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Research on Driver Emotion Classification Based on ECG Signals

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ABSTRACT

Traffic includes factors that affect people, vehicles, and the environment. According to official data, traffic accidents caused directly or indirectly by human factors account for over 90% of the total number of traffic accidents, of which 70% are caused by vehicle drivers. Studying driver characteristics and considering driver factors in traffic safety has become an increasingly popular topic in the field of traffic safety. Driving emotions, as one of the driver characteristics, have a strong correlation with driving behavior. This article designs a simulated driving experiment and collects the electrocardiogram (ECG) indicators of drivers in driving with pleasure and anger during the experiment. The KNN clustering algorithm is used to classify and analyze the driver's emotions.

Keywords: driving safety; driving emotions; electrocardiogram; clustering algorithm

INTRODUCTION

There is a strong correlation between emotions and behavior, and drivers experience different changes in driving behavior under different driving emotions. For example, drivers are more likely to engage in dangerous driving behaviors under anxiety. We can use electrocardiogram (ECG) detection equipment to detect changes in the driver's ECG characteristics, distinguish the driver's emotional characteristics, and predict dangerous behaviors in advance and issue warnings to avoid dangerous driving behaviors.

The degree of emotional changes in drivers varies, and the electrocardiogram characteristics will also change accordingly. By observing the characteristics and degrees of electrocardiogram changes, we can determine the types and degrees of emotional changes in drivers. In the state of following the car, the driver's driving behavior may change due to emotional changes. Under the influence of certain negative emotions, aggressive driving behavior can lead to traffic accidents. Studying the relationship between driver emotions and changes in electrocardiogram can monitor driver emotional changes in real-time through electrocardiogram, thereby determining possible changes in driving behavior during following, predicting the occurrence of dangerous driving behaviors, and having important implications for driver safety driving.

DRIVING EXPERIMENT

(1) Experimental equipment

The experimental equipment used in this experiment mainly includes a simulated driving device. The simulated driving device utilizes UC win/Road software and electrocardiogram devices to establish a three lane urban road scene. Through emotional stimulation, the electrocardiogram signal data of drivers in following driving under joyful and angry emotions are obtained.

Simulated driving experiments have the characteristic of higher safety compared to actual vehicle tests, and are suitable for conducting driving experiments for drivers under emotional stimulation.

FIGURE 1: Simulated Driving Equipment.

(2) Experimental subjects

In this study, we selected a total of 150 drivers, of which 82 were male drivers and 68 were female drivers. The experimental subjects were aged 20-45 years old, with an average age of 28.8 years old.

DATA DESCRIPTION AND ANALYSIS

(1) Data Collection and Preprocessing

By simulating the driving behavior of following the car and stimulating the driver's emotions during the driving process, 12 types of electrocardiogram feature data were obtained for 150 drivers under both happy and angry emotions.

TABLE 1: Partial Data of Driver's ECG Characteristics.

variable	abbreviation
R-wave average peak（uV）	RWAVE
T-wave average peak (uV)	TWAVE
Q-wave average peak (uV)	Q
S-wave average peak (uV)	S
Average heart rate (bpm)	AVHR
Atrioventricular interval (ms)	AVNN
Standard deviation of NN interval (ms)	SDNN
Percentage of NN intervals greater than 50ms (%)	PNN50
root-mean-square (ms)	RMSSD
Lowest frequency to highest frequency ratio	UVLF / VLF
Low frequency to high frequency ratio	LF / HF
total power (ms2)	TP

During the data collection process, due to the influence of experimental environment, equipment, and human factors, noise is inevitably present in the original electrocardiogram signal. The three main types of noise are as follows:

1. Motion artifact: The step change in the electrocardiogram signal is caused by the misalignment movement between the electrode and the skin.
2. Power frequency interference: Electromagnetic radiation in the experimental environment generates noise.
3. Sensor internal interference: Noise is generated by the current flowing through the internal components of the sensor.

Before analyzing data, removing noise from the original data is an important first step. PSYLAB software is used to preprocess raw electrocardiogram signal data. The definition of denoising preprocessing parameters is shown in Table 2 Through noise suppression processing, motion artifacts, power frequency interference, and sensor internal interference can be eliminated to an acceptable level. The comparison of electrocardiogram signals before and after denoising is shown in Figure 3.

TABLE 2: Definition of denoising preprocessing parameters.

White noise removal	Baseline denoising	Low pass denoising	band stop
Eliminating white noise in electrocardiogram signals	Retain high-frequency signals and cut off low-frequency signals	Preserve low-frequency signals, and Cut off the high-frequency signal.	Eliminating power frequency interference

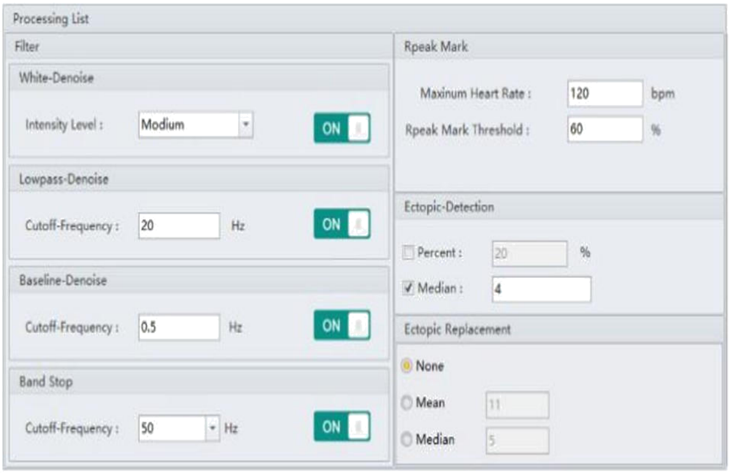

FIGURE 2：Original ECG signal denoising preprocessing interface.

