

Emotional Quality Level Recognition Based on HRV

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Abstract—This paper explores the detection of emotional levels, high, medium and low from ECG signals. Features of ECG are extracted from frequency domain, time domain and nonlinear method and normalized by z-score method. Then SFS feature selection is applied followed by LDA feature transformation. After that, the transformed features are applied to KNNR classifier. According to our results, it was found that subjects of different characteristics reveal different biosignal responses. While subjects are regarded as optimistic characteristics, they have higher responses on positive films. On the other hand, the pessimistic subjects have higher responses on negative films. When classifiers are established separately for optimistic and pessimistic subjects, we can achieve the recognition rate of 97.8%, where 7 features are selected, and 94.0%, where 8 features are selected, for optimistic and pessimistic groups respectively. When the classification is built from all the subjects, the recognition rate is reduced slightly, but it can still maintain a recognition rate of 90.4%.

I. INTRODUCTION

ACCORDING to psychology [1], [2], while a person is under high level of positive or negative emotions his sympathetic nerve will keep ascending, resulting in a disorder syndrome of autonomic nervous system (ANS). In order to prevent this circumstance, it is necessary to understand the level of emotions namely high, medium or low a person possesses when they are under an emergency or depression, particular for those who has obstacle in emotional control.

In autonomic nervous system (ANS), sympathetic nerve and parasympathetic nerve complement each other in adjusting human body. A person under emergency situation or in a high level of emotion would usually [2] result in blood pressure ascending, digestion slow, heart rate accelerating, causing the sympathetic nerve in ANS system activate. On the contrary, the parasympathetic nerve will activate in rest or

relaxing activities. In order to observe the sympathetic nerve and parasympathetic nerve system, the analysis of heart rate variability has been commonly adopted. The RR interval which is the interval of heart rate comes from measuring time points between two consecutive beats and is commonly used to indicate the normality of cardiac rhythm for diagnosing a variety of pathologic states and also the recognition of emotion after the transformation.

In the model of emotion, some approach in the psychology of emotion is to seek a small number of dimensions that capture the similarities and differences among emotions. Russell proposed a circumplex model where emotions are plotted in the two-dimension space defined by pleasantness and activation [5]. To simplify this concept and in order to describe emotional level directly, we represent our concept by indicating whether the emotional level is in high medium or low.

Based on this consideration, this paper explores the detection of emotional quality level recognition based on the analysis of HRV and extract the essential features from frequency domain, time domain and nonlinear methods, such as low frequency (LF), high frequency (HF), very low frequency (VLF), total power (TP), standard deviation of RR intervals (SDNN), root mean square of successive differences (RMSSD), mean of RR intervals (MeanNN) and Poincaré plot (SD1 SD2 SD12) etc. We provide 2 films which comprehend joy and sad emotions for the test subject to observe and their ECG responses are collected for analysis. According to our experimental results, it was found that 7 features are selected by SFS when subjects are regarded as optimistic characteristics and the recognition accuracy is 97.8%. When subjects are regarded as pessimistic characteristics, 8 features are selected and the recognition rate is 94.0%. The overall recognition is 90.4% when whole subjects are classified.

The remaining sections are organized as follows. In Section II, we give a brief overview of the experiment. In Section III, we introduce our approach by using feature extraction and classification with sequential forward selection method. In Section IV, we present our experiment results and finally conclusions are showed in Section V.

II. EXPERIMENTS

In this experiment, we provide 2 films to evoke subjects' level of joy and sad emotion. Overall, we collect 30 healthy subjects of age between 20 and 24. These subjects were regulated not to drink caffeine-like beverages and also not to stay up late before the experiment day. In order to prevent the

