Improvement of HRV Methodology for Positive/Negative Emotion Assessment

Wanqing Wu
Department of Computer Science and Engineering, Pusan National University
Busan, South Korea
wqwu@pusan.ac.kr

Jungtae Lee
Department of Computer Science and Engineering, Pusan National University
Busan, South Korea
jtlee@pusan.ac.kr

Abstract* — Heart rate variability (HRV) dynamics are particularly sensitive to changes in emotional states, and positive and negative emotions can readily be distinguished by changes in heart rhythm patterns. In this paper, we proposed an improved methodology which is a full set of methods from hardware design to software development for HRV analysis. Firstly, a multi-channel ECG acquisition device has been designed for ECG signal collection, and then we developed a full-featured ECG monitoring system which suitable for real-time ECG display, signal pre-processing, high accuracy R wave detection and HRV analysis in time and frequency domain. Moreover, this study investigates the relationship between HRV and positive/negative emotion. The experiment consists of three tasks: eyes-open, pleasant images and unpleasant images. 15 healthy, right-handed volunteers (female 5, male 10) participated in the experiment; all of them are college student between 18 and 25 years. We find that there is significant correlation between HRV and positive/negative emotion. Subjects who had high SDNN and high LF exhibit greater activation of autonomic nervous system and vice versa. These results which demonstrated the relationship between automatic nervous system and psychological response on positive/negative stimulus can help us for self-emotion management and regulation, as well as determine the clinical utility of psychological intervention.

***Keywords:* Heart Rate Variability (HRV), HRV methodology, ECG, Signal processing, Positive/Negative emotion**

I. INTRODUCTION

Heart Rate Variability (HRV) is a reflection of the many physiological or psychological factors modulating the normal rhythm of the heart which represents the variations in the beat-to-beat alteration in the heart rate [1]. HRV analysis is prevalently used to assess the effect of autonomic regulation on the heart rate. It provides a picture of the interplay between the sympathetic and parasympathetic branch such, it reflects the ways in which emotional states affect core physiology including, but not limited to, cardiac function. As sympathetic tone increases, the heart's beats (R-R intervals on the ECG) get closer together. As parasympathetic tone increases, they widen out. The ebb and flow of autonomic tone create patterns of heart rate acceleration and deceleration; thus HRV provides a picture of emotional and physiological states [2]. More important, it can play a central role in teaching normal persons or patients how to reduce their own risk by showing them how their emotional states affect their heart health.

Past 20 years have witnessed the recognition of the significant relationship between ANS and cardiovascular mortality including sudden death due to cardiac arrest. Numerous numbers of papers appeared in connection with HRV related cardio-logical issues reiterates the significance of HRV in assessing the cardiac heath [1]. The interest in the analysis of HRV is not new. Furthermore, much progress was achieved in this field with the advent of low cost computers with massive computational power, which fueled many recent advances.

However, the measurement of HRV is still a research technique and not a routine clinical tool. There are several potential reasons that can explain this situation. First, the physio-pathological mechanism of HRV establishing the direct link between mortality and reduced HRV is still not fully elucidated. Second, despite the relative evidence of the robust character of parameters such as SDNN and the HRV index, there is still no consensus about the most accurate HRV parameter for clinical use. Third, the sensitivity, specificity and positive predictive accuracy of HRV are limited. Finally, the most important reason is the clinical application of HRV assessment limited by a lack of standardized methodology due to variability of the parameters according to ECG device, signal processing, HRV analysis algorithm, individual's difference (such as gender, age, drug interferences and concomitant diseases) and so on.

The main purpose of this study is to propose an improved methodology which is a full set of methods from hardware design to software development for HRV analysis, and applied it to investigate the relationship between HRV and positive/negative emotion. The researches have significant physiological and psychological benefits, including enhanced autonomic nervous system balance as measured by HRV, improved immunity, stress management and self-regulation.

