM

A. Introduction to GMM

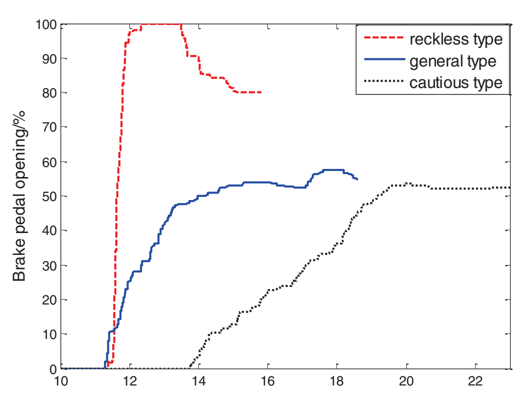

Figure 3. Brake pedal opening.

Via the analysis of the upper part, brake pedal opening is used to identify the types of the drivers and the recognition model is based on Gaussian Mixture Model.

Gaussian Mixture Model (referred to as GMM) is a parameterization method of density estimation. GMM can generate arbitrary shapes of densities, which is widely used in pattern recognition, such as speech recognition and speaker recognition. Chiyomi Miyajima of Nagoya University used GMM to model the driver's behavior and achieved a lot [8]. GMM can identify the drivers with the car working conditions based on real car test data with a high accuracy. The GMM for each driver's driving intention can be established to characterize the probability distribution of vehicle-following distance, vehicle speed, pedal position signal, and its dynamics.

GMM is a combination of multiple single Gaussian models. In regard to the probability density function for a single Gaussian model, suppose there are a set of points (x_i, i=1……n) in a high-dimensional space (dimension d). If the distribution of these points is approximately like the elliptical spherical which has a center and some variances, we can use the Gaussian density function g(x , μ , $\sum$) to describe the probability density function to produce these points [9].

However, in the case of the differences among drivers are obvious and the data distribution can't be described by a single Gaussian Models, Gaussian Mixture Model plays an important role in describing all the shapes of the data distribution.

Gaussian Mixed probability density function can be described by

$$p(x)=\sum_{j=1}^{M}\alpha_j \bullet g_j(x_j;\mu_j,\Sigma_j) \tag{1}$$

$$g_j(x_j;\mu_j,\Sigma_j)=\frac{1}{\sqrt{(2\pi)^d\left|\Sigma_j\right|}}\exp\left[-\frac{1}{2}(x_j-\mu_j)^T\Sigma_j^{-1}(x_j-\mu_j)\right] \tag{2}$$

x_j is the number j random vector, μ_j is the number j mean vector of single Gaussian Model, Σ_j is the number j covariance matrix of single Gaussian Model, α_j is the weight coefficient [10].

The most important parameters are the weight coefficient of GMM, the mean vector and covariance matrix of single Gaussian Model. Therefore, the essential of the GMM foundation is the solution of this three important parameters. In this paper, the EM algorithm is used to calculate the parameters. The first step is to estimate the weights of each single Gaussian model by knowing the parameters of each Gaussian model. The second step is to go back to determine the parameters of the Gaussian model based on the estimated weight. Repeat these two steps until the fluctuation is very small and the result of the log likelihood function approximates the extremum. The iterative formulas can be described by

1. E step

$$\varpi_i(k)=\alpha_k g(x_i\mid\mu_k,\Sigma_k)/\sum_{j=1}^{K}\alpha_j g(x_i\mid\mu_j,\Sigma_j) \tag{3}$$

$\varpi_i(k)$ is the probability generated by the number k model.

2. M step

$$\mu_k=\sum_{i=1}^{N}\varpi_i(k)x_i/N_k \tag{4}$$

$$\sigma_k=\sum_{i=1}^{N}\varpi_i(k)(x_i-\mu_k)(x_i-\mu_k)/N_k \tag{5}$$

$$\alpha_k=\sum_{i=1}^{N}\varpi_i(k)/N \tag{6}$$

Here, N is the number of random vectors [11].

Brake pedal opening is selected to be one dimension vector x input into the forward iterative formulas to calculate the 3 parameters and build the GMM.

