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Study of Stress Rules Based on HRV Features

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Abstract. In this paper, we proposed an estimation method of the ranges of HRV feature values based on improved decision tree, which used to describe stress. This method extracted HRV features from short-time (2min) ECG signals that obtained from stress-stimulate experiments. Then, multiple decision trees were summarized as a tree with universal recognition performance by utilizing the white-box classification characteristic of the decision tree. Finally, the ranges of the HRV features were extracted from the tree. The method proposed in this paper can display the ranges of the HRV features and had been experimented with 250 ECG signals collected from 114 subjects. The results show, two different states of relaxation and high-stress can be recognized by utilizing the ranges of the HRV features, and the recognition accuracy rate was 86.7%, not less than the traditional classification models. Moreover, the recognition process is simple and the practical application value is high.

Keywords: decision tree, heart rate variability, stress recognition

1 Introduction

People had paid attention to emotion recognition for a long period of time, and related research work in psychology has becoming a leading role. In recent years, rapid working rhythm and high life stress have taken a great effort on people's emotions. Sometimes it is difficult to maintain a relatively stable mood especially when in driving cars, working, traveling and doing other boring activities. Therefore, there is a need for self-emotion adjustment and mental health surveillance on the base of monitoring emotion changes. With the achievement of manufacturing portable and wearable embedded ECG acquisition device, ECG signal can be acquired convenient. As a consequence, HRV (Heart Rate Variability, the subtle changes between the successive heartbeats) can be easily gotten. HRV analysis were proved be associated with emotional stress [1-2]. Over the past decade, most studies had used HRV features by the help of traditional machine learning algorithms to construct emotion classification model. These studies were usually composed of three parts: signal acquisition and prepossessing, feature extraction and classification [3-7]. In processing part, R point of ECG were identified firstly, and then the duration of each R-R interval was accurately calculated in ms and HRV curve were drawn by these duration [8-12]. In feature extracting part, features were extracted from in time and frequent domain by the curve. The features were originally used to assess cardiac status in clinical diagnosis [13]. In building classification mode part, research works were trying on Probabilistic Neural Network (PNN) [3], k Nearest Neighbor (KNN) [3], Linear Discriminant Analysis (LDA) [4], Logistic Regression (LR) [4], Support Vector Machine (SVM) [7], Naive Bayesian Model (NBM) [7] and so on.

In previous studies, the affecting elicitation mainly included playing the movie clips and pictures, completing the mental arithmetic tasks, color vocabulary testing and playing video games [14-17]. However, due to the induction of stress was related to personal experience and individual differences, the evaluation of the emotion labels will be more subjective under variety of elicitation modes (I.e. calm state, stressful state, etc.). There need more objective strategy or method in emotion induction.

And, in the studies of emotion recognition, most of them used the black box training model, and the researchers do not understand the quantitative expression of the features and the relationship between

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emotions and features. In clinical diagnosis, the HRV feature values obtained from 24 hour ECG data in expressing the degree of heart disease [19]. This gives us a guidance to express HRV features in value range by short-time ECG.

From the above analysis, a quantitative description of stress emotion based on HRV features was proposed in this paper. Firstly, a modified game, name "Rhythm Master", was used to stimulate the subject's stress. We record the detailed game parameters, and game result to label subject's emotion state, calm and stressful. In order to label the subject's emotion more accurate, their facial expressions were recorded with the camera during the game and the questionnaires were asked immediately after game, these are introduced to label emotion auxiliary. The ECG signals of subjects were recorded through the procedure. Secondly, each HRV feature was calculated and considered as input to classification model. In this part, a modified decision tree establishing strategy was used. Finally, the quantitative expressions of each feature were gotten, and expressed in rule. The estimation process of the range of HRV features was as shown in Fig. 1.

