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Heart Rate Variability Signal Features for Emotion Recognition by using Principal Component Analysis and Support Vectors Machine

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***Abstract*—Emotion influences human health significantly. In this pilot study, a movie clips method has been designed to induce 5 kinds of emotion states. 90-sec corresponding ECG signal have been measured in the end of video stimulus. Heart rate variability (HRV) features were extracted from ECG signal by using time-domain, frequency-domain, Poincare, and statistic analysis. Then these HRV features were used to classify different emotion states by support vectors machine (SVM). Also, we used principal component analysis (PCA) to reduce the number of extracted features. Briefly, in the classification for 2 emotion states (positive/negative) and 5 kinds of emotion states, the accuracy of 71.4%, 56.9% are reached, respectively. Compared with other studies of emotion recognition using 2 or more vital signs, the accuracy in this study is lower slightly than other studies (56.9% *versus* 61.6%). However, using single ECG signal or HRV features is accessible for the daily emotion monitoring. Our results showed the feasibility of daily emotion monitoring by using extracted HRV features and SVM classifier.**

Keywords-heart rate varibility (HRV), emotion analysis, support vectors machine (SVM), Principal components analysis (PCA)

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 and associate with many diseases [1]. In addition, mental disorder also caused social dysfunction and low working efficiency. Thus, understanding and regulating self-emotion has already been an important healthcare issue.

Many physiological changes are associated with emotion, such as blood pressure and HRV [2]. A large number of scientists are focusing on emotion recognition using different physiological signals. Kim et al. reported an emotion recognition system with 61.8% accuracy for the recognition of 4 types of emotion using ECG, skin temperature variation and electrodermal activity [3]; Zong et al. used 25 features from ECG, electromyogram, skin conductivity and respiration changes to obtain 76% for 4 types of emotions. Guillaume et al. obtained 80% recognition accuracy on 3 classes using electroenphalographic [4]. All those studies demonstrated that these physiological signals primarily respond to emotion. However, those methods for emotion recognition are based on multi-physiological signals. Furthermore, those technologies are hard to operate in daily life.

A key system participated in the generation of physiological changes is autonomic nervous systems (ANS). The ANS is divided into the sympathetic nervous system (SNS) and parasympathetic nervous system (PNS) that react antagonistically to generate varying degrees of physiological arousal. During physical or psychological stress, SNS activates dominantly, producing physiological arousal in order to adapting to the challenge. An increase in pulse or heart rate, is characteristic of this state of arousal. On the contrary, during the state of safety or stability, the PNS becomes dominant and maintains a lower degree of physiological arousal and a decreased heart rate. The transition between high and low arousal states is dependent on the ability of the ANS to regulate heart rate rapidly. Thus, heart rate variability (HRV) is a real-time indicator to understand how the reaction between SNS and PNS influences on heart rate that yields information about autonomic flexibility, and thereby represents the capacity for regulated emotional responding [5].

Currently, daily ECG detection became accessible, thus using unitary HRV features to evaluate emotion state is under active investigation. [6, 7] In this study, in order to improve the accuracy of emotion recognition, we try to use more parameters to separate different emotion states. Thus, our experiment scheme has been designed to induce 5 kinds of emotions (i.e. sad, angry, happy, and fear, relax) by video stimulus. 90-sec corresponding ECG signal have been measured in the end of video stimulus. Then, 13 physiological features from various analysis domains, including time, frequency, and statistic analysis are proposed in order to find the best emotion-relevant features. A classification method, support vector machine (SVM) is utilized herein for the emotion recognition by using those HRV features.

II. METHODS

A. Subjects and Procedure

Twenty five healthy subjects, ranging in age of 29 to 39 years (32.2 ± 4.7 years) participated in this study without the history of psychiatric disease or complicating medical problems.

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Movie clips method [8], a kind of emotion inducing method more efficient than others verified by previous studies, has been adopted by preparing five kinds of clips of films (3-10 min for each one) for five kinds emotion (i.e., angry, fear, sad, happy, and relax). Before the video stimulus, Subjects were asked to look forward, relax, and breathe normally for 2 min for relax state. Then, subjects were asked to accept the sad-angry-fear-happy sequence of stimulation twice. To make sure the independences of emotion states, the each stimulation was speared by a 30-sec relax film clip. ECG data was record for 90 sec at 1 min before the end of movies.