II. SYSTEM DESCRIPTION

Fig.1 illustrates the proposed ECG monitoring system which consists of two main parts: ECG acquisition platform and a computer-based module (ECG viewer program). ECG acquisition platform includes the active electrode, pre-amplifier (instrumentation amplifier), a low and high pass filter, a main amplifier and A/D converter (ADC) module. The acquisition platform amplifies weak ECG signals in order to effectively serve the ADC. The total gain is bout 60dB; the default sampling rate is 512Hz and there is a 12-bit resolution for two-channel ECG signals. The computer-based module (*Microsoft VB.net, 2008*), is mainly composed of a 60Hz digital notch filter, a 45th order finite impulse response (FIR)

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band-pass filter using Hamming window with a cutoff frequency ranging from 2 to 40 Hz, and a waveform display module. Moreover, HRV analysis module has been developed for parameters calculation in time domain and frequency domain which consists of a multi-scale mathematical morphology (3M) filter [3], an improved R wave detection module, and a HRV parameters calculation module. Fig.1 shows the framework of proposed ECG monitoring system.

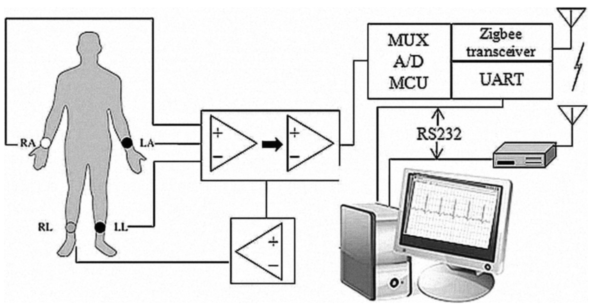

Figure 1. Framework of the proposed ECG monitoring system

A. Design of ECG Acquisition Platform

1) ECG conditioning unit

The ECG signal is an electrical signal generated by the heart's beating, which has a principal measurement range of 0.5 to 5 mV and signal frequency range of 0.1 to 140 Hz are usually weak and easy to be interfered by undesired other noise [3]. Therefore, both amplification and filtering are required for signal processing. The block diagram of ECG acquisition platform is shown in Fig.2.

To meet the requirement of our ECG amplifier, it is necessary to design an ECG conditioning unit on the basis of cascade circuit, which consists of a differential amplifier (instrumentation amplifier), low pass filter, high pass filter and a gain stage.

For the purpose of relatively high common mode rejection ratio (CMRR), the instrumentation amplifier chip INA128AIM, is selected, which is a low power, general purpose instrumentation amplifier with low input bias current. It also features a high CMRR of 120dB and a differential input impedance of 10Gohm // 2pF which can satisfy the required conditions well.

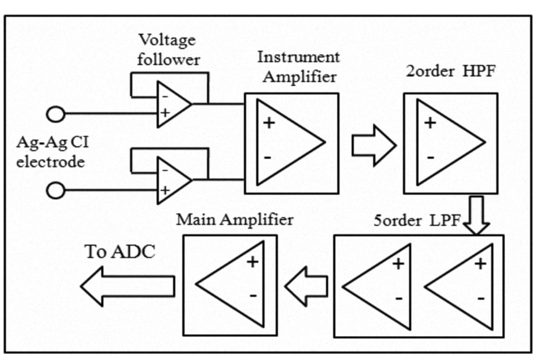

Figure 2. The block diagram of ECG conditioning unit

The output signal of instrumentation amplifier is transferred to the 2nd-order Butterworth HPF with cutoff frequency 0.5Hz to eliminate the baseline drift corresponds to typical respiratory frequencies [4] and the 5th order Butterworth LPF with cutoff frequency 50Hz to attenuate high-frequency noise interference. Finally, the signal amplified by the main inverted amplifier with 40dB gains. The specifications of conditioning unit's amplifier and filter part are given in Table I.

TableI. Specifications of unit amplifier & filter

Item	Character	Gain
Pre amplifier	Differential input impendence : 10Gohm || 2Pf CMRR:120dB Input offset voltage: 25uV	20dB
High pass filter	2nd order Butterworth filter Cutoff frequency : 0.5Hz	0dB
Low pass filter	5th order Butterworth filter Cutoff frequency : 50Hz	0dB
Main Amplifier	Invert amplifier	40dB

After amplification and filtering, the analog output of ECG conditioning unit goes to the digital circuit part. An inexpensive 8-bit 8051-based microcontroller (AT89C51) and 12-bit resolution A/D converter (LTC1274) are employed in this design.