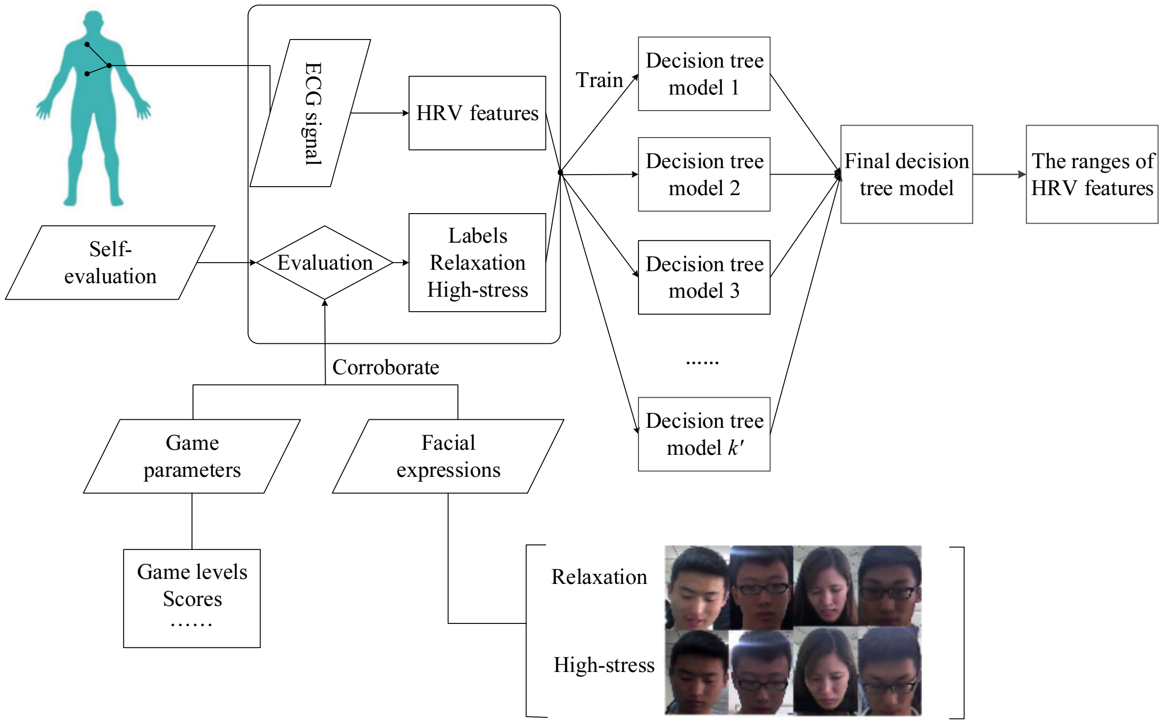


Fig. 1. Estimation process of the range of HRV features based on stress emotion

The rest of this paper was arranged as follow. The stress-stimulating method and the extraction of HRV features were described in the second section. The improvement strategy of the decision tree for classification was described in the third section. The fourth part introduced the quantitative estimation method of the HRV features. The fifth part was experimental design and results analysis. Finally, the sixth part was summary and outlook.

2 Stress-Stimulated Methods and HRV Parameters

2.1 Stress-Stimulated Method Based on the Rhythm Master Game

This article used the popular "Rhythm Master" game to stimulate the emotions. For better labeling the emotion mark, some modifications had been done on the game. We record every click during the game, the gap time between clicks were recorded, so does the faults click and missing click. These parameters along with the difficulty level of music, speed of beat, ratio of rhythm change, and the original score system of the game. By setting the difficulty level of the game to stimulate the subjects generated stresses, the facial expressions of the subjects and stress questionnaire at the end of game were assist in evaluating the stress states, at the same time, the subjects' ECG signals were recorded.

2.2 HRV Parameters

It had been proved by bio-engineering that the motion of the heart was pseudo-periodic, and had a deterministic chaotic dynamics [18]. From the physiological point of view, HRV was thought to be related to the dynamic changes of tension of vagus nerve and sympathetic nerve. So, HRV was used to assess emotions, but there was no quantified reference ranges similar to that of clinical diagnosis.

The parameters of HRV were extracted from different aspects, such as time domain, frequency domain and nonlinear domain. From the detection point of view, the PP intervals should be used to calculate HRV parameters. However, the detection of P wave was difficult. From clinical study, PP interval is same as RR interval, so PP interval was substituted by RR interval as shown in Fig. 2.