B. Training of Driver's Behavior Based on GMM

Select the data collected from all the three types of sample drivers to train the GMM model and get the optimal parameters.

The training process based on EM algorithm is to make the likelihood function value reaches the maximum and the gained optimal parameters are output. In the algorithm, a maximum number of iterations is set in advance. If the optimal parameters have been gained before reaching the maximum number of iterations, the optimal parameters are output. Otherwise, the GMM model ought to be adjusted and the algorithm calculates again.

The similarity between GMM model and brake pedal opening signal can be described by log likelihood function.

$$J(\theta)=\log[H(\theta)]=\log[\prod_{i=1}^{N}p(x_i)] \tag{7}$$

Here, $p(x_i)$ is the single Gaussian probability density function. N is the number of random vectors[10].

The data collected from every type of drivers is gathered together into a whole and segmented to M parts. The mean and the variance and 1/M as the weighting factor are the initial value of EM algorithm.

C. Recognition about Driving Behavior

In the research of personalized ADAS, we account that the driver's behavior or style is the fixed attribute. A reckless driver will always driver the vehicle more recklessly than the cautious driver, even though on a certain part of the road. The essence of the recognition is to calculate the largest result of the log likelihood function based on 3 types of optimal parameters. Considering that only a small amount of data used to perform an operation to determine the recognition result is very accidental and the recognition accuracy can't be obtained, this paper uses continuous time windows to identify the driving behavior. After all the time windows have been calculated, the results of the log likelihood function form a curve describing the similarity between the GMM model and the brake pedal opening signals. The parameter type corresponding to the largest curve corresponds to the driver's type.

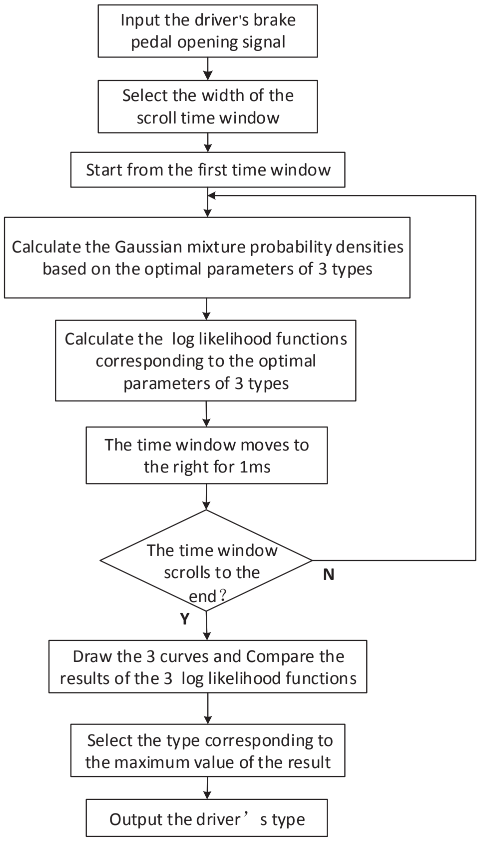

Figure 4. The flow chart of the recognition.

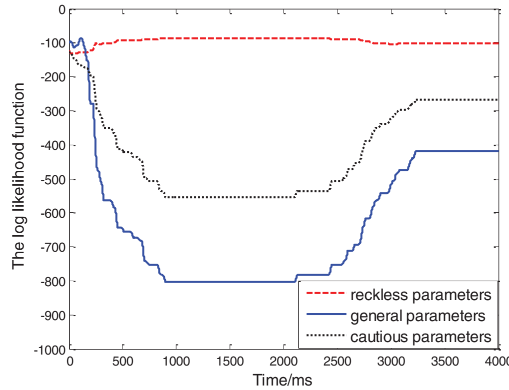

Figure 5. The identified result of a reckless driver.

