The Role of Parameter Frequency Domain Features in Recognizing Cognitively Distracted Driving State on Expressway

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Abstract: In order to study the feature difference between distracted driving and normal driving in frequency domain, this paper conducts real-vehicle experiments under cognitive distracted state to obtain driving operation parameters and vehicle operating state parameters under normal driving and distracted driving. The parameter is subject to wavelet packet decomposition to obtain the energy value of each parameter in different frequency ranges under different driving states. The support vector machine algorithm is used to establish the classification model, and the time domain feature parameters, namely the mean and standard deviation of different parameters, and the frequency domain feature parameters, namely the high and low frequency energy values of the wavelet packet decomposition of different parameters, are used as feature inputs. The model recognition rate of normal driving and cognitively distracted driving are analyzed, and the time domain recognition results are comparatively analyzed against frequency domain. The analysis results show that the frequency domain analysis method is more accurate than the time domain analysis method in identifying the two driving states. The frequency domain analysis method has an accuracy rate of 83.3% and 87.5% in identifying normal driving and distracted driving, respectively.

Keywords: traffic engineering; cognitive distracted driving recognition; distraction secondary tasks; frequency domain analysis; wavelet packet decomposition

1. Introduction

In the driving process, the driver plays a leading role. Driver features are the fundamental factor that endangers traffic safety [1]. NHTSA pointed out that distracted driving is an important cause of fatalities and injuries in traffic accidents [2].

Erwin R. Boer et al. summarized driving distraction into two categories: visual distraction and cognitive distraction [3]. Kashevnik et al classified driving distraction into three categories as manual distraction, visual distraction, and cognitive distraction [4]. Because cognitive distraction does not present the driver's head movement features shown by visual distraction, the analysis and extraction of parameters supporting effective detection of cognitively distracted driving carries great significance for the recognition, early warning and intervention of cognitive distracted driving.

Due to the existence of safety risks, the research on distracted driving is mostly based on driving simulators [5–7], and the form of questionnaires [8], [9]. Only a few studies choose the natural driving experiment [1]. This paper intends to adopt the method of real vehicle experiment to design the driving distraction secondary task and access driving behavior data in the real traffic environment.

As for the stimuli that trigger distraction, studies involved in HMI operating [10], phone using [11], [12], and in-vehicle activities like texting and eating [13] are made. In this paper, digital memory method is taken to design an 11-digit phone number memory task to simulate the distracted state of cognitive driving.

Previous studies were mostly based on the time-domain perspective to explore the differences between the driver’s operating behavior parameters and vehicle operating parameters in distracted driving conditions over time, data like drivers’ gaze activities characteristics [14], face poses [11], the lateral and longitudinal measures [6], [7], [13], [15–17] of vehicle performance are used to discriminate the distracted driving state. However, the change features of parameter data in the frequency domain are ignored. This paper adopts wavelet packet time-frequency analysis method, transforms the time-domain parameters into the frequency domain, explores the frequency-domain features of the parameters under cognitively distracted driving state, and compares them with the time-domain analysis method to verify the effectiveness of the frequency-domain analysis method.

2. Real Vehicle Experiment

2.1. Driving Distraction Secondary Task

Ullsperger believes that the P300 wave in the human brain is a parameter that characterizes the size of a person's cognitive load. By applying the task of number string memorization to the subjects, Ullsperger found that as the number string grows, the amplitude of the P300 wave also increases. The experimental results are consistent with the subject's subjective observations. Based on Ullsperger's experimental results, this paper designs a cognitive distraction secondary task of memorizing mobile phone numbers [18].

During the actual vehicle experiment, the experimental staff in the co-pilot verbally proposed the 11-digit mobile phone number memory secondary task to the driver. After the experiment staff finished the dictation, the driver repeated the 11-digit mobile phone number. The subjects had two opportunities to answer the question. Afterwards, regardless of whether the answer is correct or not, proceed to the next question.

2.2. Experimental Conditions

This paper adopts the method of real-vehicle driving experiment, chooses the straight section of the expressway with simple environment and low workload requirement for the driver, so it is appropriate to carry out the distracted driving experiment.

After research, it is determined that the experimental section is a 4km straight section of Xitai Road in Xi'an. As shown in Figure 1, the speed limit of this section is 80km/h and the traffic flow is 700veh/h.

The experimental vehicle is a Volkswagen Touran experimental platform vehicle equipped with a gyroscope, VBOX 3i host, GPS, steering wheel sensor and video acquisition equipment, as shown in Figure 2, which acquires equipment record data through the CAN protocol.

