THE INFLUENCE OF CHARACTERISTIC PARAMETERS ON THE PERFORMANCE OF FATIGUE LANE DEPARTURE RECOGNITION MODEL

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ABSTRACT

The aim of this study is to identify suitable characteristic parameters for building recognition models that can effectively detect driver fatigue. The parameters are divided into two main groups driver activity and vehicle motion state and further categorized into ten specific parameter groups (DRM No. 1 to DRM No. 10) to construct the corresponding recognition models. Based on Gaussian Mixture - Hidden Markov Models (GM-HMM) theory, we establish recognition models for fatigue lane departure (FLD) and normal lane changing (NLC) states. Using the basic principles of HMM theory, we propose the use of a Left-Right mixture Gaussian chain structure to build the recognition model. These ten groups of characteristic parameters are used as the observation chain for the GM-HMM model. After training, we obtain the characteristic parameters for the corresponding recognition models. Finally, the performance of these ten models is evaluated using three metrics: Accuracy, Sensitivity, and Specificity. The results demonstrate that the choice of parameters significantly impacts the performance of the recognition models. These findings underscore the importance of selecting appropriate feature parameters to improve driver fatigue detection systems, ultimately contributing to safer driving and the prevention of fatigue-related accidents.

Keywords: *safety, fatigue/burden, warning system, recognition/judgment, fatigue lane departure, Lane departure warning.*

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1. INTRODUCTION

Driving while fatigued is widely recognized as one of the leading causes of traffic accidents. To mitigate these risks, it is crucial to develop objective methods for accurately detecting and assessing driver fatigue. Researchers have made significant strides in this area by leveraging various characteristics of driving under fatigue, including physiological signals, driver behaviors, and vehicle states. For instance, recent studies have employed electroencephalography (EEG) signals to evaluate driver fatigue levels. A notable example is the work by Zheng et al. [1], who applied deep learning methods to EEG power spectrum data for better fatigue detection. Similarly, methods focusing on driver behavior have also gained attention. For example, Hu et al. [2] utilized eye movement and blink rate patterns to assess drowsiness, finding that these metrics are effective indicators of fatigue. Additionally, vehicle-related parameters such as steering wheel movements have been studied to gauge driver fatigue. Sun et al. [3] proposed a model based on the analysis of steering wheel angle and velocity to predict fatigue levels, which showed promising results in real-world scenarios. In the domain of sensor fusion, Liu et al. [4] integrated multiple sources of data, including head movements and gaze tracking, using machine learning algorithms to more accurately determine the driver's mental state. However, some methods like Bayesian Networks require prior knowledge, which can complicate their practical application. In response to this challenge, Zhang et al. [5] introduced an alternative using evidence theory to reduce the need for prior information, though challenges like evidence explosion still hinder widespread use. The ongoing efforts to develop effective fatigue detection systems underscore the complexity of the task, as no single method has yet achieved perfection. Each approach has its advantages and limitations, and a key challenge remains in evaluating the efficiency of these methods based on different characteristic parameters. To enhance the reliability and user acceptance of fatigue warning systems, it is critical to evaluate and compare the effectiveness of various recognition models. This study aims to analyze vehicle motion data and driver behavior to distinguish between normal and fatigue-induced lane changes. We propose a fatigue recognition model using the Gauss Mixture Hidden Markov Model (GM-HMM), and evaluate its performance based on accuracy, sensitivity, and specificity, while also considering the influence of different characteristic parameters on model efficiency.

2. TEST DESIGN

2.1. Test Elements

Lane departure state cannot be expressed directly by arithmetic model but if it happens we can express it indirectly through characteristic parameters of driving behavior (driver behavior is divided into driver's operating behavior and vehicle's motion state). So that the experiment is studied to express the characteristic parameters of driver's operating behavior and vehicle's motion state.

The paper establishes a driver in the loop test bench based on CARSIM and LabVIEW visual programming software. Use CarSimRT as its dynamic simulation software, makes the NIPXI8610 collect the driver's operating signal of steering, steering lamp, accelerator pedal and brake pedal and transfer the signal to the Advantech 610L. CarSimRT chooses C-class sedan, the structural parameter and dynamic parameter of vehicle are both set to default, the vehicle width is set to 1739mm, the tire center distance is set to 1500mm and the tire basic parameter is set to 205/55, R16.

12 volunteers (8 male, 4 female) among 25 ages to 35 ages (average age 30, average driving 3.5 years) are selected in the test to join the simulator test, and all volunteers have achieved legal driving licenses.

Fig. 1. Driving simulation flat

Under the monotonous environment of simulator, the driver will enter into extreme fatigue status after 60 min of continuous driving or above.

To quickly collect a large amount of data on driver fatigue, we chose three time points during the day: morning, noon, and evening. The normal lane change experiment was conducted intermittently during this period. When the driver was still alert and focused solely on driving, the data on normal lane changes was collected.