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case that subject may not describe its feelings properly, all subjects need to fill out the “emotion expression of obstacle scale” and those who do not qualify (score > 60) will be removed from this experiment. The experiments are conducted in a well soundproofed room and the subjects need to wear headphones while the experiments proceed. During the experiments, we request that the subjects should be in the same posture and sit still. The experiments are conducted following the procedures shown as Figure 1. At the beginning, the subjects take a rest followed by watching a joy film, then subjects take another rest and followed by a sad film. The durations of the films last about 20 minutes and each of the rest is 10 minutes long. Subjects will need to fill out the scale during the middle of the film, the end of the film and also after the initial rest, as indicated in Figure 1. In the scale of the self-report, subjects will choose one of the emotions or “calm” with a level for 1 to 10. The result of the self-reports subjects take after initial rest are used to measure the emotion of subjects during the initial rest period; the results of the self-reports taken during the middle and the end of the joy and sad films are used to measure the emotion of subjects during the former period and latter period of the films. Subjects will be considered in low level of emotion during the corresponding period if subjects choose “calm” with level higher than 3 or any other emotion with level between 1 to 3. On the other hand, if subjects choose “calm” with level lower than 3 or any other emotion with level between 4 to 6, the subjects will be regarded as medium emotion. If subjects choose an emotion other than “calm” with level higher than 7, subjects will be considered in high emotion level.

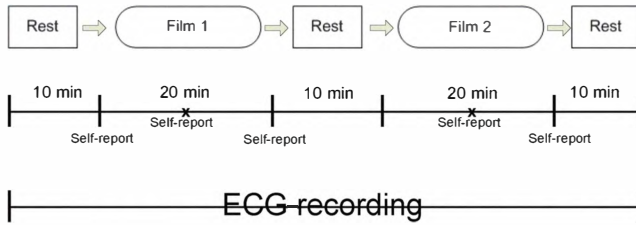


Fig. 1. Procedures for level of emotion recognition

III. METHODS

The overall structure of our methods is shown in Figure 2. First we gather subjects’ biosignals of ECG as our inputs which contain positive and negative emotions. After doing preprocessing for the signal filtering, segmentation and normalization, we calculated 13 features LF, HF, LF/HF, LF(nu), HF(nu), VLF and TP from frequency domain and SDNN, RMSSD and MeanNN from time domain and SD1, SD2 and SD12 from nonlinear methods. Then sequential forward feature selection is applied to select the most significant features. After that, LDA is applied for feature transformation followed by KNNR to classify the segment into different quality levels of emotion.

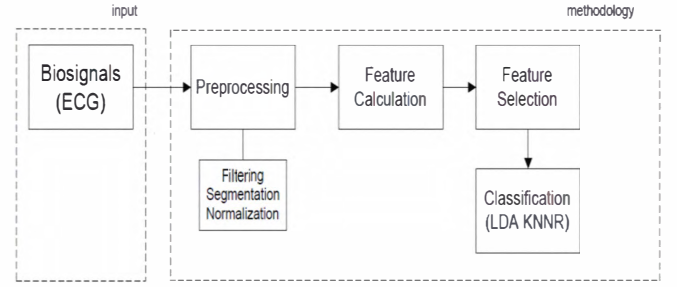


Fig. 2. Block diagram for emotional level recognition

A. Preprocessing

In order to extract features, RR interval which is the interval of heart rate comes from measuring time points between two consecutive beats is needed to be calculated essentially. The beat-to-beat is calculated by an algorithm which contains band pass filter adaptive threshold and moving window to detect the QRS wave (Figure 3(a)). Thus, we get the R peak and the differences between consecutive peaks (Figure 3(b)) for calculating features.

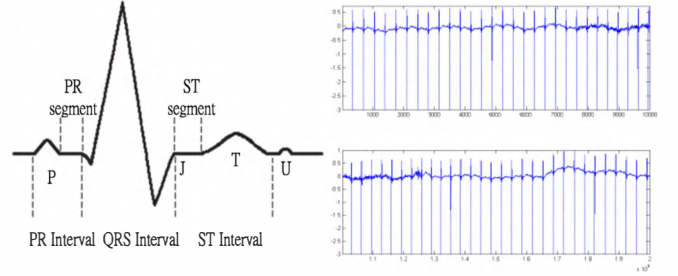


Fig. 3. (a)QRS waveform (b)Consecutive heart beats

B. Feature calculation

Power spectrum (Figure 4) of heart rate variability is often used to observe the phenomenon in frequency domain. It can be divided into 3 major frequency ranges, very low frequency (0.003~0.04 Hz), low frequency (0.04~0.15 Hz), and high frequency (0.15~0.4 Hz). The LF region is considered a measure of sympathetic nerve activity. In contrast, HF band is associated with parasympathetic nerve activity.