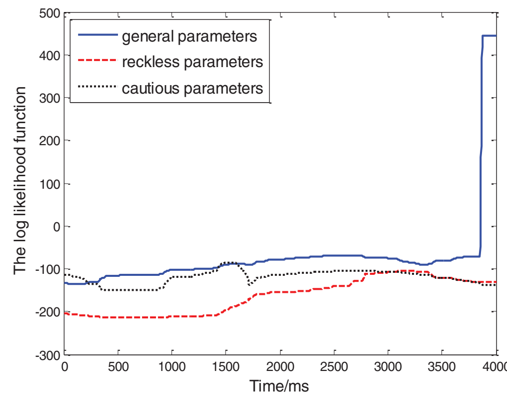

Figure 6. The identified result of a general driver.

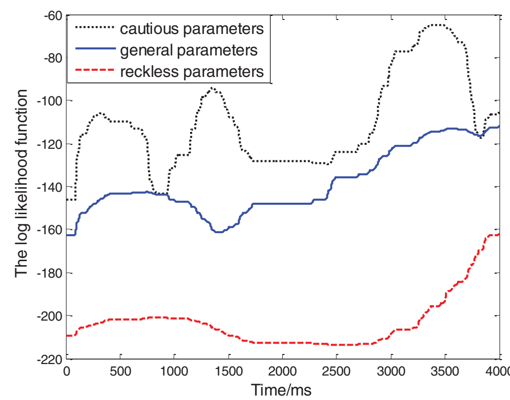

Figure 7. The identified result of a cautious driver.

Via the flow chart shown in Fig. 4, three drivers as test samples are selected for recognition, including reckless type, general type and cautious type. The data from the drivers of the 3 types are identified via the flow chart in Fig. 4 and the results are shown in Fig. 5-7.

From Fig. 5, it's obvious to conclude that the driver belongs to the reckless type because the curve calculated via the reckless parameters is at the top of the three. However, there is a short section of this curves below others. These are the time windows for inaccurate recognition. Recognition accuracy can be described by

$$\mathrm{P} = R / Q \times 100\% \tag{8}$$

Here, R is the number of time windows identified correctly. Q is the number of the total time windows. P is recognition accuracy.

In this process of recognition, the width of the time window is 2000ms, so Q is 2001. After the statistics, R is 1876. Therefore, the recognition result is reckless type and the recognition accuracy is 93.75%. From Fig. 6, it can be concluded that the driver belongs to the general type because the curve calculated via the general parameters is at the top of the three. The recognition accuracy which is 93.2% can be calculated by the (8).From Fig. 7, it's obvious to conclude that the driver belongs to the cautious type because the curve calculated via the cautious parameters is at the top of the three.The recognition accuracy is 96.7% calculated from (8).

IV. Design Of FCA Control Strategy

Based on the principle of the FCA systems, a control strategy of FCA was designed in this paper. The design and verification of the strategy were conducted under PanoSim®. The relative distance and relative velocity between the front vehicle and the host vehicle can be measured via built-in radar model in PanoSim®. With the result of the driving behavior recognition algorithm, different warning and braking strategies were designed for various drivers' types. The safety distance model was founded based on TTC (Time to Collision), which was denoted as:

$$D_s = TTC \bullet v_c + d_0 \tag{9}$$

Here, v_c is the relative velocity, and TTC is the time to collision, d_0 is a constant, generally taken as 1~5m.

In regard to the mixture system of warning and autonomous braking, two-level warning autonomous braking is added for the cautious drivers to guarantee their reaction time and the comfort. On the other hand, only autonomous braking features ought to be added for the reckless drivers to guarantee the safety and driving fun. Besides, the reckless drivers tend to the larger deceleration and the change of the deceleration is violent. The general drivers tend to the middle deceleration and the deceleration changes normally. Finally, the cautious drivers tend to the smaller deceleration which attains and the change of it is gentle. In summary, the strategy of classification warning and autonomous brake is established based on TTC. The road is assumed to be dry and the pavement adhesion coefficient is the normal 0.8.