This paper selects five parameters collected by the equipment for research, including the vehicle's steering wheel angle, steering wheel acceleration, yaw rate, lateral acceleration, and longitudinal acceleration. The steering wheel is directly controlled by the driver, so the steering wheel angle and the steering wheel angular velocity can more directly reflect the driver's operating behavior; while the yaw rate, longitudinal acceleration, and lateral acceleration reflect the running state of the vehicle. The experimental equipment is shown in Table 1.

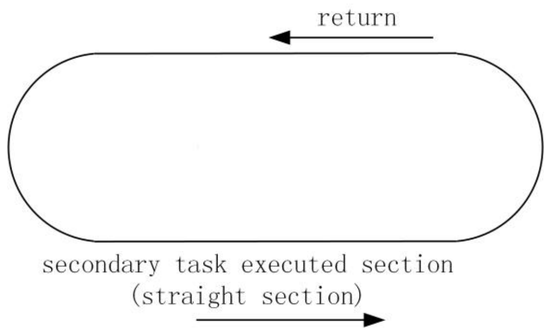

Figure 1. Simulation diagram of experimental route

Figure 2. Multi-sensor platform vehicle

Due to the high safety risks of distracted driving experiments, this study only recruited 6 skilled drivers, aged between 30-50 years old, with more than 10 years' driving experience, who have no traffic accidents in the past 3 years. Before the experiment, inform the test drivers of the safety risks of the experiment, let them fill in the informed consent form, and purchase insurance for each test driver.

Table 1. Experimental equipment

Equipment name	Function	Sampling frequency (HZ)
video capture system	real-time monitoring of the traffic environment and driver's driving behavior in 360° of the experimental vehicle	24
imu02 gyroscope	acquire the three-axis motion state parameters of the experimental vehicle (lateral and longitudinal acceleration, yaw rate)	20
vbox3i gps	access speed, latitude and longitude information of the experimental vehicle	100
steering wheel sensor	collect the steering wheel angle and the steering wheel angular velocity parameters of the experimental vehicle	20

2.3. Experimental Process

Before the formal start of the experiment, a pre-experiment was carried out, allowing the test driver to drive normally according to his usual driving habits to adapt to the experimental vehicle and the experimental road section. After the start of the formal experiment, in order to reduce the driver's workload, the vehicle was turned on in a cruise mode with a speed of 50km/h. Drivers were required to perform normal driving experiments (comparative experiments) and cognitively distracted driving experiments on the experimental straight line section. Where, the cognitive distraction secondary task was applied on the straight line section shown in Figure 1, which lasted about 100s. Normal driving operations were carried out on the straight line section at bending and returning.

3. Frequency Domain Difference Analysis Based on Wavelet Packet Algorithm

The experiment finally collected the experimental parameters of the driver in normal driving and cognitively distracted driving. The wavelet packet analysis method is used to decompose the five parameters of steering wheel angle, steering wheel angular velocity, lateral acceleration, longitudinal acceleration and yaw rate to obtain the parameter components in the high and low frequency bands. The energy value of the same parameter in the high and low frequency bands was compared under different driving conditions to obtain the difference in frequency domain between normal driving and distracted driving.

3.1. Wavelet Packet Analysis Method

The wavelet packet analysis method is a time-frequency analysis method. Its principle is to describe the original signal using the wavelet basis function. By changing the scale parameter of the wavelet function, the short-term and high-frequency data are simulated separately, and the translation parameter of the wavelet function is changed to make it move in the entire signal time axis so that the entire signal can be measured. Through this wavelet transformation process, the similarity coefficient between the original signal and the wavelet packet function is obtained, namely, the wavelet packet coefficient. The original signal can be reconstructed through the wavelet packet coefficient.

Perform a layer of wavelet packet decomposition on the original signal, as shown in Figure 3. Obtain the high-frequency component and low-frequency component of the original signal, that is, the wavelet packet coefficient of the high-frequency component and the wavelet packet coefficient of the low-frequency component of the signal. The high frequency and low frequency components of the original signal can be obtained through the wavelet packet coefficient reconstruction, that is, the original signal is divided into a high frequency band and a low frequency band, and the result is represented by wavelet coefficients. If the sampling frequency of a known signal is fs, let $f=\frac{1}{2}fs$, then the frequencies of the frequency band represented by low and high frequencies are $\left[0,\frac{1}{2}f\right]$ and $\left[\frac{1}{2}f,f\right]$ respectively.