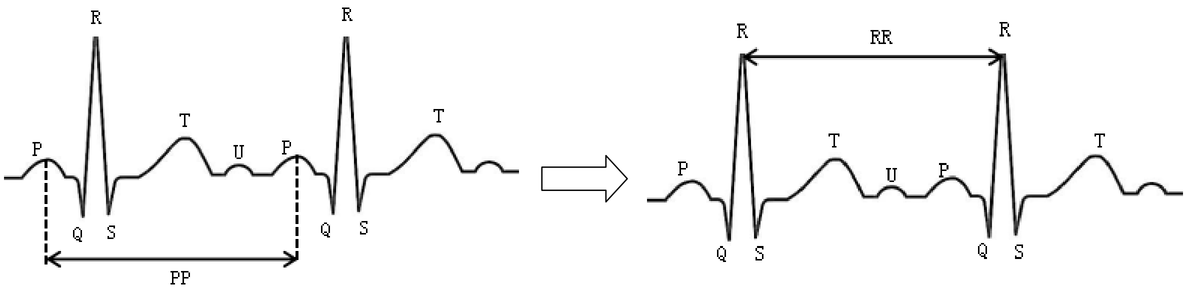


Fig. 2. Schematic diagram of the ECG waveform position that can obtain HRV data

Research work of the paper was depended on 5-minute HRV parameters in clinical diagnosis [20], including some time domain parameters, such as SDNN for assessing the overall change in heart rate variability, RMSSD is for reflecting the rapidly changing component of heart rate, the NN50 is for measuring the tension of vagus, PNN50 is responding to the vagus activity sensitively. According to HRV as shown in Fig. 3, some parameters in frequency domain were calculated, most of work was done through Fourier transform to obtain the power spectral density distribution curve of HRV curve. The obtained parameters included low frequency (LF) that reflects the sympathetic nerve activity, high frequency (HF) that reflects vagal activity and LF/HF that reflects the balance of both sympathetic and vagal nerve tension, as shown in Fig. 4. In addition, the HRV nonlinear analysis was also valuable, such as the vector angle index (VAI) in Poincare plot, and the Poincare plot of an individual in different states (calm, high-stress) is shown in Fig. 5.

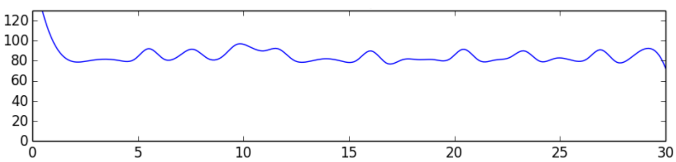


Fig. 3. HRV curve

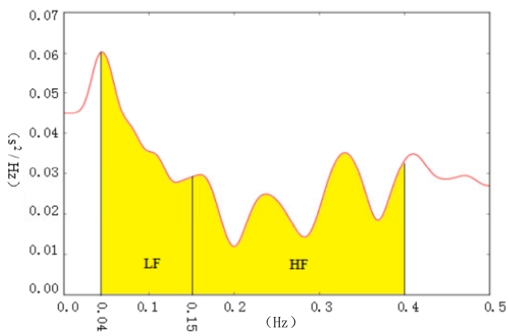


Fig. 4. HRV power spectral density based on the Lomb-Scargle method

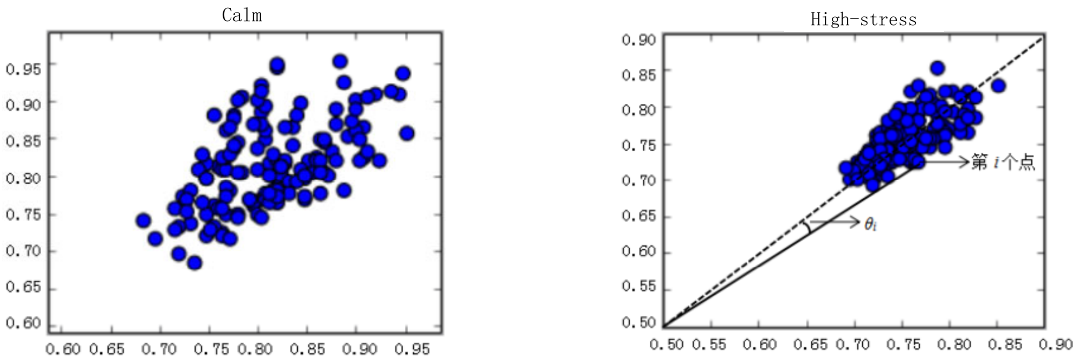


Fig. 5. Scatter diagram of nonlinear components of HRV

In this paper, the emotional classification system was built based on the above features. The formulas and annotations these HRV features were as shown in Table 1.

Table 1. The HRV features used in this article

Feature	Unit	Formula or annotation
SDNN	ms	$\mathrm{SDNN}(ms) = \sqrt{\sum_{i=1}^{N}(RR_i - \overline{RR})^2 \Big/ (N-1)}$
RMSSD	ms	$\mathrm{RMSSD}\ (ms) = \sqrt{\sum_{i=1}^{N}(\Delta RR_i)^2 \Big/ N}$
NN50	piece	The number of interval differences of successive RR intervals more than 50ms
PNN50	%	The percentage of interval differences of successive RR intervals more than 50ms
LF	ms^2	Low frequency power (0.04-0.15Hz)
HF	ms^2	High frequency power (0.15-0.4Hz)
LF/HF		ratio of LF and HF
VAI	°	$\mathrm{VAI}\ (°) = \sum_{i=1}^{N} \lvert\theta_i - 45\rvert \Big/ N$

3 Estimation Strategy of HRV Features value Based on Decision Tree

Decision tree is a basic classification and regression method. From its result, classification was expressed in rules, and each rule was composed by a sequence judgment. The judgment was done on exact range of parameters. This was met with our consideration on parameter value range partition.