2) active electrodes

With respect to the power-line noise arising from the magnetic field, we used the electrode line in twisted-pair form, aimed at reducing the surface area of loop circuit which is constituted by electrode lines, according to Maxwell's equations. Regarding the noise caused by the electric field, we used active electrodes (composed by voltage followers) in place of conventional Ag-AgCI electrodes in order to overcome the imbalanced electrode-skin impedance which results in the noise's transform from common mode to differential mode. Therefore, even if with the higher common mode rejection ratio (CMRR), noise can still be magnified. Fig.3 shows the terminal of one active electrode.

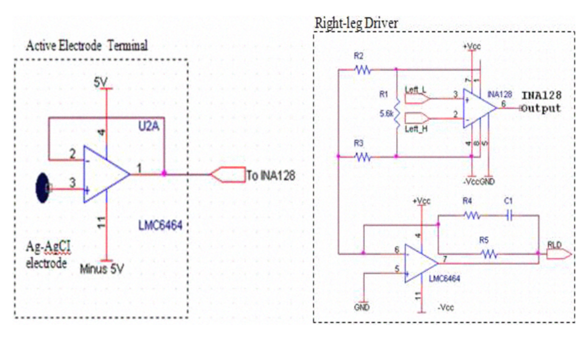

Figure 3. The active electrodes and right-leg driver circuit

3) Right- leg driver

Specially, the Right Leg Driver (RL-Driver) is implemented in this ECG measurement system to counter

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common mode noise in the body, and resist the 60Hz power line noise. The common-mode voltage on the body is inverted amplified and then fed back to the right leg. This negative feedback drives the common mode voltage to a low value. The circuit of right leg driver is also shown in Fig.3.

B. ECG Viewer program

Electrocardiographic (ECG) signals may be corrupted by various kinds of noise, typically examples are: power line interference, electrode contact noise, motion artifacts, muscle contraction, baseline drift, instrumentation noise generated by electronic devices used in signal processing, electrosurgical noise and other, less significant noise sources [4]. The disastrous effect of noise is severe distortion of ECG waveform, the loss of important ECG signal information and deviation of HRV parameters.

Because the noises cannot be filtered completely by ECG conditioning unit, so a computer-based module named as ECG Viewer which comprised of waveform display component, a multi-scale mathematical morphology filter (3M filter), R wave detection module, and a signal analysis component is developed for waveform display, signal processing and HRV parameters analysis. Fig.4 shows the flowchart of ECG Viewer.

A digital 60Hz notch filter was integrated to waveform display component for minimizing the power line interference in real time. Moreover, a Finite impulse response (FIR) band-pass digital filter was realized for correction of baseline wander and respiration noise rejection.

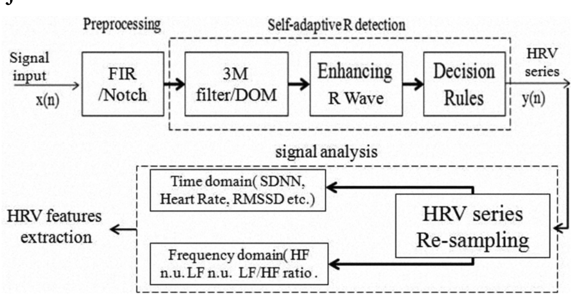

Figure 4. The flowchart of d ECG Viewer

1) Multi-scale Mathematical Morphology(3M) filter

Mathematical morphology, based on set operations, provides a way to analyze signals using nonlinear signal processing operators that incorporate the geometry information of the signal. The shape information of the signal is extracted by using a structure element to operate on the signal, such operators serve two purposes, i.e. extracting the useful signal and removing the artifacts [5].

Erosion and dilation are the two basic morphological operators, termed by $\oplus$ and $\ominus$, respectively. The dilation and erosion of a signal f (t) by a structuring element (SE), g(s) are depicted as follows, respectively [5]:

$$(f \oplus g)(t) = \max_s\{f(t-s) + g(s)\} \quad (1)$$

$$(f \ominus g)(t) = \min_s\{f(t+s) - g(s)\} \quad (2)$$

Another two popular morphological operators are opening and closing, defined respectively as:

$$f \circ g = (f \ominus g) \oplus g \quad (3)$$

$$f \bullet g = (f \oplus g) \ominus g \quad (4)$$

An important property of opening and closing is that they can remove sharp peaks and valleys, respectively. Nonetheless, new filters can be designed by combining these elementary operators.

