Drivers Pressures States Recognition based on Heart Rate Variability

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Abstract: Drivers pressures are major causes of road accidents, and thus drivers' pressures states recognition become an important topic in Advanced Driver Assistant System (ADAS). Physiological signals provide information about the internal functioning of human body and thereby provide accurate, reliable and robust information on the driver's state. In this work, the several features, which are 8 heart rate variability features and 10 mathematical features, are trained using three classifiers: Support Vector Machine (SVM), K-nearest-neighbor (KNN) and Ensemble. The algorithms based pNN5 and LF/HF achieved best performance in HRV linear features evaluation, and the accuracy (AC), sensitivity (SE), specificity (SP) for Stress Recognition in Automobile Drivers data are 89.0%, 91.8% and 77.3% respectively. The mathematical features result in 98.6%,99.1% and 91.5% for accuracy (AC), sensitivity (SE), specificity, respectively.

1 INTRODUCTION

It is easy for drivers to have mental stress during the driving process, due to monotonous driving behavior. For example, long-time traffic jams or driving on heavily congested roads will increase the risk of driver accidents. It is found potential hazards caused by various driver pressures (Gibson 2000). However, the recognition and classification of driver pressure levels can be used as a monitoring and early warning technology for ADAS, which has developed rapidly in recent years.

In the selection of driver's physiological parameters, the mental state recognition method based on EEG has been proposed (Su 2008, C 2010, F 2012, Hashemi 2014), but it is difficult to put into actual use, due to the poor noise immunity and difficulty of deployment of EEG acquisition in the vehicle scene. It is proved that drivers' skin conductance and heart rate parameters are more clearly related to their stress levels, according to experiments (Singh 2014). In addition, driving fatigue state detection has also been proposed, based on analysis method of facial image and vehicle driving data (Mbouna 2013, Jo 2014, Cyganek 2104). However, these methods require special equipment to be installed in the vehicle, such as a camera for facial image collection or a data recording device for accessing vehicle driving data.

Based on the driver's heart, the pressure detection method has also attracted much attention. According to the principle that sleep affects the driver's autonomic nervous system (ANS) and heart activity, fatigue detection is carried out, based on the physiological parameters of the heart. In 2005, It is proposed the most practical method to detect the driver's condition during actual driving based on heart rate detection (Healey 2005). In 2016, it is (Chui 2016) et al. proposed a fatigue detection method based on driver's electrocardiogram. The psychological impact of the road traffic environment on drivers and the resulting physiological burden and changes in driving behavior were studied (Domestic 2001). In addition, some researchers detect fatigue driving behavior based on Photo Plethysmo Graphy (PPG) signals (Lee 2011). Although experiments show that this method can obtain good performance, it is difficult to stably obtain good ECG or PPG signals, due to the influence of car motion.

Nevertheless, the heart rate variability (HRV) extracted from ECG and PPG signals has a strong anti-noise ability, which is an effective sign to identify the internal state of the human body.

Based on the MIT-BIH autopilot pressure recognition data set, this paper carried out research on the pressure state recognition algorithm by using the driver's HRV. After the ECG signal is preprocessed, 8 kinds of HRV parameters are extracted, and then 10

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mathematical features with statistical significance are obtained. After sorting all the features, support vector machine (SVM) and K nearest neighbor (KNN) are trained in two classifiers.

The structure of this article is as follows: in the second section, we will introduce the new system structure. The third section introduces the analysis methods of the studied variables. The experimental results are shown in the fourth section. Finally, this article reviews the main conclusions and discusses future work in the fifth section.

2 DRIVER STATE FEATURE EXTRACTION BASED ON HEART RATE VARIABILITY

2.1 Heart Rate Variability

The R wave is the highest peak in the ECG, and the RR interval (RRI) is defined as the interval between the R wave and the next R wave. HRV is the fluctuation of RRI, a physiological phenomenon that reflects the activity of the cardiac autonomic nervous system. Therefore, HRV analysis is used to monitor stress and cardiovascular disease. Although there are two features of HRV: linear finite element features and nonlinear features, this study mainly uses linear finite element features, as the extraction of non-linear features requires long-term RRI measurement to keep the output features stable, which can't be used in real time, for example, fatigue driving early warning. Linear HRV features are divided into time domain features and frequency domain features.

Time-domain features include:

- MeanNN: the average value of RRI.
- SDNN: standard deviation of RRI.
- RMSSD: root mean square error of adjacent RRI.
- TP: total power change of RRI.
- pNN50: the number of sample pairs where the difference between adjacent RRIs is greater than 50ms in a given measurement time.

Frequency-domain features include as follows.

The first one is Low Frequency (LF), which is the power in the low frequency band of the PSD (0.04 Hz-0.15 Hz). LF mainly reflects the regulation of sympathetic nerves, with the main function of sympathetic nerves to strengthen the heartbeat and muscle work ability. The sympathetic nerve has an inhibitory effect on the smooth muscle of the bronchioles, making the bronchi dilate, which is conducive to lung breathing. Sympathetic nerve activity increases when the body is under tension and requires intense ventilation.