2.2. Sample screening

Combining the experimental video and the lateral location of vehicle parameters to select effective samples, when determining the lane departure samples, the following rules can be referred to:

(1) The steering wheel turns to left is positive, turn to right is negative. Therefore when select samples we will classify left lane departure and right lane departure.

(2) In lane departure state, the vehicle is still under the control of the driver; ensure the lane departure is not too big which can lead to abnormal samples.

(3) Select the data at the time the speed over 60km/h.

According to above requirements, the experimenters observe lane departure situation in video; divide lane departure into 4 cases: left normal lane changing, right normal lane changing, left fatigue lane departure, and right fatigue lane departure. The normal lane changing samples chiefly originate from Mandatory lane change (MLC) and Discretionary lane change (DLC). Based on the fatigue lane deviation onset time determined above, we take the time interval from the onset to the end of lane departure as the recognition time window width of a sample. Through the box plot analysis of the fatigue detection window width values of 12 tested drivers, combined with the analysis method based on the fusion analysis with Receiver Operating Characteristic Curve (ROC) [6], we select the recognition time window of normal lane changing sample is 3s.

3. PARAMETRIC ANALYSIS OF FATIGUE LANE DEPARTURE

In the process of analyzing the characters of driving behavior (including the character of driver's operating behavior and vehicle motion state) [7] toward two states normal lane changing and fatigue lane departure, we see that:

(1) When compare the case which the fatigue cause fatigue lane departure and the case of normal lane

changing, the result shows that, the law of change of characters is not similar.

(2) While analyze the character of operating behavior of the driver the standard error at normal lane changing state is bigger than it at fatigue lane departure state. Steering wheel angle velocity also expresses the law of similar statistics and by analyzing steering wheel angle entropy can see the difference of two states of lane departure.

(3) Analyze and count the characters of motion state of the vehicle toward normal lane changing and fatigue lane departure state. The result shows that lateral acceleration, yaw velocity, lateral location of vehicle, average lateral velocity all of these can distinguish clearly two states of lane departure normal lane changing and fatigue lane departure.

4. RECOGNITION MODEL BUILDING OF FATIGUE LANE DEPARTURE

4.1. Classify fatigue lane departure recognition model

To evaluate the influence of the number and type of characteristic parameters on the recognition efficiency of the model. First, we proceed to build a method to recognize FLD based on GM-HMM [6]. Next, we proceed to determine the efficiency of 10 models built corresponding to 10 parameter groups from DRM1 to DRM10 shown in Table 1.

The efficiency of the models is determined by calculating 3 feature parameters: "Accuracy", "Sensitivity" and "Specificity". From there, we can evaluate the efficiency of each model, and at the same time determine the most optimal model.

Table 1. The width of the road regulations

Departure recognition model	Parameter list							
	Sample set	Sa	Se	Sv	La	Yv	Lv	Av
DRM No.1	Driver's operating behavior & vehicle's motion state	√	√	√	√	√	√	√
DRM No.2	Driver's operating behavior	√	√	√				
DRM No.3	Vehicle's motion state				√	√	√	√
DRM No.4	Steering wheel angle entropy (Se)		√					
DRM No.5	Steering wheel angle velocity (Sv)			√				
DRM No.6	Yaw velocity (Yv)					√		
DRM No.7	Average lateral velocity of vehicle (Av)							√
DRM No.8	Lateral location of vehicle (Lv)						√	
DRM No.9	Steering wheel angle (Sa)	√						
DRM No.10	Lateral acceleration (La)				√			

4.2. Determine sample

According to the sample selection method above, select the lane departure samples of different drivers, at last select 320 sample groups in which the fatigue lane departure sample is 160 groups, normal lane changing is 160 groups.

Base on the requirements when building the fatigue lane departure recognition model, classify lane departure samples into 2 sets: one set is the training sample set, the other is test sample set. Each set accounts up 50% the total amount of samples. In which training sample set is used to optimize model parameter, test sample set is used to determine lane departure.

4.3. Model Test

The model test procedure involves inputting test samples into the Departure Recognition Model (DRM) to identify the predicted model that best explains the current observation sequence, i.e., the assessment problem in the Hidden Markov Model.

Furthermore, the test sample of normal lane changing model DRM No. 1 (NLC1) is added into the training set. Input the test set into the DRM No. 1 model, evaluate the probabilities of the observation sequence caused by the normal lane changing model and fatigue departure model (FLD1) using the forward-backward algorithm, and select the model with the higher probability as the predicted model. Classification scatter diagram is taken to show the recognition results achieved in departure recognition model DMR No. 1, and the result is shown in Fig. 2.