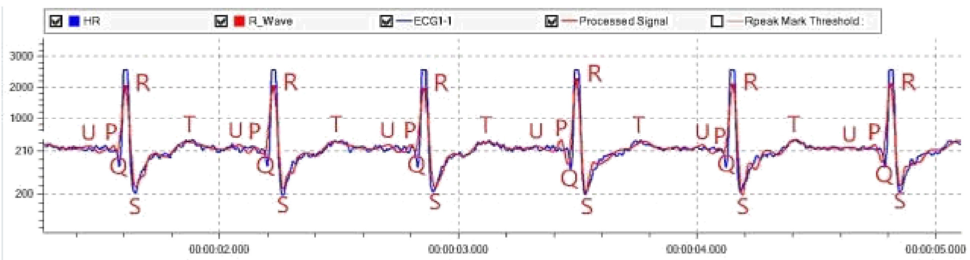

FIGURE 3: Comparison of electrocardiogram signals before and after denoising.

(2) Data Collection and Preprocessing

Perform differential analysis on 12 types of data using SPSS software to determine whether there is a correlation between these 12 electrocardiogram features and emotions.

TABLE 3: Difference test of average peak value of R-wave.

		Levene test for variance equation		T-test for the mean equation						
		F	Sig.	t	df	Sig. (Bilateral)	Mean difference	Standard error value	95% confidence interval of difference: lower limit	95% confidence interval of difference: upper limit
RWAVE	Assuming equal variance	.083	.774	-.197	298	.024	-9.91880	50.42568	-109.15435	89.31675
	Assuming unequal variances			-.197	297.981	.024	-9.91880	50.42568	-109.15438	89.31678

By comparing the partial electrocardiogram characteristics of drivers under different emotions, it was found that there were significant differences in the average peak value of R wave, T wave, Q wave, average heart rate, atrioventricular interval, total power, and other data between happy and anxious driving states. Compared with the happy state, the anxious state showed that drivers had faster heart rate, shorter heart interval, more frequent heart rate fluctuations, and longer cardiac conduction time, Myocardial manifestations are more pronounced.

From the data, it can be seen that there are significant differences in the electrocardiogram data of drivers under different emotions during car following. In the car following model, we can quantify the driver's emotions based on the driver's electrocardiogram data, thereby quantifying the driver's emotional factors in the car following model. This is of great significance for the study of car following models.

ESTABLISHMENT OF KNN MODEL

(1) Algorithm Introduction

The K-Nearest Neighbors (KNN) algorithm is a classification algorithm whose idea is that a sample is the most similar to k samples in the dataset. If most of these k samples belong to a certain category, then the sample also belongs to that category.

Figure 4 Classification accuracy when K is taken as 1-10.
The advantages of K-nearest neighbor algorithm:
1) Simple and effective.
2) Low cost of retraining.
3) Low algorithm complexity.
4) Suitable for class domain cross samples.
5) Suitable for automatic classification of large samples.

(2) Data processing

After removing variables that are not related to emotions from the electrocardiogram data of drivers driving with cars, the K-nearest neighbor model is used to classify emotions based on the electrocardiogram data. 130 sets of data on pleasure and anger emotions were taken as the training set, and 20 sets of data on pleasure and anger emotions were taken as the test set. When K was taken as 1-10, the classification accuracy was shown in the following figure.

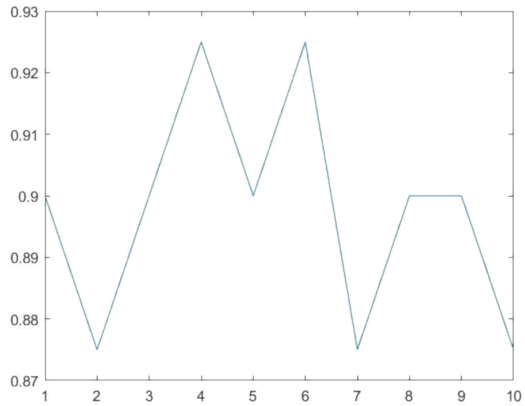

FIGURE 4: Classification accuracy when K is taken as 1-10.

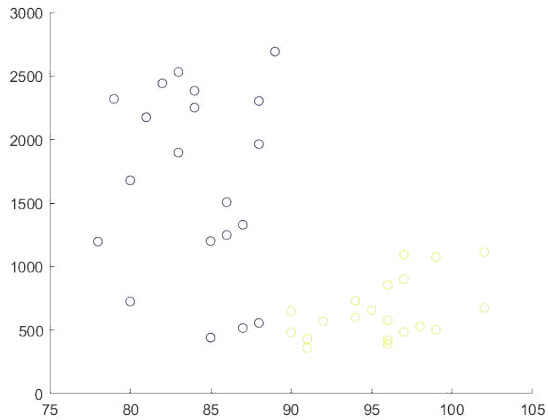

FIGURE 5: Classification diagram when K is taken as 4.

CONCLUSION AND OUTLOOK

Based on driver electrocardiogram data, the accuracy of driver emotion classification using KNN algorithm can achieve high accuracy. This study suggests that electrocardiogram signals can be used to identify the anxiety and pleasure emotional states of drivers during driving. This system can be used for the development of a driving warning system to predict unsafe driving behaviors caused by anxiety and send alarm signals to drivers. In addition, the research results can also be used to develop personalized driving warning systems for different types of drivers. The results of this study have important theoretical significance and application value for the development of intelligent transportation systems. Further research requires more participants to confirm the above findings and collect more data from each participant to improve the accuracy and reliability of the experiment.

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