Based on the strategy described in TABLE Ⅰ, the algorithm is verified in PanoSim®. The test verification condition is set in the virtual environment of PanoSim® as the data acquisition condition, and the front vehicle stationary condition which is the most dangerous in FCA is selected in this paper. The initial vehicle speed is 50km/h, and the initial relative distance to front vehicle is 85m. The pavement adhesion coefficient is set to 0.9. The results of the 3 strategy considering different driving behaviors are shown in Fig. 8 and Fig. 9.

From Fig. 8, it can be concluded that the algorithm is able to simulate driver's deceleration characteristics of different types, both for the maximum of the deceleration and the trend of the deceleration. The velocity characteristics can reflect different driving styles of different driver's types which will be shown in the next section. Fig. 9 verifies that the three modes can stop behind the front vehicle securely and efficiently.

TABLE I. STRATEGY OF WARNING AND AUTONOMOUS BRAKE.

Driver's style	Analyzing Conditions	Execution
Cautious type	TTC⩾3.5	No execution
	2⩽TTC<3.5	Primary warning. Deceleration:1.5m/s^2
	1⩽TTC<2	Secondary warning. Deceleration:2.5m/s^2
	TTC<1	Emergency braking. Deceleration:3.5 m/s^2
General type	TTC⩾2.5	No execution.
	1⩽TTC<2.5	Primary warning. Decelerate by 2m/s^2
	TTC<1	Emergency braking. Decelerate by 5m/s^2
Reckless type	TTC⩾1	No execution
	TTC<1	Emergency braking. Decelerate by 8m/s^2

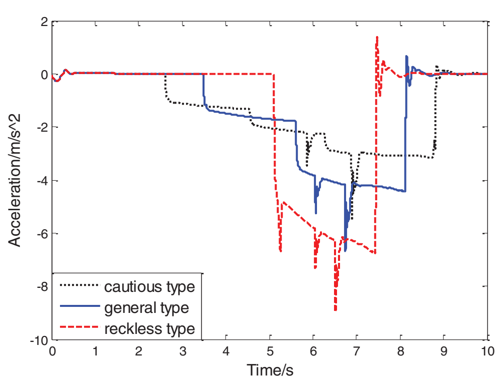

Figure 8. The acceleration of three modes corresponding to different drivers.

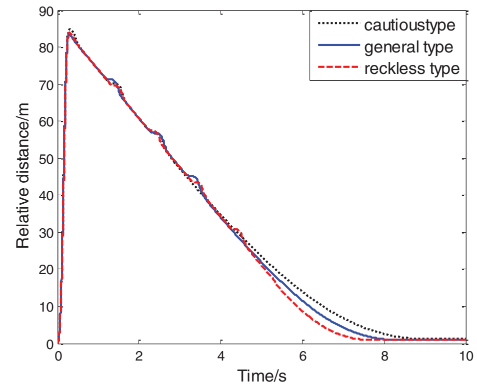

Figure 9. The relative distance of the three modes corresponding to different drivers.

V. SIMULATION AND EXPERIMENT

In order to verify the algorithm proposed in this paper, it has been simulated and analyzed in Matlab/Simulink® and the environment of PanoSim-RT®. A random driver is selected to drive in the driving simulator via PanoSim-RT®, and the data in the process of brake is intercepted to identify. Next, the

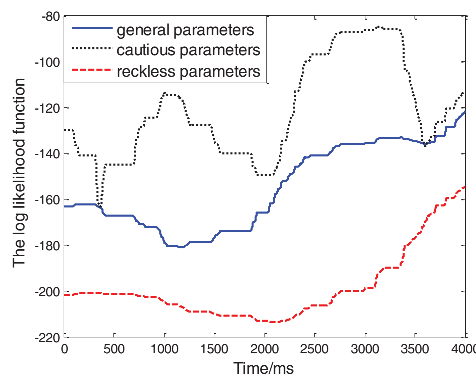

Figure 10. The recognition result of the driver.