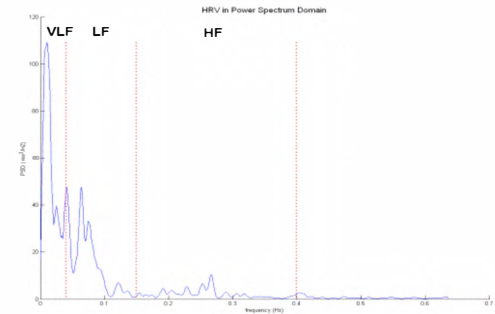


Fig. 4. Power Spectrum Domain (PSD)

In time domain methods, mean (MeanNN), standard deviation (SDNN), and RMSSD are computed from RR intervals. These features are described as follows.

MeanNN is the mean of RR intervals for time between normal-to-normal complexes.

$$\text{MeanNN} = \frac{1}{N} \sum_{k=1}^N \text{RR}_k \quad (1)$$

SDNN is the standard deviation of RR intervals where RR_k denotes the value of the k^{th} RR interval. N is the total number of successive intervals. $\overline{\text{RR}}$ is the mean value of RR intervals. SDNN reflects the overall variation within the RR interval series include both the short-term and long-term [6].

$$\text{SDNN} = \sqrt{\frac{1}{N-1} \sum_{k=1}^N (\text{RR}_k - \overline{\text{RR}})^2} \quad (2)$$

RMSSD is the root mean square of successive differences between adjacent normal RR_j intervals. RMSSD statistic is shown to represent a high-pass filter that effectively passes lower frequency fluctuations that can include sympathetic influences.

$$\text{RMSSD} = \sqrt{\frac{1}{N-1} \sum_{j=1}^{N-1} (\text{RR}_{j+1} - \text{RR}_j)^2} \quad (3)$$

In nonlinear method, Poincare' plot which represents the correlation between the two successive RR intervals is commonly used. Figure 5 shows the poincare plot where the horizontal-axis ($\text{RR}(n)$) is the RR interval of point n , and the vertical axis ($\text{RR}(n+1)$) represents the interval for point $n+1$. The poincare' plots can be represented by a coordinate transformation of a rotation $\theta = \pi/4$, as shown in Figure 6. Then the new axis x_1 and x_2 are the rotation of $\text{RR}(n)$ interval and $\text{RR}(n+1)$, related to the set of the original axis by a rotation $\theta = \pi/4$, as follows:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} \text{RR}_n \\ \text{RR}_{n+1} \end{bmatrix} \quad (4)$$

After such transformation, according to [7] the dispersion on x_1 axis SD1, measured by standard deviation, indicates the level of short-term HRV describing the activation of parasympathetic nerve. On the other hand, the standard deviation around x_2 axis, SD2 indicates the long-term of HRV which describes the ratio of sympathetic nerve and parasympathetic nerve. SD12 which is defined as the ratio of SD1 divided by SD2 is an indicator of sympathetic nerve activation.

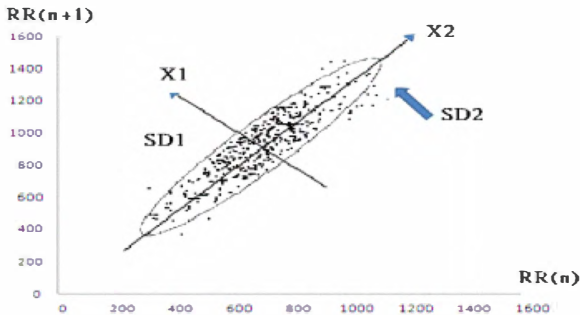


Fig. 5. Poincare' Plot

C. Feature Normalization

In order to classify the level of emotion, we need to obtain the disparity between each segment of different level of emotions. In this paper z-score method is applied to reduce the value range differences. Let x_{ij} , where $i=1 \dots 13$ and $j=1 \dots 65$, represent the value of 13 extracted features in 65 segments from time domain, frequency domain or nonlinear method. Also let μ_i be the average value of the i^{th} feature from the 65 segments, and σ_i be the standard deviation of the i^{th} feature. Then the z-score is performed on each feature value obtained from each segment, as follows:

$$z_{ij} = \frac{x_{ij} - \mu_{x_i}}{\sigma_{x_i}} \quad \text{where } \begin{cases} i = 1 \dots 13 \\ j = 1 \dots 65 \end{cases} \quad (5)$$

According to the description in Section II, one complete experiment lasts for 70 minutes. Based on medical reports, an effective HRV value has to be obtained from an ECG segment lasting for at least 5 minutes [8]. As such, we divide the collected ECG signals into segments, each consisting of 5-minutes ECG signals with 4 minutes overlapping. Since during the first 10 minutes the subjects are in rest status, the first 6 segments contain only ECG signals with the subject in rest, shown in Fig. 6. Similarly, we know that segment 12 to segment 19 and 20 to 27 contain only ECG signals when the subjects were watching the film of Joy. Segments 41 to 49 and segments 50 to 57 contain ECG segments collected when the subjects were watching the sad film. For each subject, let the $V^R = [v^R_1, v^R_2, v^R_3, \dots, v^R_{13}]$ represent the mean of the Z values of the first 6 segments, that is $v^R_i = \frac{1}{6} \sum_{j=1}^6 z_{ij}$, $V^{J1} = [v^{J1}_1, v^{J1}_2, v^{J1}_3, \dots, v^{J1}_{13}]$ and $V^{J2} = [v^{J2}_1, v^{J2}_2, v^{J2}_3, \dots, v^{J2}_{13}]$ denote the mean of Z values during the former period (from segments 12~19) and the latter period (from segments 20~27) respectively of the joy film, that is $v^{J1}_i = \frac{1}{8} \sum_{j=12}^{19} z_{ij}$ and $v^{J2}_i = \frac{1}{8} \sum_{j=20}^{27} z_{ij}$, $V^{S1} = [v^{S1}_1, v^{S1}_2, v^{S1}_3, \dots, v^{S1}_{13}]$ and $V^{S2} = [v^{S2}_1, v^{S2}_2, v^{S2}_3, \dots, v^{S2}_{13}]$ represents the mean of Z values during the former period (from segments 41 to 49) and the latter period (from segments 50 to 57) respectively of the sad film, that is $v^{S1}_i = \frac{1}{17} \sum_{j=41}^{49} z_{ij}$ and $v^{S2}_i = \frac{1}{17} \sum_{j=50}^{57} z_{ij}$. Thus, V^R , V^{J1} , V^{J2} are used as the vectors of their corresponding period.



Fig. 6. segmentation

After the normalized features are obtained, we applied sequential forward selection (SFS) method is applied to select features which give higher discrimination accuracy. SFS (Figure 7) is a bottom-up feature selection approach which sequentially adds the feature that results in the objective function [8].

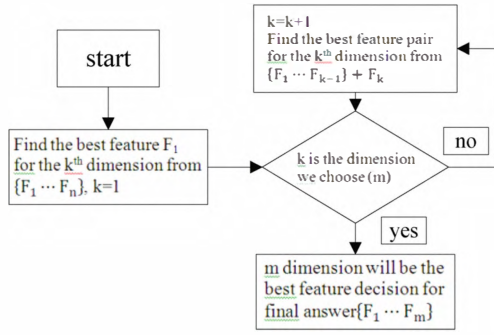


Fig. 7. SFS Algorithm

D. LDA & KNNR

After feature selection, linear discriminant analysis (LDA) is applied for transforming the data into more discriminant space. LDA is to look for the transformation matrix based on optimization computed from the within-class and between-class measurements. The within-class matrix (S_w) and between-class matrix (S_B) are defined as follows:

$$S_w = \sum_{i=1}^c \sum_{k \in C_i} (x_k - m_i)(x_k - m_i)^t \quad (6)$$

$$S_B = \sum_{i=1}^c n_i (m_i - \bar{m})(m_i - \bar{m})^t \quad (7)$$

where n is the number of total samples and n_i is the number of samples in class C_i ($i=1..3$). m_i is the mean of the samples in class C_i and \bar{m} is the mean of all samples [10], defined as follows:

$$m_i = \frac{1}{n_i} \sum_{x \in C_i} x \quad (8)$$

$$\bar{m} = \frac{1}{n} \sum_{i=1}^c x_i = \frac{1}{n} \sum_{i=1}^c N_i m_i \quad (9)$$

