Identifying Strong Stress and Weak Stress Through Blood Volume Pulse

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***Abstract*—This paper explored the difference between weak stress (WS) and strong stress (SS) on the relative ejection period (REP) of the blood volume pulse (BVP). Features were extracted from the REP series to recognize WS and SS. The blood volume pulse data were acquired during the defense of 31 graduate students for their master's degree under the real stress environment. The result shows that, in the real stress situation, the features of REP have obtained a correct rate of 91.93% in distinguishing strong stress state and weak stress state.**

***Keywords*—blood volume pulse; ejection period; real situation; strong stress; weak stress**

I. Introduction

Recent studies have shown that stress, anxiety and depression caused by working are the second major reasons leading to people's health problems [1]. Liao et al. [2] have extracted features from physical performance (facial expressions, eye movements and head movements) and analyzed the degree of stress through the dynamic bayesian network (DBN). Sharma et al. [3] have investigated the stress of male and female during their reading by using artificial neural network (ANN) to classify galvanic skin response (GSR) data of stress and non-stress status. Carneiro et al. [4] have analyzed the level of acute stress caused by human behavior patterns in a virtual environment. Akane Sano et al. [5] have classified different levels of pressure with the physiological and behavioral indicators. Karthikeyan et al. [6] have applied short-term electrocardiogram (ECG) and heart rate variability (HRV) to recognize pressure, and the recognition accuracy with probabilistic neural networks (PNN) and k-nearest neighbor (KNN) are 91.66% and 94.66%. Stress can also be automatically identified by the semantics features, phonetic features and gesture [7]. A speech with the audience assessment in real life is an effective way to arouse stress [8]. Many people have reported stress and anxiety during public speaking [9]. Some studies have shown that exercise can help people relieve stress, but this result still needs more validation [10].

As to the data processing and analysis, Iacoviello et al. [11] have applied wavelet transform, principal component analysis (PCA) and support vector machine (SVM) in their study of emotion recognition; Huang et al. [12,13] have proposed a single-hidden layer feed-forward neural network (SLFN), namely extreme learning machine (ELM) which has acceptable generalization performance and faster learning speed than the traditional feed-forward neural network algorithm.

In terms of physiological signals, the period of blood volume pulse signal can be used to effectively estimate the effects of epinephrine on the human left ventricle [14]. However, the features related to the period of blood volume pulse has seldom been used to identify strong stress under real situations in literature. Therefore, this paper has explored the stress status aroused in real stressful situation and its response in the relative ejection period of the blood volume pulse. In the following sections, Section II is about the data acquisition, Section III describes the data processing and analysis, and Section IV gives the conclusions.

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II. Data Acquisition

Data acquisition included two parts: The first part was to acquire pulse data from the graduate students one week before the thesis defense when they were practicing their thesis presentation without the presence of any audience; The second part was to acquire pulse data from the graduate students during their thesis defense for the master's degree.

A. *Participants*

Thirty-two graduate students (21 male and 11 female) were recruited to complete this experiment, and one of them was excluded from data acquisition because of pathological changes in heartbeat dynamics. Before data acquisition, the subjects signed the informed consent and filled in two trait anxiety scales, i.e. the speech anxiety scale and the negative evaluation fear scale [15].

B. *Experiment Procedure*

Before the first part of data acquisition, E4 wrist band which had a blood volume pulse sensor was put on the left wrist of the subject. Then, the subject began to have a presentation about their thesis work in a classroom without any audience. The presentation time was controlled to be about 10 minutes. A camera was set about 4 meters away from the subject. After the data acquisition, the subject reported the degree of stress during the presentation. According to the self-report of the subjects, they were elicited weak stress during the presentation.

Thirty minutes before the second part of data acquisition, E4 wrist band was put on the left wrist of the subject. Then, the subjects started the thesis defense. The duration of the defense was not controlled by the experimenter, but by the academic authority of the defense. After the data acquisition, the subject also reported the degree of stress during the defense. According to the self-report of the subjects, they were elicited strong stress during the thesis defense.

III. Data Processing And Analysis

A. *Data Preprocessing*

Figure 1 shows the location of maximum and minimum of BVP signal in each period. As is shown in Figure 2, a pulse period was divided into ascending branch and the rest of the pulse period. The ascending branch corresponds to the rapid ejection period of one heartbeat.