In this application, the algorithm uses two steps to process the ECG signal: impulsive noise suppression and waveform normalization. The block diagram of the algorithm is shown in Fig.5.

The design of the structuring element (SE) depends on the shape of the signal that is to be preserved, since the opening and closing operations are intended to remove impulses, the SE must be designed so that the waves in the ECG signal are not removed by the process. The values of SE is largely determined by the duration of the major waves and the sampling rate, denoting the duration of one of the waves as T sec and the sampling rate as S Hz, the length of the SE must be less than T $\times$ S [6].

Impulsive noise suppression is performed by processing the data through a sequence of opening and closing operations. The ECG signal is estimated by processing the data using an opening operation followed by a closing operation. A second estimate of the signal is formed by processing the data using a closing operation followed by an opening operation. The result from this step is the average of the two estimates. Due to the shape of impulsive noise is similar to a triangle, so the SE used for impulsive noise suppression has a triangular shape and length 5 (0, 2.5, 5, 2.5, 0).

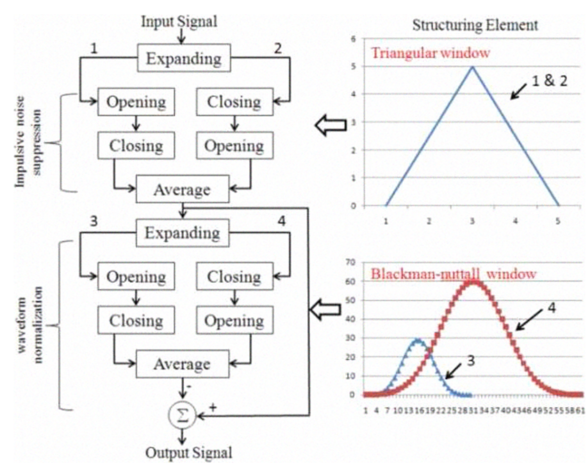

Figure 5. Block diagram of the algorithm for suppressing impulsive noise and normalizing background drift

Waveform normalization is performed by estimating the drift in the raw ECG signal, and subtracting it from incoming data. The waveform drift is estimated by removing the ECG signal from the data. In this step, two structuring elements are used: one for removing peaks

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and the other for removing the pit left after the previous operation. To remove the wave, a structuring element must have its length L greater than $T \times S$. The second structuring element is used to remove the pit left by the first operation, thus its length must be roughly 2L [7]. Correction of the baseline roll and drift is then done by subtracting the baseline drift estimate from the result obtained from the previous step. By considering of the shape information of ECG signal, the SE is modeled as Blackman-Nuttall window which has similar shape to R wave. The ECG signal filtered by 3M filter can be illustrated in Fig.6.

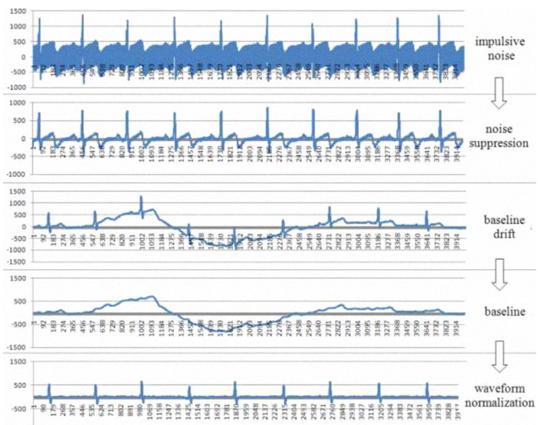

Figure 6. The results of suppressing impulsive noise and normalizing background drift

2) R peak detection

After the multi-scale mathematical morphology filtering, the output ECG sequence is differentiated by Differential Operation Method (DOM) [8] in order to further remove motion artifacts and baseline drifts.