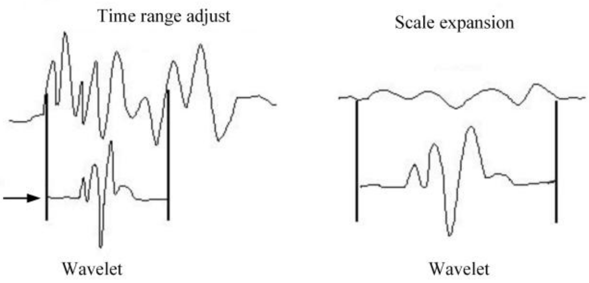

Figure 3. Wavelet analysis data process

Decompose the operating parameters of the driver and the operating parameters of the vehicle in the normal driving state and the cognitively distracted driving state to obtain the signal components of each parameter in the high frequency band and the low frequency band under the two driving states. That is, the changes in the high and low frequency signal content of the same parameter can be analyzed under the two driving states. If the high and low frequency energy values of the same parameter produce significant differences under different driving states, it means that this parameter can be used as a feature parameter to characterize distracted driving.

Based on the matlab platform, single-layer wavelet packet decomposition is performed on the parameters collected in cognitively distracted driving and normal driving through the wpdec function, each node is reconstructed through wprcoef to obtain the specific energy value of each node. An increase in high frequency energy indicates an increase in short-term and great changes in the parameter. For example, if the steering wheel is turned sharply in an emergency, an increase in low frequency energy indicates an increase in small changes in the parameter, such as fine-tuning of the steering wheel at intervals. The frequency domain feature extraction and recognition process is shown in Figure 4.

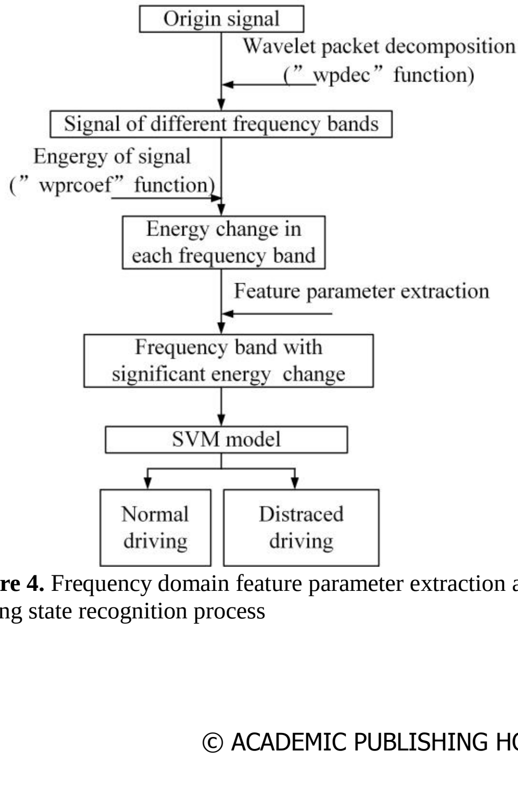

Figure 4. Frequency domain feature parameter extraction and driving state recognition process

3.2. Differences of Different Driving States in the Frequency Domain

In this paper, each parameter of 10s operating data of the driver under normal driving and cognitively distracted operating states is separately decomposed by wavelet packet single layer, and the node coefficients are reconstructed to obtain the energy distribution of each parameter at low and high frequencies. Analyze the energy distribution difference of each parameter at low and high frequency under the two operating states.

After wavelet packet decomposition and node reconstruction of the steering wheel angle, steering wheel angular velocity, yaw rate, longitudinal acceleration and lateral acceleration data, the energy value obtained is indicated by a box-and-whisker diagram, and the results shown in Figures 4, 5, and 6 are obtained. Since the sampling frequency of the parameters studied in this paper are all 20 Hz, node 1 represents the frequency band of the lower frequency range, that is, [0,5]Hz, node 2 represents the frequency band of the higher frequency range, i.e. [5,10]Hz.

It can be seen from Figure 5 that at node 1, high-frequency energy value of the steering wheel angle under cognitively distracted driving has larger distribution range than the high-frequency energy value of the steering wheel angle under normal driving. It can be considered that in the cognitively distracted driving state, there is more instantaneous and great change in steering wheel. For its reason, under cognitively distracted state, the driver has more emergency operations after realizing that the vehicle has deviated from the original driving route. The low-frequency energy value of the lateral acceleration can be used as a frequency domain feature parameter for identifying the cognitively distracted driving state.