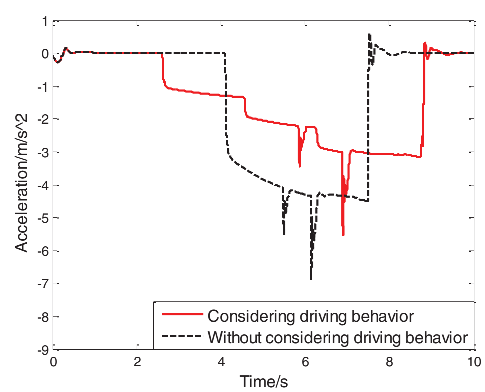

Figure 11. The comparison about acceleration.

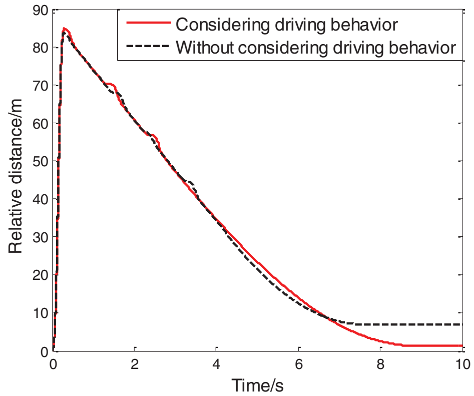

Figure 12. The comparison about relative distance.

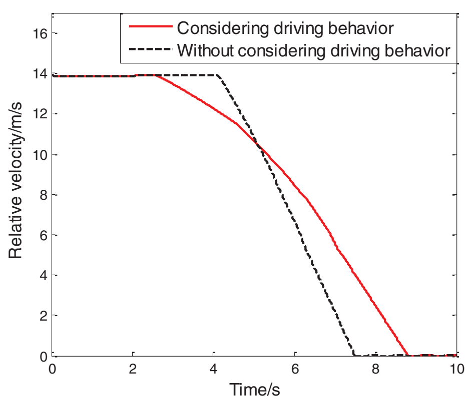

Figure 13. The comparison about relative velocity.

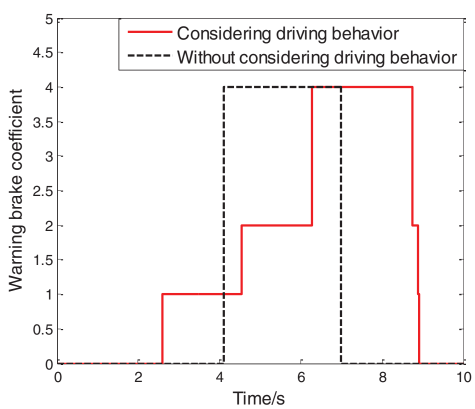

Figure 14. The comparison about warning brake coefficient.

recognition result is input to the strategy of the FCA. The recognition result is shown in Fig. 10. It can be concluded that the driver's type is cautious, and the recognition accuracy is 96.55% calculated from (8).

Meanwhile, the FCA considering driving behavior works well. The working results contrast with the system without considering driving behavior are shown in Fig. 11-14. In Fig. 14, 1 represents the Mild-warning of the system. 2 represents Severe-warning of the system, and 4 represents emergency brake of the system. It's obvious that the working mode of the system is the cautious type which is consistent with the recognition result based on GMM shown in Fig. 10. In addition, if the selected driver is reckless or general, the corresponding action of the system will be like the curves shown in Fig. 8 and Figure. 9. The assisting driving mode can adapt to the driver's driving style well. The different warning brake coefficient designed by different drivers' TTC improved their human acceptance.

VI. Conclusions

GMM was proposed in this research to train drivers' braking when facing a front stationary obstacle, and for driver classification, which can be grouped into three types, i.e., cautious, general and reckless. The data were collected from a dSPACE®-based driving simulator with PanoSim-RT®. For different types of drivers, the corresponding strategies of FCA were designed based on TTC. Finally, the proposed method was verified under PanoSim-RT® by data collected from a random drivers' driving. The results were compared with systems without considering driving behavior, which demonstrated that the proposed system is effective to improve drivers' comfort, safety, and fun to drive.

There are other factors which may affect drivers' driving behavior, such as road pavement and its adhesion coefficient, variation of drivers' gender and age, to name a few. These may be further investigated in the future research.

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