After each film clip, subjects are asked to complete a short post-film questionnaire to rate the intensity of their feelings of 4 kinds (i.e. sad, angry, fear, and happy) of emotions on a scale of 0 (none) to 5 (extreme) [8] to make sure the emotional induction successfully. We did not use subject's ECG signal at the intensity of 0 and 1 in this study. Thus, the sample size of ECG signal at each emotion induction is not the same.

B. Apparatus and data collection

One-lead ECG signal was sampled at 200 Hz and collected using a wearable ECG device (XYZlife Bio-Clothing 1 (BC1), Kinpo Inc., New Taipei City, Taiwan). During recording, subject wears a clothing with electrode pad and BC1 device, as shown in Figure 1(A). ECG signals were collected and saved in a tablet PC via BC1 device (Figure 1(B)) and relative software. 10-sec of ECG signal logged from BC1 device has been shown in Figure 1 (C).

Each 90 sec of ECG data under 4 emotional states and the peace state have been processed, including the original ECG signal denoising and extraction of R waves to obtain the original HRV signal, which was computed every 0.25 sec. Subject's HRV signal was analyzed and parameters of time, frequency and nonlinear domain, which can reflect short-term HRV have been calculated and extracted for further study.

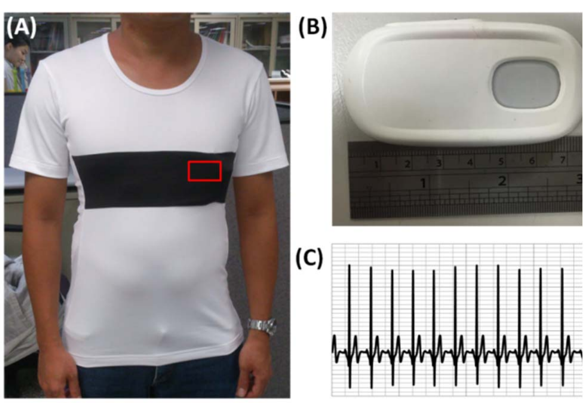

Figure 1. (A) A fitting clothing with the electrode was used to collect the ECG signals by the device placed in front of the left chest (red square). (B). The one-lead ECG device BC1. (C). 10-sec ECG signal logged from the BC1 device. [9]

C. Data analysis

According to our experimental scheme design and based on current HRV studies on emotion, we selected several indicators to discover the parameter sensitive to emotion. Here 90-sec HRV data have been analyzed and obtain the parameters of time, frequency domain and statistics for the further study.

1. Time domain analysis

i. Mean RRI: average of resultant RR intervals.

ii. CVRR: coefficient of variation (CV) of RR intervals, the ratio of the standard deviation and mean of RR intervals.

iii. SDRR: stand deviation of the RR intervals.

iv. SDSD: standard deviation of the successive differences of the RR intervals.

2. *Frequency domain analysis*

Spectral analysis was carried out on HRV signals by using fast Fourier transform (FFT) methods. The parameters we used as follows:

i. LF (low frequency): standardized LF power (0.04-0.15 Hz)

ii. HF (high frequency): standardized HF power (0.15-0.4 Hz)

iii. LHratio: the ratio of LF/HF

3. *Statistic analysis*

To evaluate the distribution probabilities of HRV, three statistic parameters were considered here. The shapes of the probability distributions were evaluated by the Kurtosis coefficient. The coefficient was calculated by using:

$$\mathrm{Kurto}(X) = \frac{\sum[(X-\mu)^4]}{\sigma^4}$$

Where X represents the HRV data set, μ is the mean value, and σ represents the standard deviation.

The amount of asymmetry in a data set probability distribution can be evaluated by the Skewness value determined by:

$$\mathrm{Skew}(X) = \frac{\sum[(X-\mu)^3]}{\sigma^3}$$

Where X represents the HRV data set, μ is the mean value, and σ represents the standard deviation.

