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An Emotional Analysis Method Based on Heart Rate Variability

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***Abstract*—In this paper, we propose a method to evaluate human's emotion and stress based on heart rate variability (HRV). Firstly, experiment scheme has been designed to induce 4 kinds of emotions and the corresponding electrocardiogram (ECG) changes have been measured in a laboratory setting; Secondly, an improved fast denoising method based on wavelet transform threshold denoising was proposed to process the noisy ECG signal, then we realize automatic extraction of HRV sequences; Finally, a wide range of physiological features from various analysis domains, including time, frequency, nonlinear analysis is proposed in order to find the best emotion-relevant features and to correlate them with emotional states, some important conclusions have been obtained.**

***Key words*—Emotion monitoring, HRV, autonomic nervous system, Physiological signal processing**

I. Introduction

Emotion influences human health significantly. Affective states of depression, anxiety and chronic anger have been shown to impede the work of the immune system, making people more vulnerable to viral infections, and slowing healing from surgery or disease[1]. Using emotion recognition technology, which can potentially aid in assessing and quantifying stress, anger and other emotions harmful to health, we can take reactions to negative emotions and improve the coordination of autonomic nervous system (ANS) to live in a better physiological, mental and working status. With the help of rapid development of wearable sensor technology[2], the acquisition and monitoring of human's physiological parameters such as ECG and heart rate is quite convenient, which makes emotion monitoring system based on physiological signals in daily life promising and feasible.

A large community of researchers has been focusing on emotion recognition using different physiological channels. K. H. Kim et al.[3] reported a emotion recognition system with 78.4% and 61.8% accuracy for the recognition of 3 and 4 classes of emotions using ECG, skin temperature variation and electrodermal activity; Cong Zong et al.[4] used 25 features from ECG, electromyogram, skin conductivity(SC) and respiration changes by Hilbert-Huang transform to obtain 76% accuracy for 4 classes; Picard et al.[5] used 40 features from heart rate, muscle tension, temperature and SC to get 81% recognition accuracy on 8 classes; Guillaume et al.[6] obtained 80% recognition accuracy on 3 classes using electroencephalographic(EEG). These researches reinforce that physiological changes primarily respond to emotion.

Since the acquisition of ECG is much easier than other physiological signals such as EEG, making users feel less uncomfortable, it may be conducive to the daily monitoring. Also HRV extracted from ECG expresses the regulation on cardiovascular system from ANS and indicates sympathetic parasympathetic tension and balance, reflecting changes in human's emotional state objectively and dynamically[7]. Therefore, we mainly focus on HRV to conduct emotional evaluation studies using ECG analysis, supplemented by emotional self report. 4 kinds of emotions including fear, relaxed, happy and stress have been monitored and corresponding physiological signals have been analyzed to explore their trends under different emotional states.

II. Methods

A. Experimental Scheme

26 subjects between 18 and 23 years old were recruited and all of them are Asian, 13 are men and 13 are women. History and physical examination verified that they were healthy subjects without illnesses that might affect ANS activity.

Movie clips method[8], a kind of emotion inducing method more efficient than others verified by previous studies, has been adopted by preparing three kinds of clips of films(3-10 min for each one) for fear, relaxed and happy. As for stress, we used picture-matching game, in which subjects should complete the task within the appropriate time to induce stress. Subjects were asked to accept the fear-relaxed-happy-stress sequence of stimulation and ECG data have been recorded. Meanwhile, to make accurate analysis of properly induced emotional data, their subjective emotional experiences have been recorded by filling in self-report form.(here the widely used self-report rating scale Likert table [9] was used to assess the subject's emotional scale, which has a higher reliability than the other scale of same length. Likert table of 13 adjective checklist 5-point quantitative have been designed).

B. Data Processing

Each three minutes of ECG data under 4 emotional states and the calm state (baseline) have been processed, including the original ECG signal denoising and extraction of R waves to obtain the original HRV signal.

1) ECG wavelet denoising algorithm

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It is very important for improving the HRV detection accuracy to eliminate the noise in ECG, this paper proposes an improved ECG denoising method based on wavelet transform to extract the RR interval.

The basic idea of wavelet threshold denoising was proposed by Donoho[10]: the signals can be decomposed into high and low frequency subbands by wavelet transform(WT), some larger WT coefficients should mostly result from the signal components, while the noise part with small-valued ones. It can be completed in three steps:

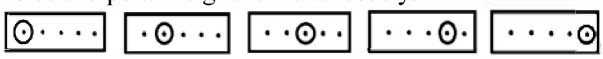
a) decomposition: select appropriate wavelet basis function and scale number K, decompose noisy signals, obtain the low and high frequency coefficients V_k and W_k (k=1~K).

b) thresholding: estimate the noise threshold σ_k in each of coefficients W_k in each layer, then conduct the filtering processing on W_k according to the threshold function F_σ .

c) reconstruction: reconstruct denoised signal by using inverse WT on low frequency coefficients V_k in layer K and the filtered high frequency coefficients W_k from layer 1 to K.