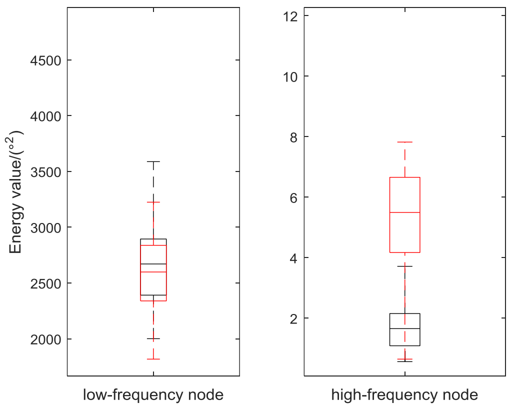

Figure 5. Energy box and whisker diagram of 1 layer wavelet packet decomposition of the steering wheel angle

Similarly, it can be seen from Figure 6 that the high and low frequency energy values of the steering wheel angular velocity in the cognitively distracted state are greater than the energy values in the corresponding normal driving state, which indicates that there are more instantaneous great change and intermittent fine-tuning of the steering wheel angular velocity in the cognitively distracted driving state.

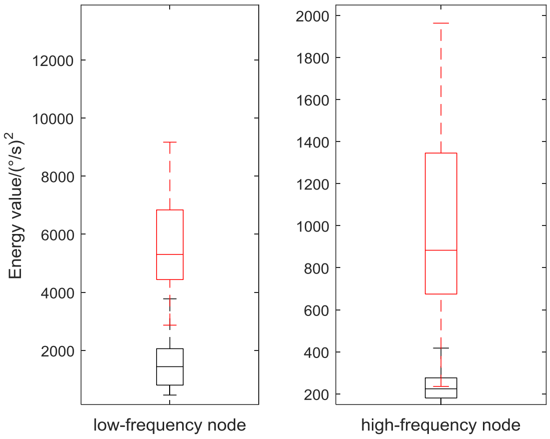

Figure 6. Energy box and whisker diagram of 1 layer wavelet packet decomposition of the steering wheel angular velocity

Figure 7 shows that the low-frequency energy value of lateral acceleration in cognitively distracted state increases relative to normal driving, which indicates that the vehicle's lateral control ability deteriorates in cognitively distracted state, and the vehicle has a tendency to intermittently deviate from the original driving trajectory, so lateral movement of the vehicle needs to be fine-tuned.

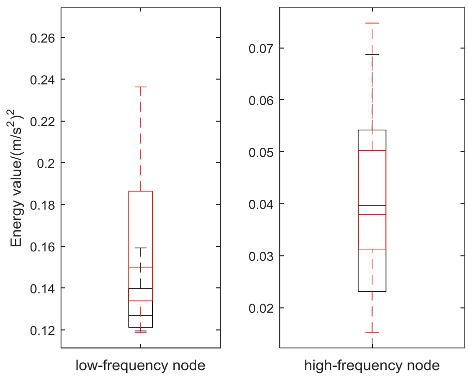

Figure 7. Energy box and whisker diagram of 1 layer wavelet packet decomposition of lateral acceleration

For the yaw rate and longitudinal acceleration, the wavelet packet decomposition energy shows that the high and low frequency energy values have a serious overlap between the normal driving state and the distracted driving state, which cannot be used as a feature parameter to identify the cognitively distracted state.

4. Cognitive Distraction State Recognition Model Based on Support Vector Machine

Support vector machine [5], [13], random forest classifier [10], [13], [16], linear logistic regression [10], [13], convolution neural network [19], [20] are the commonly used driving distraction recognition algorithm. Since this paper aims to verify the effectiveness of frequency domain analysis method, there are no high requirements for algorithms. Therefore, based on the Matlab2016a platform, this study invokes the support vector machine toolkit, uses fitcsvm function to establish a cognitive distraction state recognition model based on time-domain feature parameters and frequency-domain feature parameters.

Input the low-frequency energy value of the steering wheel angle, the high-low-frequency energy value of the steering wheel angular velocity, and the low-frequency energy value of the lateral acceleration as frequency domain feature parameters into the support vector machine model, and the final model obtained by different parameter combinations has different accuracy in recognizing cognitively distracted driving. Finally, it is shown that the best recognition effect is obtained when the high and low frequency energy value of the steering wheel angular velocity are used as the model input. The accuracy in identifying normal driving is 83.3%, and the accuracy in identifying cognitively distracted driving is 87.5%. The recognition result is shown in Figure 8.