Entropy, used to characterize the randomness of data set, is defined as:

$$\mathrm{Entropy}(X) = -\mathrm{sum}(p \times log_2(p))$$

Where p contains the histogram counts of data set.

4. *Parameters of Poincare plot*

The Poincare plot of RR intervals is used to evaluate HRV. The resulting point cloud is usually characterized by its length (SD2) along the line of identity and its breadth across this line (SD1). According previous study [10], SD1 and SD2 can be determined by the following formulas:

i. $SD1^2 = 1/2 SDSD^2$

ii. $SD2^2=2SDRR^2-1/2SDSD^2$

iii. SD2SD1ratio= the ratio of SD2/SD1

D. Feature selection with PCA

Principal component analysis (PCA) is often used as technique for data reduction/compression without any loss of information. [11] In this study, we use PCA to compress the number of extracted features. It makes to use of Eigen value decomposition of the covariance matrix and projects the data on Eigen basis defined by the respective Eigen vectors. Only few of the Eigen values will be significantly higher and rest are considerably very small and do not contribute to the data variations. Therefore, 5 significant Eigen values are selected for the classification of emotion state.

E. Support Vector Machines

SVM is an efficient classification algorithm based on the structural risk minimization principle of machine learning methods [12]. Multiple SVM classifier can be integrated by using one-against-one or one-against-all approach for the classification with more than two classes. LIBSVM library was employed in this study by using one-against-all approach to classify 5 kinds of emotion states [13].

In order to experiment with SVM using HRV features, several types of SVM and kernels were tested and a c-SVM with linear kernel was implemented for this study. 90-sec ECG signal was analyzed and extracted to 5 HRV features. Then, we picked the same sample size of 5 emotion states (i.e. one-third of whole data sets) randomly for the SVM training. The rest of samples were used for the evaluation of emotion recognition.

III. RESULTS AND DISCUSSION

In this study, total 150 segments of ECG signal were collected from 5 emotional states at 25 subjects. As Table 1 shown, different sample size at each emotion state is due to the different intensity of subjects' feeling after movie induction.

TABLE 1 THE AMOUNT OF ECG SIGNAL OF SUCCESSFUL EMOTIONAL INDUCTION

Emotion	Sad	Angry	Fear	Happy	Relax
Induced ECG signals	33	14	40	38	25

* There are 25 subjects for the emotion-eliciting film stimulation. The numbers for each emotion are the subjects' numbers of successful induction.

After extraction of HRV features, we picked up 10 data sets from each emotion group randomly for the training of SVM classifier. The rest of data were used to test the accuracy of emotion recognition. The effectiveness of the PCA features selector was studies.

A. Performance of the Classifier

In this study, the HRV features were used to separate into four categories, namely time-domain, frequency, Poincare and statics features. The accuracy rate of the SVM classifiers for the emotion recognition was compared. Also, the accuracy rate was compared using total features and selected features.

Firstly, we separated 5 emotion states into 2 groups: negative and positive groups. Sad, fear, and angry states were included in negative group. Relatively, happy and relax were included in positive group. As the Table 2 shown, the average accuracies are between 31.9% and 54.3% by using individual categories of HRV features. When total features were used for the SVM classifier, the higher accuracy can be achieved (70.4%). In addition, using PCA to select 5 features (i.e. CVRR, LF, HF, HFratio, SD1) from the total 13 features for the 2-types emotion recognition, the accuracy is 71.4%, higher slightly than using total features. Similarly, in the 5-types emotion recognition (i.e. sad, angry, fear, happy, relax), the lower accuracy was obtained using individual domain analysis. 52% and 56.9% accuracies are achieved by using total HRV features and selected features, respectively. (Table 3)

Notably, from these 2 tables, the accuracy of emotion recognition by using selected features is higher slightly than using total features. This finding indicated that parts of HRV features herein are not usable for emotion recognition. In addition, 3 out of the 5 selected features belong to the frequency features. The accuracy using frequency features is higher than using other categories of HRV features. Frequency features were demonstrated to be significant for the emotion cognition.