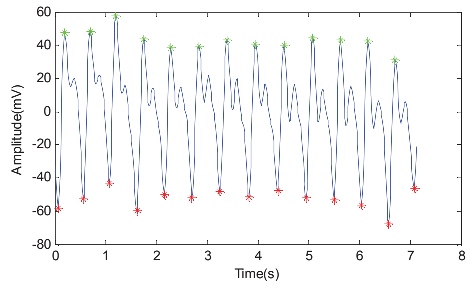

Fig. 1. The location of maximum and minimum of BVP in each period.

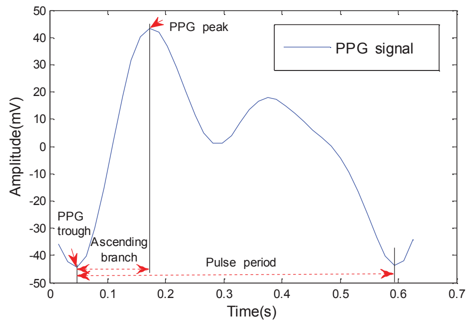

Fig. 2. Rapid ejection phase in one pulse period.

The pulse period series *x*, the ascending branch series *y* and the relative ascending branch series in the form of *y*/*x* were shown in Figure 3. For each of the 31 subjects, a weak stress sample and a strong stress sample of the relative ascending branch series were obtained. Each sample contained a relative ascending branch series of 120-second length.

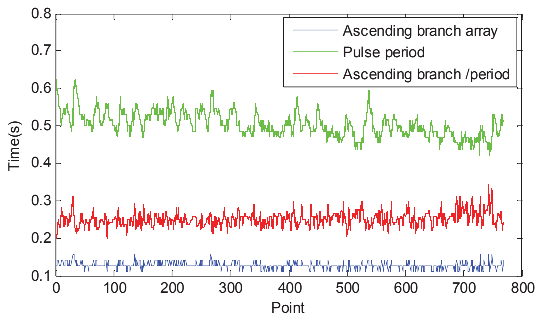

Fig. 3. The relative ejection period time series.

B. *Feature Extraction, Selection and classification*

Twenty-seven features were extracted from the REP time series, as shown in Table Ⅰ.

TABLE I. THE CHARACTERISTICS AND FORMULAS OF THIS PAPER

Features	Interpretations
μ_x	$\mathrm{bvp}_{\mathrm{mean}} = \frac{1}{N}\sum_{i=1}^{N}\frac{B(i)-B_{\min}}{B_{\max}-B_{\min}}$
σ_x	$\mathrm{bvp}_{SD} = \sqrt{\frac{1}{\mathrm{N}}\sum_{i=1}^{N}[\overline{B}(i)-\overline{B}(mean)]^2}$
RMSSD	$IBI_{RMSSD} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(IBI_{i+1}-IBI_i)^2}$
Diff_mean	
2Diff_mean	$\mathrm{bvp\_dlraw}_i = \frac{\overline{B}(i+1)-\overline{B}(i)}{t_{i+1}-t_i}$
3Diff_mean	
Power spectrum density	$P(w) = \lim_{T\to\infty}\frac{\vert F_T(w)\vert^2}{2\pi T}$
0_order Legendre moments	$1 \le i \le N$
4_order Legendre moments	
24_order Legendre moments	$x_i = (2i-N-1)/(N-1)$
26_order Legendre moments	
28_order Legendre moments	$L_p = \frac{2p+1}{N-1}\sum_{i=1}^{N}P_p(x_i)f(x_i)$
32_order Legendre moments	
34_order Legendre moments	$P_p(x) = \frac{1}{2^p}\sum_{k=0}^{p/2}(-1)^k\frac{(2p-2k)!}{k!(p-k)!(p-2k)!}x^{p-2k}$
36_order Legendre moments	
38_order Legendre moments	$x \in [-1,1]$
42_order Legendre moments	
44_order Legendre moments	
0_order Krawtchouk moments	
2_order Krawtchouk moments	
4_order Krawtchouk moments	$x, n = 0,1,\ldots,N,\ N>0,\ P\in(0,1)$
6_order Krawtchouk moments	
8_order Krawtchouk moments	$K_{\mathrm{n}}(x;p,N) = \sum_{k=0}^{N}a_{k,n,p}x^k = {}_2F_1(-n,-x;-N;\frac{1}{p})$
10_order Krawtchouk moments	$\bar{K}_{\mathrm{n}}(x;p,N) = K_n(x;p,N)\sqrt{\frac{\omega(x;p,N)}{\gamma(x;p,N)}}$
12_order Krawtchouk moments	
14_order Krawtchouk moments	
16_order Krawtchouk moments	