After observing the HRV parameters in previous early experiments, we found that the values of the most parameters in high pressure samples were relative smaller than that of in relaxation sample. And the values of all HRV parameters were continuous. Classical C4.5 can be selected, except it's binary tree structure. In the study, we needed to divide the space into three parts when determined the range of each HRV features. The three parts were [∞, low value], [low value, high value] and [high value, ∞]. So the C4.5 algorithm was modified to fit that. Following was the description of three procedures in our proposed classification under tree manipulation.

3.1 The Construction of Decision Trees

The core of C4.5 algorithm was using the information gain ratio at each node of the trees to select the attribute, and constructed the decision trees recursively.

In this paper, the HRV features and the training sets represented by pressure labels are expressed as:

$$D = \{(x_1, y_1), (x_2, y_2), \cdots, (x_N, y_N)\} \tag{1}$$

D is training set, $x_i = (x_i^{(1)}, x_i^{(2)}, \ldots, x_i^{(n)})^T \in \chi \subseteq R^{n}$, is HRV features matrix, n is the number of feature, $y_i \in \gamma = \{c_1, c_2, \ldots, c_m\}$ is the category, in the paper, $m = 2$, where $c_1 = 0$ represents the relaxed state, $c_2 = 1$

represents the stressful state, N is the number of sample. Assuming that the attribute set of D is $A = \{A_1, A_2, A_3, ..., A_n\}$, then the procedure of the tree model T was shown as follows:

(1) Find high and low threshold values. For each attribute A_i in A, the value of the training set D on this attribute was sorted in ascending order. Then, searching for the first sample which category was different from the category of the minimum value, this attribute value of this sample was defined as a low threshold (l_i, $i = 1, 2, ..., n$) for division, the values of the training set on one attribute that less than the low threshold were recorded (l_sample_i, $i = 1, 2, ..., n$). Similarly, for each attribute A_i in A, the value of the training set D on this attribute was sorted in descending order. Then, searching for first sample from the maximum which category was different from the category of the maximum value, the attribute value of this sample was defined as a high threshold (h_i, $i = 1, 2, ..., n$) for division, the values of the training set on one attribute that greater than the high threshold were recorded (h_sample_i, $i = 1, 2, ..., n$). If $l_i > h_i$, set $(l_i+h_i)/2$, as the only threshold of the attribute.

(2) Used the high and low thresholds to segment data set, and found the maximum information gain ratio of the attributes. For each attribute A_i ($i = 1, 2, ..., n$) in the A, the data set was divided into a number of nonempty subsets D_i ($2 \leq i \leq 3$) according to the corresponding low threshold l_i and high threshold h_i. Then, information gain ratio of D_i ($2 \leq i \leq 3$) to D was calculated, and selected the attribute with largest gain ratio.

3.2 Selection of Decision Trees

Assume tree set was sign as F. N samples were divided into d groups on average randomly, the number of sample of each group was N/d. Each group was divided into training set and test set by the ratio of x':y'. After tree construction, p was defined as minimum accuracy rate. If the recognition accuracy of T was greater than or equal to $p(0 \leq p \leq 1)$, added T to F. In each group k trees were constructed. Finally, k' eligible trees $\{T_1, T_2, T_3, ..., T_{k'}\}$ were gotten.

3.3 Merging of the Decision Trees

Use the following strategy to merge the trees selected in Section 3.2. The specific process is shown in Fig. 7.