TABLE 2 PERFORMANCE OF THE CLASSIFIER USING DIFFERENT CATEGORIES OF FEATURES FOR 2-TYPES EMOTION RECOGNITION

	Negative	**Positive**	**Average**
Time (4)	49.6	51	50.3
Frequency (3)	58.8	49.8	54.3
Poincare (3)	46.8	50.8	48.8
Statics (2)	30	33.8	31.9
Total (13)	**69.6**	**70.8**	**70.4**
Selected (5)	**71.8**	**71**	**71.4**

* the number in the parentheses is the amount of the features.

B. Comparison with other methods

The performance of the proposed method was compared to other emotion cognition methods. Table 4 summarizes that our study and comparative methods. Kim et al. used ECG, skin temperature variation, and skin electrodermal activity to classify emotion states. The 78.4% and 61.8% were reported to classify 3 and 4 emotion states, respectively. Zong et al. used ECG, electromyogram, skin conductivity and respiration changes to obtain 76% accuracy for 4 types of emotions. Rigas et al. used electromyogram (EMG), ECG, respiration, and skin electrical activity, to identity 3 emotion types and reported the accuracy of 61.67%. The three systems were designed using 3 or more vital signs to identity subject's emotion state. The accuracies using those vital signs are 60% to 80% for 3 or 4 emotion types.

In our system, we used single HRV features and SVM classifier to obtain 54.6% accuracy for 5 emotion types. The accuracy is lower slightly than the previous studies, however, 3 and 4 vital sign sensors are hard to use in the daily emotion monitoring. Thus, using single ECG signal or HRV features is an accessible technique in the future. In this pilot study, we have demonstrated that single HRV features could be used for the classification of emotion states via SVM classifier. However, this system is required to improve in the future. For the training of SVM classifier, the data sets in this study are not good enough (10 data sets from each emotion states, training accuracy of 72%). More subjects should be recruited to obtain bigger data sets at each emotion states. It is helpful for the extraction of HRV features and the accuracy of SVM classifier. Also, more different HRV features will be considered for extraction of PCA and emotion recognition.

TABLE 3 PERFORMANCE OF THE CLASSIFIER USING DIFFERENT CATEGORIES OF FEATURES FOR 5-TYPES EMOTION RECOGNITION

	Sad	Angry	Fear	Happy	Relax	Average
Time (4)	39.1	0	26.7	28.6	20	22.9
Frequency (3)	43.5	25	33.3	35.7	33.3	34.2
Poincare (3)	13	25	26.7	17.8	0.2	19.2
Statics (2)	8.7	0	10	17.8	13.3	9.9
Total (13)	**52.7**	**50**	**60**	**50.4**	**46.7**	**52**
Selected (5)	**60.9**	**50**	**66.7**	**53.5**	**53.3**	**56.9**

*the number in the parentheses is the amount of the features.

TABLE 4 COMPARSION WITH OTHER RELEVANT METHODS.

Method	Emotion types	Accuracy	Subjects	Vital signs
Kim[2]	3	78.4%	50	3
Kim[2]	4	61.8%	50	3
Zong[3]	4	76%	44	4
Rigas[13]	3	61.67%	9	4
This study	2	71.4%	25	1
This study	5	56.9%	25	1

IV. CONCLUSION

This study proposed to use PCA and SVM to classify emotion states via HRV features. We used 13 HRV features to classify 2 and 5 emotion states and obtain 70.4% and 52% accuracy, respectively. Then 5 selected features by PCA were used to obtain 71.4% and 56.9% for the classification of 2 and 5 emotion states, respectively. In this pilot study, we demonstrated that single HRV features could be used for the classification of emotion states via SVM classifier. Compared to other studies using 3 or 4 vital signs for emotion recognition, we used HRV features only and obtain similar accuracy rate. Next step, more subjects will be recruited to obtain bigger data sets at each emotion state. It is helpful for the extraction of HRV features and the accuracy of SVM classifier. Also, more HRV features will be considered for emotion recognition.

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