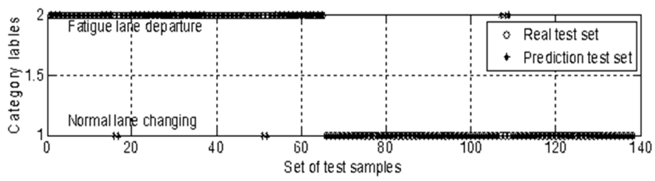

Fig. 2. The result of recognition GM-HMM based fatigue lane departure model

Determine the number of times of wrong prediction on factual samples by testing then determine the accuracy of the research model. Enter test sample set into the model DRM No. 1, the factual test sample set includes 65 samples of fatigue lane departure state, and 73 samples of normal lane changing state. From Fig. 2, the result of recognition appears errors (the result of recognition is not coincided with factual data)

To evaluate the weak and strong points of the model we carry out to determine the accuracy, sensitivity and specificity. The feature parameters are determined according to following formula (1) [7].

$$\begin{aligned} &\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \times 100\% \\ &\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \\ &\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100\% \end{aligned} \quad (1)$$

The recognition model appears 4 kinds of result: True Positive (TP) is the number of times determine fatigue lane departure in fatigue lane departure sample set; False Negative (FN) is the number of times not determine fatigue lane departure in sample set fatigue lane departure; True Negative (TN) is the number of times not recognize fatigue lane departure in sample set normal lane changing; and False Positive (FP) is the number of times recognize fatigue lane departure in sample set normal lane changing.

Through probability comparative analysis of 4 kinds of this result, carry out to assess qualitatively the effect of recognition model.

Based on the formula (1), we determine the accuracy, sensitivity and specificity of fatigue lane departure state is 94.20%, 93.85% and 94.52%, it indicates that the reliability of the recognition is high. From there, we can say that, applying the GM-HMM method into recognizing fatigue lane departure state is effective.

5. THE INFLUENCE OF CHARACTERISTIC PARAMETERS ON RECOGNITION EFFICIENCY

To evaluate the impact of specific parameter symbol forms, models 2-10 are constructed and tested similarly to DRM No. 1. After testing different parameters, we calculate the results of the corresponding models, the results of which can be shown in Table 2.

Table 2. The recognition accuracy, sensitivity and specificity corresponds to the 10 characteristic parameter groups

Model	Feature set category	Accuracy (%)	Sensitivity (%)	Specificity (%)
DRM No. 1	Driving behavior	94.20	93.85	94.52
DRM No. 2	Driver's operating behavior	92.03	90.91	93.06
DRM No. 3	Vehicle's motion state	82.61	83.61	81.82
DRM No. 4	Steering wheel angle	86.23	83.82	88.57
DRM No. 5	Steering wheel angle entropy	88.41	86.57	90.14
DRM No. 6	Steering wheel angle velocity	89.86	88.06	91.55
DRM No. 7	Lateral acceleration	76.81	74.63	78.87
DRM No. 8	Yaw velocity	73.91	70.42	77.61
DRM No. 9	Lateral location of vehicle	41.30	38.57	44.12
DRM No. 10	Average lateral velocity	63.77	60.87	66.67

Looking at Table 3, we can clearly see: The DRM No. 1 model shows the best recognition efficiency, which aligns with the theory that increasing the attribute's multidimensional space improves model efficiency.

The GM-HMM model's accuracy is higher when using the driver's operating behavior parameters than when using the vehicle's motion state parameters. It proves that driver's operating behavior expresses the fatigue lane departure state more clearly than the vehicle's motion state. This is consistent with the fact that driver fatigue, first affects operating behavior, which then influences the vehicle's motion state. The steering wheel angle velocity most accurately reflects fatigue lane departure, while the vehicle's lateral position is less accurate. Besides, the sensitivity and specificity of DRM No. 2 model are bigger than the sensitivity and specificity of DRM No. 3 model respectively. This proves when carry out to recognize the fatigue lane departure state in fatigue lane departure test sample set, the recognition model based on driver's operating behavior is able to detect more accurately than the model based on vehicle's motion state . And when carry out to recognize the normal lane changing state from normal lane changing test sample set, the recognition model based on driver's operating behavior is able to eliminate fatigue lane departure state is better than the model based on vehicle's motion state.

When using single characteristic parameters, the model with steering wheel angle velocity has the highest sensitivity and specificity (88.06%, 91.55%), while the model with lateral vehicle location has the lowest (38.57%, 44.12%). It means that steering wheel angle velocity is the most effective characteristic parameter in expressing driver's state of fatigue.

In contrast, the vehicle's lateral location is less effective in recognizing fatigue lane departure and causes confusion with normal lane changing. Additionally, driver behavior parameters distinguish fatigue lane departure and normal lane changing better than vehicle motion state parameters.

6. CONCLUSION

This study demonstrates that using driver behavior parameters, particularly steering wheel angle velocity, significantly improves the accuracy of detecting driver fatigue and fatigue lane departure compared to vehicle motion state parameters. The DRM No.1 model, based on driver activity, shows the highest recognition efficiency, confirming that driver behavior is a more effective indicator of fatigue. The results indicate that the model based on driver behavior has higher sensitivity and specificity, effectively distinguishing between FLD and NLC. These findings highlight the potential of using driver behavior parameters to enhance fatigue detection systems, contributing to safer driving and reducing fatigue-related accidents. The proposed models can be effectively applied in real-time driver monitoring systems to improve road safety.

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