Then, the sequential backward selection (SBS) was performed to select the best feature combination in distinguishing strong stress from weak stress. The SBS algorithm started from selecting all the original features. In each step of the iteration, the worst feature was removed, and the dimension of the feature space was gradually reduced. After the dimension of the feature space was reduced to be one, the algorithm terminated. The best feature combination was the one which had the best value of the evaluation function. The evaluation function was set to be the total classification error rate, i.e. false positive rate (FPR) and false negative rate (FNR). The ELM served as the classifier to obtain the classification results in a leave-on-out cross validation process. The sigmoid function was applied as the activation function of ELM and the number of hidden layer neurons was set to be 8. The best total correct classification rate is 91.93%. The confusion matrix of binary classification between the strong stress and the weak stress is shown in Table Ⅱ.

TABLE II. CONFUSION MATRIX OF BINARY CLASSIFICATION BY ELM AND LEAVE-ONE-CROSS VALIDATION

	Strong stress (SS)	Weak stress (WS)
Identified as SS	90.32%（28/31）	6.45%（2/31）
Identified as WS	9.67%（3/31）	93.54%（29/31）

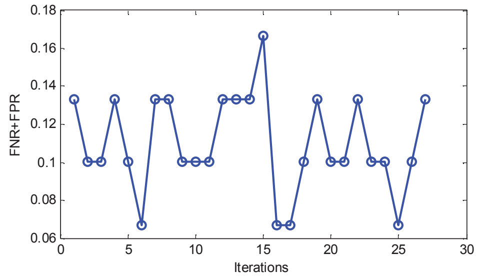

Fig. 4. The iteration process of SBS algorithm.

The feature selection process is shown in Figure 4, and the best feature combination in the binary classification of strong stress and weak stress includes two features: power spectrum density and 10_order Krawtchouk moment. Figure 5 and Figure 6 respectively give the scatter plot of the two best features.

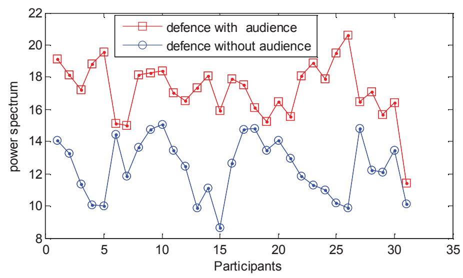

Fig. 5. The power spectrum density feature values of REP time series in strong stress status and weak stress status.

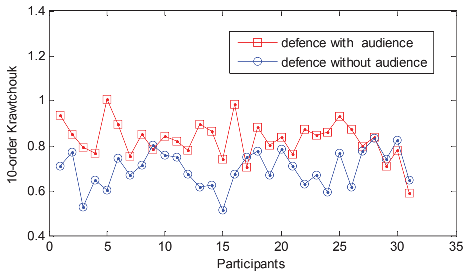

Fig. 6. The 10_order Krawtchouk moment feature of REP time series in strong stress status and weak stress status.

T-test were performed to reveal whether the above two best features have significantly different values under two different levels of stress, i.e. strong stress and weak stress. The results of t-test are shown in Table Ⅲ and Table Ⅳ, and both of the best features exhibit statistically significant difference regarding the strong stress and the weak stress.

TABLE III. THE T-TEST RESULTS OF POWER SPECTRUM DENSITY

H	P	C_H	C_L	Ts	Df	Sd
1	2.543E-015	-3.6178	-6.0523	-10.5668	60	1.8015

TABLE IV. THE T-TEST RESULTS OF 0_ORDER KRAWTCHOUK MOMENTS

H	P	C_H	C_L	Ts	Df	Sd
1	5.657E-008	-0.0751	-0.1880	-6.2010	60	0.0835

(*H=0~original hypothesis, H=1~alternative hypothesis, P~probability of original hypothesis is accepted, C_H~higher confidence limit, C_L~lower confidence limit, Ts~the value of the test statistic, Df~test degree of freedom, Sd~the overall standard deviation of the estimated value of the merger)*

IV. CONCLUSIONS

The experimental results show that during the thesis defense, the REP of pulse has significantly larger power spectrum density and 10-order Krawtchouk moment than that during the presentation of thesis work without audience. The subjects have reported strong stress during thesis defense and weak stress during thesis presentation without audience. Therefore, the power spectrum density and the 10-order Krawchouk moment are promising features to distinguish strong stress from weak stress.

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