Finding the optimal W is equivalent to finding the eigenvectors satisfying $S_B W = \lambda S_w W$ for $\lambda \neq 0$ and can be obtained by applying the eigenvalue decomposition to the matrix $S_w^{-1} S_B$ while S_w is nonsingular.

$$J(w) = \arg_w \max \frac{|w^t S_B w|}{|w^t S_w w|} \quad (10)$$

After we get the optimal matrix W , then the data transformation is obtained by the projection as follows:

$$y = W^T x \quad (11)$$

The transformed data is applied to KNNR for classifying into three emotion levels of high, medium and low. Assume that $\{y_i, C_i\}$, i from 1 to n , are the training samples, where y_i is the feature vector after LDA projection and C_i is the class type for feature vector y_i . Given a query vector y , K nearest neighbors classifier is applied to determine the class [11]. In this paper, we set $K=1$, and the classification is conducted as:

$$\text{Knnr}(x) = C_t \quad t = \arg \min_i \text{dist}(y - y_i) \quad (12)$$

IV. EXPERIMENTS RESULTS

In our experiments, the ECG segments are collected from 30 subjects under experimental emotion joy and sad stimulation as described in Section II. Each ECG segments are under time domain, frequency domain and nonlinear transformation followed by z-score normalization for obtaining features. Then LDA is applied for feature transformation followed by KNNR to classify the segment into different quality level of emotion, high, medium and low. Then, leave one out cross validation is applied to calculate the accuracy, where a single data is used as test while the remaining are used for training classifier.

In our experiments we have particularly observed the output situation from different aspects. The first situation is observed when the subject's joy emotions are larger than sad emotions (regarded as optimistic trait) from self-scaling reports. In this category of data, 7 features (SD12 SD1 VLF LF HF SDNN RMSSD) are selected after SFS. We also found that these 7 features have mostly the highest values on the joy segments, followed by the sad segments and the rest segments have the smallest values. The distribution of the two features of the most discriminability following LDA projection obtained from this category of data is shown in Figure 8. From Figure 8, we can see that the projected data are well separated after the LDA projection and therefore the recognition rate achieves 97.8%, as shown in Table I.

TABLE I
SELECTED FEATURES

Situation	Accuracy	Selected Features
Joy > Sad	97.8 %	SD12 SD1 VLF LF HF SDNN RMSSD
Sad > Joy	94.0%	SD1 SDNN VLF SD12 SD2 LF LFnu Ratio
ALL	90.4%	SD1 SDNN VLF
Average	94.06%	MeanNN SD2 SD12 LF

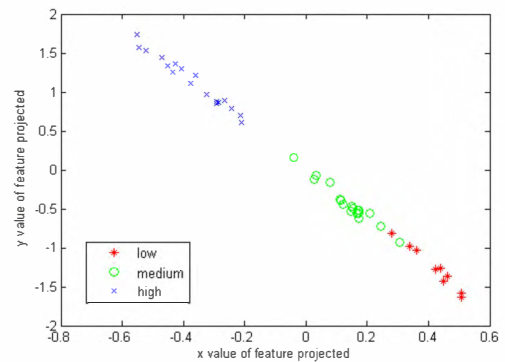


Fig. 8. Joy>sad>rest

The second observation is performed on the cases where the subject's negative emotions are larger than positive emotions (pessimistic trait) on the self reports. From these cases, 8 features (SD1 SDNN VLF SD12 SD2 LF LFnu LF/HF) are selected after SFS. It is also found out that the 9 features have mostly the largest values on the sad segments, followed by those on joy segments and the rest segments have the smallest values. The distribution of the two features of the most discriminability following LDA projection obtained from this category of data is shown in Figure 9, which shows data are well separated with slightly overlapping. As a result, the recognition accuracy achieves 94.0 percent, shown in Table I.