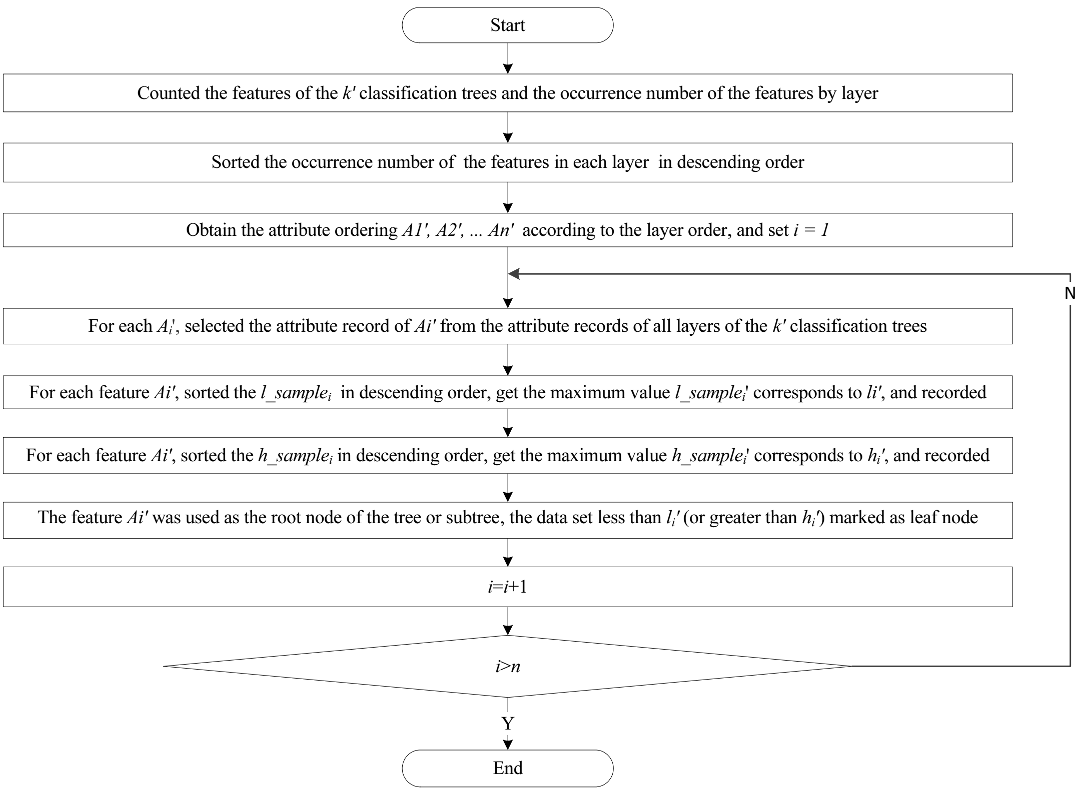


Fig. 7. Merging of the decision trees

(1) To each tree of F, attribute name and occurrence time in each layer were recorded and counted.

(2) For each layer of the decision trees, sorted the number of occurrences of each attribute in descending order, and get the corresponding attribute ordering. If the attributes used in different layers were duplicated, sorted by the number of occurrences at the highest layer, that is, each attribute was only sorted once. Finally, according to the sequence, a total attribute ordering was obtained (A_1', A_2', .., .A_n').

(3) For each A_i' (i = 1, 2, ..., n), the attribute record of A_i' was selected from the attribute records of all the layers of the k 'classification trees, denoted as set B. Then, in the set B, the l_sample_i was sorted in descending order to get $l\_sample_i' = max\{l\_sample_1', l\_sample_2', ...\}$, and the h_sample_i was sorted in ascending order to get $h\_sample_i' = max\{h\_sample_1', h\_sample_2', ...\}$.

(4) A new tree was constructed based on the information obtained from steps (2) and (3), the attributes selection and the thresholds selection were also done. First, selected an attribute as the root node of the tree or subtree at a time, the attribute selection followed the result in step (2). Then, low threshold was l_i', corresponding to l_sample_i', high threshold was h_i', corresponding to h_sample_i'. Finally, recorded the information of each node (A_i', l_i', h_i').

(5) For leaf nodes less than l_i', the results were marked as $c_2 = 1$, for leaf nodes larger than h_i', the results were marked as $c_1 = 0$. For samples fell within low threshold and high threshold intervals, transfer steps 3) to 5) recursively to construct the sub-tree until all attributes were used or each HRV feature vector was classified accurately.

(6) The newly constructed tree model was used to predict the input M HRV eigenvectors, and get the recognition accuracy p'.

3.4 Estimation of the Range of HRV Features

The ranges of HRV features were estimated according to the optimal tree T'' obtained from the above steps, the relaxation range of attribute A_i' was $[0,l_i']$, and the high-stress range was $(h_i',+\infty)$. (i = 1, 2, ..., n)

This study could identify two different states of relaxation and high stress directly through the range of the HRV features in the tree.

4 Experiment and Result Analysis

4.1 The Collection of Experimental Data

In this paper, ECG signal was used which obtained by laboratory self-developed device. The ECG device' sample rate is 250Hz, and it collects one lead (V5) ECG signal. Data collection was carried out in a quiet, enclosed room. Some personal information was record before experiment.

In the experiment, the data collection process of each group was divided into two stages, two minutes resting and game playing, the two stages were label as relaxation and high-stress, as shown in Fig. 8.