The commonly used threshold functions(TF)[11] include three kinds: hard threshold function, soft threshold function and semi-soft threshold function. The signals after the processing of the hard threshold function are not continuous at the threshold point which might produce Pseudo-Gibbs effect; although soft threshold function is of good overall continuity, the constant deviation exits, which affects directly the approximating degree of the reconstruction signals to the original signals; Compared with hard TF, the semi-soft TF lowers the degree of discontinuity at threshold point, while decreases the constant deviation compared with soft TF. Nevertheless, the semi-soft TF is single threshold TF so that it's very sensitive to the estimation error that always exists in practice. Thus, we propose a novel multi-model fast denoising method based on hard TF. The proposed denoising scheme not only solves the Pseudo-Gibbs effect to filter the signal effectively but also preserves the signal details to retain the diagnostic information.

In this method, we propose multi-model domain pattern (MMDP), whose main idea is to replace each coefficient with the maximum mean value among the candidate domain models to be compared with the threshold, producing the output after the thresholding step. This method can filter noise and pertain signal simultaneously.



(a)pattern 1 (b)pattern 2 (c)pattern 3 (d)pattern 4 (e)pattern 5

Fig. 1. Schematic diagram of MMDP(t=5)

At first, select pending data point P and set the steplength of the domain to be t , then produce t kinds of patterns around point P, as shown in Fig.1 (take $t = 5$ for example). The rectangle in the figure defines the domain of patterns and the circled point is pending data P. Then, calculate the mean values of the different patterns respectively and replace point P with the maximum mean value as the characteristic value of P to act as the input of the thresholding step by being compared with the threshold. The advantages of MMDP are:

a) Optimization of noise reduction by eliminating the threshold estimation error

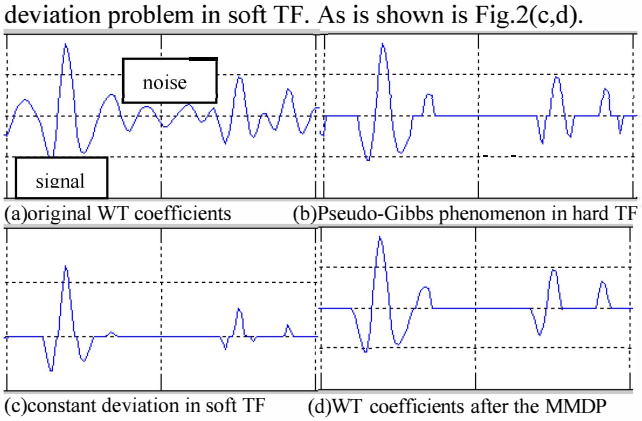
The magnitude of some noise points might outstrip the threshold, which would omit the thresholding process of those noise points. However, it is the domain mean value being comparing with the threshold as the characteristic value in MMDP. So, the average smoothing effect by calculating the mean value can lower the magnitude of those few unusual high noise points, guaranteeing the better denoising.

b) Extenuation of Pseudo-Gibbs phenomenon

To lessen the influence of Pseudo-Gibbs phenomenon in hard TF, the absolute maximum mean value in candidate patterns is used to replace original P with small magnitude. In this way, by uplifting lower signal points with the help of averaging higher ones in the domain, it can be avoidable that smaller signal points are directly filtered and set to zero, losing the useful signal information. Shown in Fig.2(b,d).

c) Elimination of the constant deviation

In MMDP, we keep the entire reservation of those signal points greater than threshold, eliminating the constant deviation problem in soft TF. As is shown is Fig.2(c,d).



(a)original WT coefficients (b)Pseudo-Gibbs phenomenon in hard TF

(c)constant deviation in soft TF (d)WT coefficients after the MMDP

Fig. 2. Diagram of WT coefficients after different methods

As is shown in Fig.3, the proposed method in this paper is proven to be better than hard TF, semi-soft TF and traditional improved TFs like VisuShrink, SureShrink, BayesShrink[12], with higher Signal to Noise Ratio (SNR) and Correlation coefficient(CC) of the average result of 100 experiments on American MIT-BIH database shown in Table I .

2) R wave detection and HRV calculation method

ECG data with higher signal to noise ratio after denoising have been used to obtain more accurate RR interval using the classic differential threshold method[13], and then obtain the HRVdata, the RR interval sequence in millisecond, using the effective method in [14].