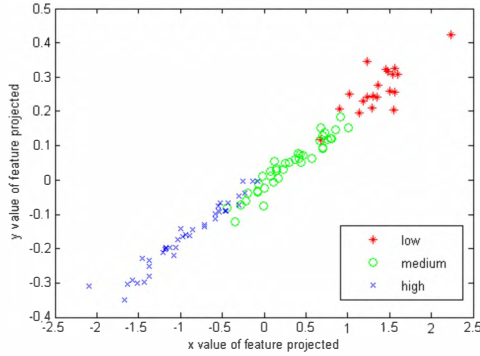


Fig. 9. Sad>joy>rest

In some situation when it is impossible to know the subjects' emotion characteristics, the subjects' emotion trait (optimistic or pessimistic) cannot be predefined. To evaluate an application under such situation, the method is also tested by using all the data. In this situation, 7 features (SD1 SDNN VLF MeanNN SD2 SD12 LF) are selected after SFS (as Fig. 11). The distribution of the two features of the most discriminability following LDA projection obtained from all the data is shown in Fig. 10. Similar to the case of pessimistic subjects discussed previously, these features have slightly overlap, but with good separability. Thus, the recognition rate is 90.4%, shown in Table I.

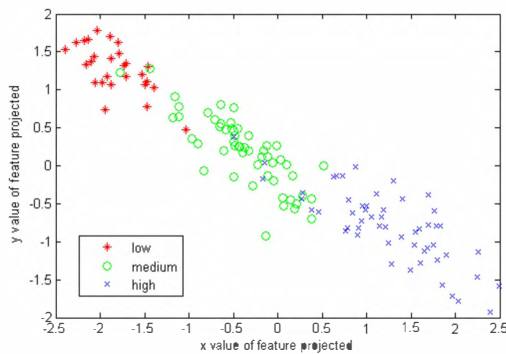


Fig. 10. Joy, sad, rest

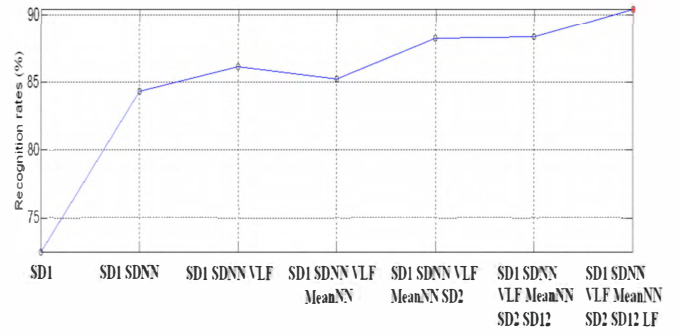


Fig. 11. 7 features(SD1 SDNN VLF MeanNN SD2 SD12 LF) selected by SFS

V. CONCLUSION

Extremely high level of positive or negative emotions would cause a disorder syndrome of autonomic nervous system (ANS). In this paper, the recognition of emotion levels high, medium and low from ECG segments is explored. In order to understand whether personal emotion characteristic would affect the physiological responses in different emotion situations, experiments were conducted separately on subjects of different emotion characteristics. In the experiment, our stimulation comprehends positive and negative emotions. It was also found out that when subjects were provided with the same positive stimulation, some might feel only slightly happy or even calm, while others might laugh or feel extremely excited. We also found that those with optimistic characteristic usually reveal higher biosignal responses when stimulated with positive films. On the other hand, those with more pessimistic characteristic reveal higher signals when stimulated with negative films. Thus, when the classifications are performed separately on the two groups of people, higher recognition rates, 97.8% and 94.0% for optimistic and pessimistic respectively, can be achieved. We also found out when the classification is applied on the whole subjects, a recognition accuracy of 90.4% can be achieved.

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