The second one is High Frequency (HF), which is the power in the high frequency band of the PSD (0.15 Hz–0.4 Hz). HF mainly reflects the adjustment of the parasympathetic nerve to the body. The function of the parasympathetic nerve is opposite to the sympathetic nerve. The two jointly regulate the body's heart rate, respiration, glandular secretion, and the blood flow distribution of important organs, such as the liver and adrenal glands, which can slow the body's heartbeat, lower blood pressure and shrink the bronchi, so as to reduce unnecessary energy consumption and reflect the activities of the parasympathetic nervous system.

The third one is LF/HF, that is, LF to HF ratio, which shows the balance between the activities of the sympathetic nervous system and the parasympathetic nervous system. When the body holds still, the activity of the parasympathetic nerve increases. However, it may cause the body to fatigue after a long time. LF/HF must change continuously within a certain range, so as to maintain human health.

2.2 Mathematical Characteristics of Heart Rate Variability

After the ECG signal is filtered, the mathematical features of each linear feature are obtained based on linear HRV feature extraction. There are 12 time-domain linear features, including mean, median, standard deviation (SD), variance, maximum, minimum, skewness, kurtosis, power, root mean square (RMS), approximate entropy and Hurst exponent.

3 DATA SET OF DRIVER HEART RATE

3.1 Date Set

This research uses MIT-BIH's Stress Recognition in Automobile Drivers data set. Each sample in the data set uses electrocardiogram (ECG), electromyography (EMG), skin conductance (EDA) and respiration rate. The sampling frequency of ECG is 496 Hz, the sampling frequency of skin conductance and respiration is 31 Hz and the sampling frequency of EMG is 15.5 Hz, with a total of 17 driving tests. The labeled information comes from a questionnaire of all drivers, including the perception of low, medium, and high stress during rest, highway and city driving, with two scoring methods, free scoring and mandatory ranking. Drivers score the driving event amid the free scoring method, with the scoring standard from "1" to "5", where "1" represents the feeling of "no pressure" while "5" represents the feeling of "high pressure". Mandatory ranking requires drivers to rank events on a scale from 1 to 7, where "1" is assigned to the least stressful driving event, while "7" is assigned to the most stressful driving event. Drivers are asked to rate events by using this scale, including encounters with toll booths, mergers and exits and other city, and highway driving tasks. The values of the two stress levels in each questionnaire are standardized, and then the average and standard deviation are calculated and inversely transformed. The test analysis of all categories shows that the overall score and the comparison score are significantly different ($p>0.001$), which supports the rationality of the data set.

3.2 Data Preprocessing

The original ECG data collected from the driver includes noise caused by various reasons. First, it is needed to use a filter with a cutoff frequency of 3-100 Hz to eliminate noise. Then the heartbeat is detected by QRS complex scanner using Pan and Tompkins algorithm (Karegar 2017). The HRV signal is obtained by accurately measuring the R peak value from the ECG signal based on the wavelet transform technique (Zhao 2012).

3.3 Feature Extraction

The preprocessed ECG signal is first subjected to HRV linear feature extraction to generate 8 HRV features, including MeanNN, SDNN, RMSSD, TP, NN50, LF, HF and LF/HF. The time-domain features are extracted by algorithms to generate mathematical features, with a total of 5*10+3=53 types of features. The significant difference values of the mathematical characteristics of the sample categories are shown in Table 1.

Table 1: Significant differences of varies characteristics.

Time-frequency characteristics	**Time-frequency characteristics**
Mean	Skewness
Median	Kurtosis
Standard variance	power
variance	Root Mean Square (RMS)
Hurst index	Approximate entropy

3.4 Classifier

SVM, KNN and ensemble classifiers are used to classify features in the experiment. 75% of the data is used for training the classifier, while 25% of the data is used for testing. Support vector machine is a classic binary classification algorithm, which seeks the optimal linear decision surface between classes by minimizing structural risks (Zhang 2015). KNN is a super machine learning algorithm that uses autoregressive features and each form to classify various low alert states, which is better than quadratic discriminant analysis (QDA) and linear discriminant analysis (LDA) (Bhuvaneswari 2015).

3.5 Evaluation Method

We can calculate true positive (TP), false negative (FN), true negative (TN) and false positive (FP), so we can calculate performances of accuracy (AC), sensitivity (SE) and specificity (SP). For example:

$$AC(\%) = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{1}$$

$$SE(\%) = \frac{TP}{TP+FN} \times 100 \tag{2}$$

$$SP(\%) = \frac{TN}{TN+FP} \times 100 \tag{3}$$

In addition, because our test data is biased (the pressure-free interval is more than the pressure interval), it is important to have two parameters, namely, the balance accuracy (BA) and the geometric mean (GM), such as

$$BA(\%) = \frac{1}{2}\left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP}\right) \times 100 \tag{4}$$

$$GM(\%) = \sqrt{\frac{TP}{TP+FN} + \frac{TN}{TN+FP}} \times 100 \tag{5}$$

4 THE RECOGNITION OF DRIVER'S STRESS STATE

This research carried out the following experiments. the first one is to extract 5 kinds of heart rate variability features, and then calculate 20 kinds of time-frequency domain features, and then input the heart rate variability features as training data into the classifier for training and evaluation. The second one is to extract 5 kinds of heart rate variability features, and then calculate 20 kinds of time-frequency domain features, and then input each time-frequency domain feature as training data into the classifier for training and evaluation. The difference between the two experiments is to focus on the characteristics of heart rate variability and time-frequency domain characteristics. And the contribution of various features to the performance of the classifier is tested through the experiments.