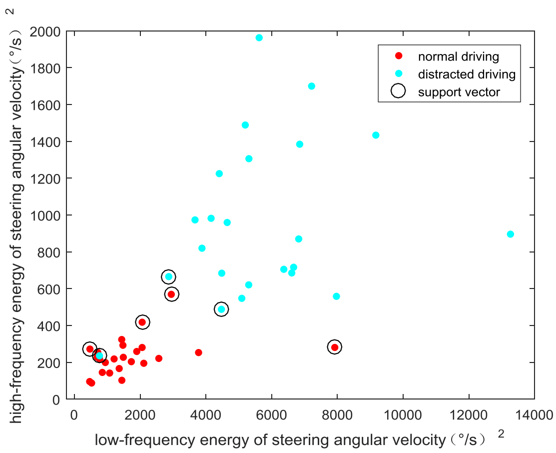

Figure 8. Support vector machine model classification results

The mean and variance of the selected steering wheel angle, steering wheel angular velocity, yaw rate, lateral acceleration, and longitudinal acceleration within 10s are input to the support vector machine model as time-domain feature parameters. The result shows that the model accuracy in identifying normal driving is 75%. The accuracy rate for cognitively distracted driving is 79.2%, and the maximum recognition rate is obtained when all the mean and variance of the five parameters are used as the model input. The time domain feature parameters are shown in Table 2 and Table 3.

Table 2. Time domain feature parameters under normal driving

	No.	1	2	3	…	50
steering wheel angle (°)	mean	2.32	2.27	2.13	…	4.08
	var.	6.19	7.17	5.44	…	1.28
steering wheel angular velocity (°/s)	mean	0.36	0.67	0.29	…	-0.35
	var.	20.0	40.6	7.63	…	8.57
yaw rate (°/s)	mean	0.02	0.02	0.02	…	0.01
	var.	2e-4	2e-4	2e-4	…	3e-4
lateral acceleration (m/s2)	mean	7e-3	0.03	0.02	…	0.01
	var.	2e-4	1e-4	1e-4	…	2e-4
longitudinal acceleration (m/s2)	mean	0.02	0.02	0.01	…	0.01
	var.	3e-4	2e-4	2e-4	…	3e-4

Table 3. Time domain feature parameters under cognitive distraction

	No.	1	2	3	…	50
steering wheel angle (°)	mean	1.29	2.19	2.04	…	2.78
	var.	8.38	4.31	5.91	…	3.98
steering wheel angular velocity (°/s)	mean	0.32	0.28	0.14	…	-0.53
	var.	36.4	29.5	24.8	…	42.4
yaw rate (°/s)	mean	0.02	0.02	0.02	…	0.01
	var.	2e-4	3e-4	3e-4	…	4e-4
lateral acceleration (m/s2)	mean	0.04	0.02	0.02	…	0.04
	var.	1e-4	1e-4	2e-4	…	1e-4
longitudinal acceleration (m/s2)	mean	0.02	0.02	0.02	…	0.01
	var.	3e-4	3e-4	3e-4	…	4e-4

5. Conclusion

(1) The frequency domain analysis result of wavelet packet decomposition of the experimental parameters shows that the high-frequency energy value of the steering wheel angle parameter during cognitively distracted driving is generally greater than the high-frequency energy value of the steering wheel angle in the normal driving state, the high and low frequency energy values of the steering wheel angular velocity are all greater than the corresponding high and low frequency energy value under normal driving state, and the low frequency energy value of lateral acceleration is greater than the low frequency energy value under normal driving state in overall.

(2) This paper uses the support vector machine algorithm. When the model input is the time domain feature parameter, that is, when the mean and variance of the five parameters in the two driving states are used as input, the algorithm has accuracy rates of 75% and 79.2% respectively in identifying normal driving state and cognitively distracted driving state. When the model input is the frequency domain feature parameters, the energy values of the high and low frequency bands after the first layer decomposition of the wavelet packet under the two driving states are used as the input, and the accuracy rates in identifying normal driving and cognitively distracted driving state are 83.3% and 87.5%, respectively.

(3) This paper uses 10s as a unit to study the difference between normal driving and cognitively distracted driving behavior. Distracted driving often occurs in a shorter period of time. Therefore, a collection device with a higher collection frequency can be used later to shorten the research time unit.

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