C. Data Analysis

According to the experimental scheme design and current HRV studies on emotion, we selected short-term indicators of HRV to discover the parameters sensitive to emotion. In this part, HRV data have been analyzed and parameters of time, frequency and nonlinear domain which can reflect short-term HRV have been calculated and extracted for further study.

1) Time Domain Analysis

a) MEAN ms: average of adjacent RR intervals, which reflects the average level of RR interval;

*b) SDNN Index ms*ms:* standard deviation of difference between adjacent RR intervals, which reflects the average level of the short-term HVR;

c) PNN50: percentage of those whose difference between adjacent RR intervals greater than 50ms, which reflects the sudden change in RR interval and the vagus nerve activities;

d) CVrr: HRV coefficient, the ratio of the standard deviation and mean, which reflects the degree of HRV.

2) Frequency Domain Analysis

According to our experiment on the comparison to the classic power spectrum estimation methods (such as the periodogram and Welch method), AR model method can get more accurate low frequency(LF) and high frequency(HF) power spectrum estimation with higher frequency resolution to describe power spectral density of HRV more precisely. Therefore, we select the AR model(here, we chose Final prediction error rule (FPE) to determine the order, resulting minimum average error) for power spectrum estimation method. The parameters are as follows:

a) LHrate, the ratio of LF to HF (LF/HF): reflects the sympathetic- parasympathetic balance;

b) LFnorm, standardized LF power (0.04-0.15Hz): is influenced by the combined effect of the sympathetic and parasympathetic nerve system;

c) HFnorm, standardized HF power (0.15-0.4Hz): is mediated by the vagus nerve.

3) Nonlinear Analysis

a) Scatter Plot

Scatter Plot contains the linear and nonlinear HRV trends and can be used to discover the subjects' functional status of the autonomic nervous. Vector angle index (VAI), defined in (1) reflects changes in the fast component, while the vector length index (VLI), defined in (2) reflects the slow changes components of HRV.

$$VAI = \sum_{i=1}^{N} \left| \theta i - 45 \right| \Big/ N \qquad (1)$$

N is the total number of heart beats, θi is the vector angle between the line connecting each data point to the coordinate origin and the horizontal axis.

$$VLI = \sqrt{\sum_{i=1}^{N} (li - L)^2 \Big/ N} \, (ms) \qquad (2)$$

li is the vector length between each data point and the coordinate origin. L is the average vector length of N points.

b) Fractal Dimension

We estimated the fractal dimension[15] using box-counting dimension, which can reflect regulation on cardiovascular system from sympathetic-parasympathetic nerve system[16].

III. Results

The final valid 22 out of 26 test data have been selected according to the induced intensity(2.78, 3.35, 3.30 and 3.58 respectively) of Likert table for 4 fragments. The parameters mentioned above, including time, frequency, nonlinear domains have been used to correlate them with emotional states and some important conclusions have been obtained.

Seen from Fig.4, we can know that:

1) Compared to the calm state (baseline), RR intervals of four induced emotional states decreased by some degree, indicating the varying degrees of acceleration of heart rate. Amongst, heart rate increased much more in negative emotional states like fear and stress than positive emotions like relaxed and happy, which is consistent with the findings of Ekman et al.[17]

2) SDNN Index, short-range variations of HRV under negative emotions were higher than positive emotions, indicating that HRV is larger under negative emotions, especially in stress situations.

3) PNN50 indicates that vagus nerve activity was inhibited under stress state.

4) With CVrr coefficient, HRV under fear and stress have greatly increased.

Seen from Fig.5(a),we can know that:

5) Compared to the calm state, LHrate increased under negative emotional states like fear and stress, which was probably caused by tension.

6) Under stress, LF/HF increased while HF decreased, indicating vagus nerve activities decreased, which is consistent with the findings of Schubert et al.[18] in 2009.

7) Seen from Fig.5(b), we can know that: both VAI and VLI increased under negative emotions like fear and stress, indicating the fast and slow components of HRV tended to increase while those under positive emotion showed a decreasing trend.

8) Seen from Fig.5(b), the fractal dimension significantly decreased under the negative emotions of fear and stress, indicating HRV reduced at those times and the sympathetic nerve activity increased while vagus nerve activity decreased in physiological performance.

IV. Discussion and Conclusion

In the aspect of experimental scheme, we designed the movie clips and picture-matching game inducing methods and removed some special samples using emotional scale self report, eliminating the subjectivity of test and improving the experimental repeatability, which is conducive to follow-up study. In data processing, we propose an improved ECG denoising method based on wavelet transform to extract the RR interval and obtain HRV. We analyze and extract a wide range of physiological features from various analysis domains, including time, frequency, nonlinear analysis to draw some important conclusions. Under negative emotions, the heart rate were significantly faster, LF/HF significantly increased, while the fractal dimension decreased, indicating HRV reduced and the sympathetic nerve activity increased while vagus nerve activity decreased.