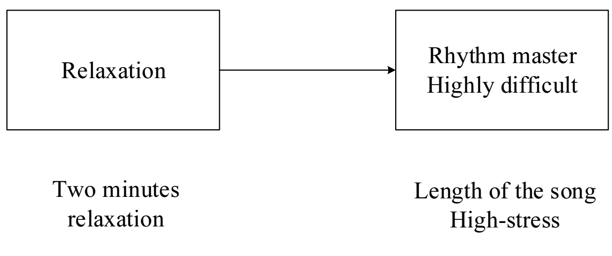
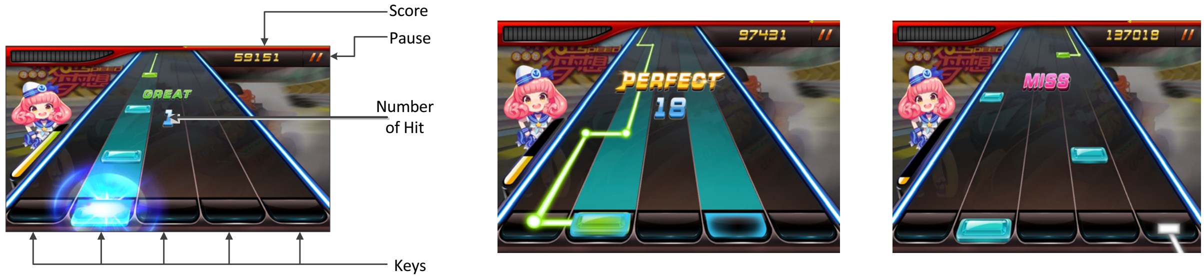


Fig. 8. Experimental procedure

In the experiment, the Android mobile game — rhythm master (self-designed) was used as high-stress stimulation. The interfaces for the different operations of the game were as shown in Fig. 9. Speed dream sung by Dangel, five-keys simple mode was selected, other parameter were 3 times speed, level 5 (level from 1 to 5 represents the level from low to high). The data of the relaxed state was obtained while the subject was in resting status. The subject's face images were also recorded by from camera in the experiment. At the end of the experiment, the subjects were asked to fill in a self-stress assessment report to assess labeling his/her stress state.



(a) Game interface

(b) Interface with a high score after accurate click

(c) Interface with a wrong click

Fig. 9. The rhythm master game of Mobile version

114 (male 83, female 31) healthy students (aged from 18 to 25) were selected in the experiment. Each subject will provide one or two group experiment data. Each group contains two minutes relaxation data and three minutes high-stress data. In the end, 205 groups of data were gotten.

4.2 Experiment Procedure

From experiment data, 105 two-minutes relax data and 100 three minutes high-stress data were randomly selected. Before experimenting, all data were truncated first two minutes preprocessing as experiment data. In the experiment procedure, firstly, HRV features were extracted from the 205 data as processed data. Secondly, the 205 data were divided into three parts by almost average, each part contained 68 or 69 data. Thirdly, in each part, training and test data ratio was set to 8:2, and selected $k \in [10,200]$, $k_d = 5$, $p \in [0.80, 1.00]$, $p_d = 0.01$, the optimal parameters in each group were determined $k = 25$, $p = 0.90$, that is 25 decision tree models need to be constructed in each group, and selected the tree models which recognition accuracy rate greater than 90%. Finally, 52 tree models were selected from the three part, and a new tree was managed according to the proposed algorithm in section 3.3. The process is shown in Fig. 10.

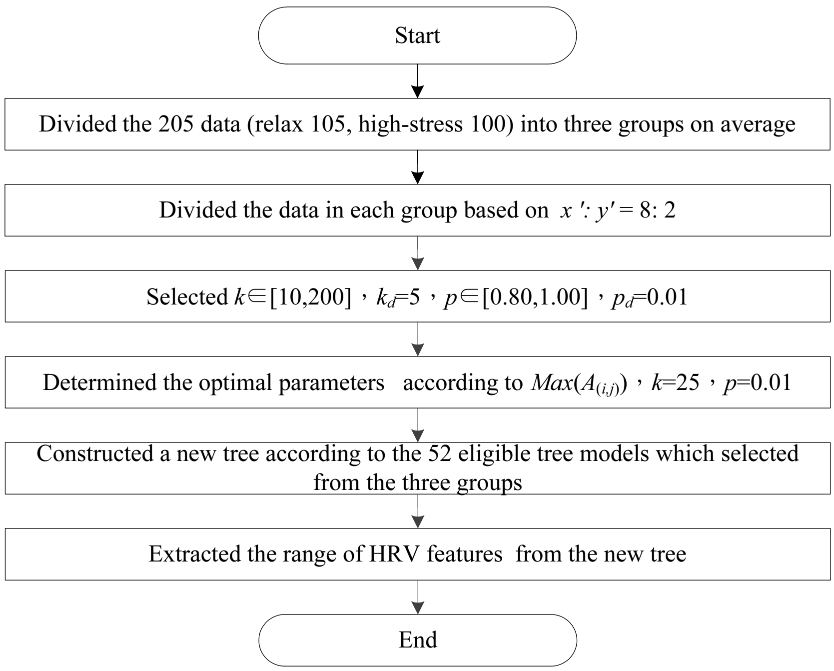


Fig. 10. Experimental procedure

4.3 Results and Analysis of the Experiment

From the merged tree, rules were gotten as shown in Table 2 and Table 3:

Table 2. The rules in relax state

No.	LF/HF	LF	SDNN	HF	VAI	PNN50	RMSSD	NN50	State
1	(0, 2.830)								
2		(0, 0.0358)							
3			(0, 0.0336)						
4				(0, 0.01038)					Relax
5	[2.830, 4.4705]	[0.0358, 0.0870]			(0, 0.46297)				
6			[0.0336, 0.03559]	[0.01038, 0.01328]		(0, 0.60241)			
7					[0.46297, 0.68994]	[0.60241, 0.63694]	(0, 0.01646)		
8							[0.01646, 0.02210]	(0, 3.0)	

Table 3. The rules in stress state

No.	LF/HF	LF	SDNN	HF	VAI	PNN50	RMSSD	NN50	State
1	(4.4705, +∞)								
2		(0.0870, +∞)							
3			(0.03560, +∞)						
4				(0.01038, +∞)					Stress
5	[2.8299, 4.4705]	[0.03583, 0.0870]			(0.68994, +∞)				
6			[0.03356, 0.03560]	[0.01038, 0.01328]		(0.63694, +∞)			
7					[0.46297, 0.68994]	[0.60241, 0.63694]	(0.02210, +∞)		
8							[0.01646, 0.02210]	[3,+∞)	

From the above rules, the ranges of the HRV features in two different states (relaxation and high-stress) were obtained, and the ranges were used to predict the states of 45 data (23 relaxation and 22 high-stress), the recognition accuracy rate was 86.7%.

Quickly and easily detect the psychological stress is of great significance for improving people's physical and mental health and the quality of life. This paper presented a complete set of stress quantification methods based on HRV features. The decision tree was used in this paper to determine the ranges of HRV features due to the model ultimately needed to be expressed by quantified rules and should has the advantages of explication, reduction and space division. Since the values of HRV features can be treated as continuous values, the C4.5 algorithm was chosen to carry out the estimation research. However, the tree structure of C4.5 algorithm was a binary tree, and we need to divide the space into three parts when determined the ranges of the features, the three parts were [∞, low value], [low value, high value] and [high value, ∞), so the C4.5 algorithm need to be improved.

The experimental data in this paper was obtained from the acquisition equipment of ECG signal which independently researched and developed by the laboratory, with the advantage of convenient and easy to get. The popular "rhythm master" game was used in this article to stimulate emotions, the speed of the beat and the rate of change were related to the difficulty level of the game, it was the use of this point to carry out the research of emotional elicitation and recognition. First, using different difficulty levels of the rhythm master game to stimulate the stress of the subjects, and collected the ECG signals of the subjects. In order to evaluate the stress labels scientifically and objectively, the stress states of the subjects were evaluated according to the difficulty level of the game, the parameters in the game (click accuracy, number of errors, score), facial expressions and questionnaire results. As the data and parameters settings were different, the tree models and classification accuracy were also different, the results were contingent. Therefore, we extracted the time domain, frequency domain and nonlinear domain features of HRV from ECG signals. Then, the tree models were constructed by using the improved C4.5 algorithm, and the appropriate tree model was selected by using the proposed tree selection strategy and the theory of parameters control. Next, the multiple tree models were merged based on the merging strategy. Finally a new tree was constructed, the ranges of the features were extracted from the new tree, and the feature quantization ranges corresponding to the stress were obtained which similar to the ranges of the HRV features in medicine. The ranges of the features derived in this paper can accommodate individual differences, and has universal significance.

Using the ranges of HRV features the relaxation and high-stress states could be distinguished, which similar to the ranges of the various indicators in the blood test, it’s very convenient. This method is no longer dependent on the data and classification models like the traditional classifiers, but objective and with universal significance. It has a high practical application value, can directly analysis whether somebody is in a high stress state through only one ECG waveform, and give people early warning about high-stress, for people to improve the quality of life, self-regulation, improve physical and mental health is of great significance.

5 Summary

Living in an increasingly competitive society, we are accompanied by the pressure all the time. Appropriate stress is helpful for people to work and study, but excessive stress can have a great impact on physical and mental health. Therefore, detect the psychological stress rapidly and conveniently is of great significance to improve people’s physical and mental health and the quality of life.

In this article, the ECG data both in relaxation and high-stress states can be obtained by using the electronic game which could stimulate the subjects to produce stress. Then, the time domain and frequency domain features of HRV were extracted, and the HRV features related to stress were excavated from multiple decision trees took the advantage of the white-box feature of the decision tree. Finally, the range of each relevant HRV feature was derived. The range of the features derived in this paper can accommodate individual differences, and has universal significance. As the HRV features can distinguish the two states of relaxation and high-stress, the high-stress warning of the human bodies can be carried out easily and efficiently, which has a high application value in practice.