Experiment 1 uses various HRV features extracted by the heart rate variability analysis method, carries out training modeling and obtains experimental results. It can be seen from Table 2 that SDNN and RMSSD can get better recognition results, while RRI and pNN50 are slightly less effective, and features got by TP are the worst. This reflects that the sensitivity of these features has a high degree of discrimination for identifying the driver's stress state.

Table 2: Driver status recognition results based on the characteristics of heart rate variability.

HRV	Classifier	Accuracy AC (%)	Sensitivity SE (%)	Specificity SP (%)	Balance accuracy BA (%)	Geometric mean GM (%)
MeanNN	SVM	69.0	77.2	32.6	54.9	104.8
	KNN	75.0	81.9	41.2	61.6	111.0
SDNN	SVM	78.0	84.1	47.6	65.9	114.8
	KNN	77.0	83.1	49.5	66.3	115.1
RMSSD	SVM	72.0	78.7	47.2	62.9	112.2
	KNN	79.5	84.8	57.3	71.0	119.2
TP	SVM	69.0	75.4	49.2	62.3	111.6
	KNN	69.0	75.1	51.2	63.1	112.4
pNN50	SVM	88.0	91.1	74.5	82.8	128.7
	KNN	89.0	91.8	77.3	84.6	130.1
LF	SVM	74.3	79.1	60.9	70.0	118.3
	KNN	72.7	77.3	60.9	69.1	117.5
HF	SVM	71.5	75.8	61.2	68.5	117.0
	KNN	75.6	79.4	66.1	72.8	120.6
LF/HF	SVM	89.0	91.3	82.0	86.6	131.6
	KNN	92.0	93.7	86.8	90.2	134.3

Experiment 2 uses various HRV features extracted by the time-frequency analysis method, carries out training modeling and obtains experimental results. It can be seen from Table 3 that the model recognition accuracy of features such as mean, variance, mean square deviation, and maximum value is higher, which reflects that these features contain more discernable information about the driver's state. However, the Hurst index, skewness, kurtosis, Q1 and other parameters have little effect on the performance of the recognizer, with the recognition rate at the range of 50%±5.

Table 2: Driver status recognition results based on time-frequency characteristics

Mathematical characteristics	Classifier	Accuracy AC (%)	Sensitivity SE (%)	Specificity SP (%)	Balance accuracy BA (%)	Geometric mean GM (%)
features	SVM	98.6	99.1	91.5	95.3	138.0
	KNN	98.2	98.8	90.7	94.8	137.7
mean	SVM	96.0	97.4	78.9	88.2	132.8
	KNN	92.0	94.7	68.6	81.6	127.8
median	SVM	92.0	94.6	71.4	83.0	128.8
	KNN	95.0	96.6	81.8	89.2	133.6
standard deviation (SD)	SVM	94.0	95.9	80.6	88.3	132.9
	KNN	95.0	96.6	84.6	90.6	134.6
variance	SVM	91.0	93.6	76.9	85.3	130.6
	KNN	92.0	94.3	80.2	87.3	132.1
Hurst index	SVM	85.0	88.8	70.0	79.4	126.0
	KNN	86.5	89.8	73.5	81.7	127.8

Skewness	SVM	89.0	91.7	78.4	85.1	130.4
	KNN	88.9	91.5	79.3	85.4	130.7
Kurtosis	SVM	87.1	89.9	77.7	83.8	129.5
	KNN	89.2	91.5	81.5	86.5	131.5
power	SVM	68.0	71.4	61.0	66.2	115.1
	KNN	70.5	73.7	64.0	68.8	117.3
Root mean square(RMS)	SVM	93.5	94.8	89.4	92.1	135.7
	KNN	94.4	95.5	91.1	93.3	136.6
Approximate entropy	SVM	84.3	86.5	79.3	82.9	128.7
	KNN	85.4	87.3	81.1	84.2	129.8

5 CONCLUSION

This study uses the ECG physiological signal data set to study the method of identifying the driver's stress. The results show that the features perform better in detecting the three categories of low pressure, medium pressure and high pressure, according to the results of the classifier, with classification accuracy rates at 93.1%, 96.6%, and 96.6%, respectively. With the improvement of ECG performance, other physiological signals can also be combined to improve the detection accuracy of low vigilance. In the future, vehicle and behavior-based methods can be combined with physiological methods to develop reliable detection methods of driver state.

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