There are some improvements for the next step:

1) In the experimental design, we can combine with psychology, electrophysiology studies and further analyze and extract more effective physiological parameters to conduct quantitative establishment of the correspondence between emotion and autonomic nervous system.

2) We will collect more data in the next step, including subjects of different ages and different occupations to establish emotional physiological signal database.

The experimental and analytical results indicate that there are significant different emotional changes in HRV including time, frequency, nonlinear domain. These changes can be used for the evaluation of emotion, laying a good theoretical basis for research on future emotion recognition system. The application of wearable emotion monitoring and dynamic analysis will be very meaningful combined with convenient ECG acquisition and booming wearable sensors. This application can create correspondence between physiological signal changes and emotion to make evaluation results and realize timely detection of human negative emotions. Thus, it can indicate the user's current emotional state to guide us to relieve the stress and learn the positive emotional self regulation, which is beneficial to improve efficiency and conducive to human health.

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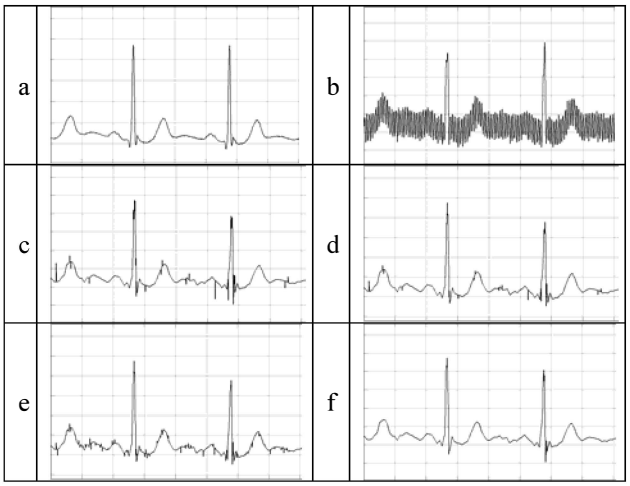


Fig. 3. (a) original ECG signal; (b) noisy ECG signal; (c),(d),(e) and (f) are denoised signals filtered respectively by hard TF, semi-soft TF, algorithm proposed in [12] and method proposed in this paper.

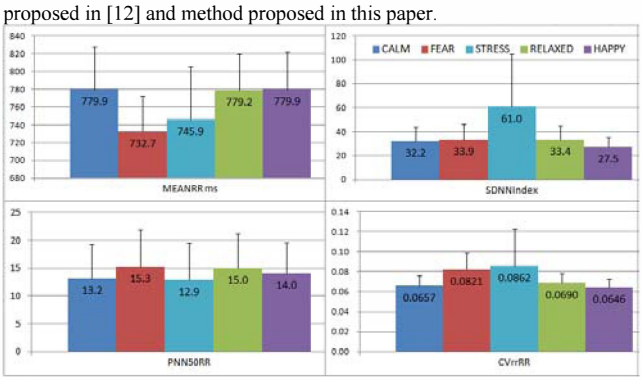
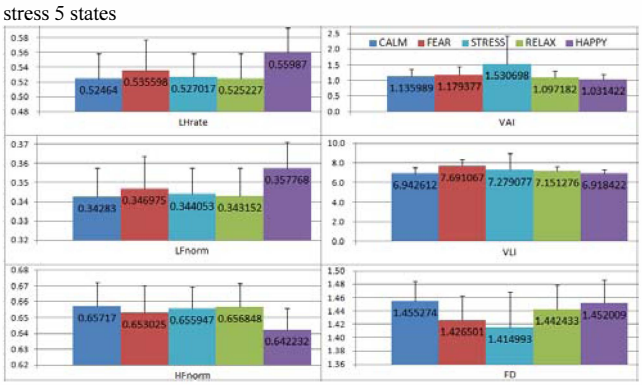


Fig. 4. Time Domain Analysis of HRV under calm, fear, relaxed, happy and stress 5 states



(a) (b)

Fig. 5. (a)Frequency Domain (b) Nonlinear Analysis of HRV under 5 states

TABLE I

THE DENOISING RESULTS OF DIFFERENT METHODS ON ECG

	Method A	Method B	Method C	Method D
SNR	12.4298	13.1650	13.4062	14.1855
CC	0.9715	0.9756	0.9769	0.9805

A: hard TF algorithmin B: semi-soft TF algorithm

C: algorithm proposed in [12] D: method proposed in this paper