In the study, it was uncontrollable to use the ready-made electronic game to stimulate stress, so the calibration of the labels may not be accurate. The future work will focus on developing games which can record the more objectively parameters of the game operation, and dig out more parameters related to high-stress state by machine learning algorithms, and help us to label emotion status more scientifically and accurately.

And for the experiment individuals, we need collect more in amount and more exactly in each individual’ detail changing, that will help us to find more close relationship with HRV features and human emotion status.

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References

[1] D.S. Quintana, A.J. Guastella, T. Outhred, Heart rate variability is associated with emotion recognition: direct evidence for a

relationship between the autonomic nervous system and social cognition, International Journal of Psychophysiology 86(2)(2012) 168-172.

[2] R.R. Singh, S. Conjeti, R. Banerjee, A comparative evaluation of neural network classifiers for stress level analysis of automotive drivers using physiological signals, Biomedical Signal Processing & Control 8(6)(2013) 740-754.

[3] P. Karthikeyan, M. Murugappan, S. Yaacob, Detection of Human stress using Short-Term ECG and HRV signals, Journal of Mechanics in Medicine & Biology 13(02)(2013) 1-29.

[4] B. Kaur, J.J. Durek, B.L. O'Kane, Heart rate variability (HRV): an indicator of stress, in: Proc. SPIE 9118, Independent Component Analyses, Compressive Sampling, Wavelets, Neural Net, Biosystems, and Nanoengineering XII, 91180V, 2014. doi:10.1117/12.2051148.

[5] H.W. Guo, Y.S. Huang, C.H. Lin, Heart rate variability signal features for emotion recognition by using principal component analysis and support vectors machine, in: Proc. International Conference on Bioinformatics and Bioengineering, 2016.

[6] G.Valenza, L.Citi, A. Lanatá, Revealing Real-Time Emotional Responses: a personalized assessment based on heartbeat dynamics, Scientific Reports 4(5)(2014) 4998.

[7] D. Mcduff, S. Gontarek, R. Picard, Remote measurement of cognitive stress via heart rate variability, in: Proc. Engineering in Medicine and Biology Society Conf Proc IEEE Eng Med Biol Soc, 2014.

[8] H. Khamis, R. Weiss, Y. Xie, QRS detection algorithm for telehealth electrocardiogram recordings, IEEE Transactions on Biomedical Engineering 63(7)(2016) 1377-1388.

[9] J. Kim, H. Shin, Simple and robust realtime QRS detection algorithm based on spatiotemporal characteristic of the QRS complex, Plos One 11(3)(2016) e0150144.

[10] M.S. Manikandan, K.P. Soman, A novel method for detecting R-peaks in electrocardiogram (ECG) signal, Biomedical Signal Processing & Control 7(2)(2012) 118-128.

[11] K.H. Choi, J. Kim, O.S. Kwon, Is heart rate variability (HRV) an adequate tool for evaluating human emotions? – a focus on the use of the International Affective Picture System (IAPS), Psychiatry Research 251(2017) 192-196.

[12] J.S. Wang, C.W. Lin, Y.T.C. Yang, A k-nearest-neighbor classifier with heart rate variability feature-based transformation algorithm for driving stress recognition, Neurocomputing 116(10)(2013) 136-143.

[13] H. Dong, Study on ECG Waveform Detection and Heart Rate Variability Analysis, Lanzhou University of Technology, Lanzhou, China, 2012.

[14] B. Zhang, Y. Morère, L. Sieler, C. Langlet, B. Bolmont, G. Bourhis, Reaction time and physiological signals for stress recognition, Biomedical Signal Processing and Control 38(2017) 100-107.

[15] F. Li, L. Yang, H. Shi, C. Liu, Differences in photoplethysmography morphological features and feature time series between two opposite emotions: happiness and sadness, Artery Research 18(2017) 7-13.

[16] S.N. Yu, S.F. Chen, Emotion state identification based on heart rate variability and genetic algorithm, in: Proc. Engineering in Medicine and Biology Society IEEE, 2015.

[17] G. Valenza, L. Citi, A. Lanatà, E.P. Scilingo, R. Barbieri, A nonlinear heartbeat dynamics model approach for personalized emotion recognition, in: Proc. International Conference of the IEEE Engineering in Medicine and Biology Society Conf Proc IEEE Eng Med Biol Soc, 2013.

[18] J. Yang, Study on ECG Health Analysis Based on Chaotic Characteristics, Chinese Academy of Sciences University, Beijing, China, 2016.

[19] V.E. Papaioannou, A.O. Verkerk, A.S. Amin, Intracardiac origin of heart rate variability, pacemaker funny current and their

possible association with critical illness, Current Cardiology Reviews 9(1)(2013) 82-96.

[20] D. Chen, J. Zhou, Research and application of heart rate variability, Advances in Cardiovascular Diseases 35(4)(2014) 435-439.