After signal preprocessing, the processed signal enters the decision stage, the steps in the decision are shown in Fig.7.

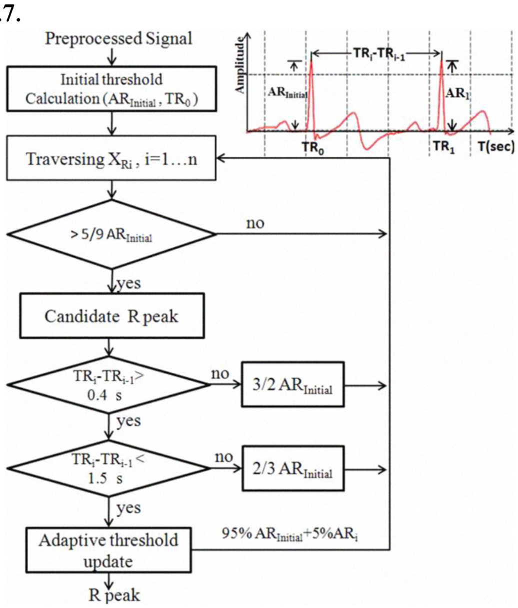

Figure 7. Schematic of R peak detection algorithm steps

This adaptive R wave detection algorithm includes three steps: candidate R wave detection, R peak judgment and adaptive threshold update. The first step is to search the preliminary amplitude threshold ($AR_{Initial}$) and the location of the first R peak in initial 512 samples. And then according to general R-R interval (0.4 to 1.5 sec), decision processes make the final determination as to whether or not a detected event was a R peak, if the detected R-R interval is greater than 1.5 sec (40bpm), normally implied a false detection of R wave, else if the detected R-R interval is less than 0.4 sec (150bpm), probably generated a missing detection. Finally, Adaptive amplitude thresholds applied to the sample series based on continuously updated estimates of the peak signal level and R-R interval.

3) HRV Re-sampling and parameters calculation

In the frequency-domain methods, a power spectrum density (PSD) estimate is calculated for the R-R interval series. The regular PSD estimators implicitly assume equidistant sampling and, thus, the R-R interval series is converted to equidistantly sampled series by interpolation methods prior to PSD estimation. In the software a cubic spline interpolation method is used and the HRV spectrum is calculated with FFT based Welch's periodogram method. In the Welch's periodogram method the HRV sample is divided into overlapping segments (128 points). The spectrum is then obtained by averaging the spectra of these segments. This method decreases the variance of the FFT spectrum. The frequency-domain measures extracted from the PSD estimate for each frequency band include absolute and relative powers of VLF (0-0.04 Hz), LF(0.04-0.15 Hz), and HF(0.15-0.4 Hz) bands, LF(n.u.) and HF(n.u.) band powers in normalized units, the LF/HF power ratio, and peak frequencies for each band [9].

The time-domain methods are the simplest to perform since they are applied straight to the series of successive RR interval values. The most evident such measure is the mean value of R-R intervals ($\overline{RR}$) or, correspondingly, the mean HR ($\overline{HR}$). In addition, several variables that measure the variability within the RR series exist, such as Standard Deviation of Normal-to-Normal Intervals (SDNN), Root Mean Square Successive Difference (RMSSD), pNN50 and so on. In this application, we adopted the standard deviation of R-R intervals (SDNN) for emotion analysis which is defined as:

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}(RR_j - \overline{RR})^2} \qquad (5)$$

Where RR_j denotes the value of j'th RR interval and N is the total number of successive intervals.

TableI. Description and definitions of HRV parameters[9]

Variable	unit	Units Description
Selected Time Domain Measures of HRV		
SDNN	ms	Standard deviation of all NN interval
Selected Frequency Domain Measures of HRV		
LF/HF ratio		reflect sympatho-vagal balance
Normalized LF	n.u.	Reflect sympathetic activity

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Normalized HF	n.u.	Reflect parasympathetic activity

The successful implementation of the ECG signal acquisition hardware and computerized signal processing program are evidenced in the overall results where a clean stream of ECG signals was displayed in real time and analyzed on the PC as shown in Fig.8 and Fig.9.

Figure 8. Waveform display module of ECG Viewer

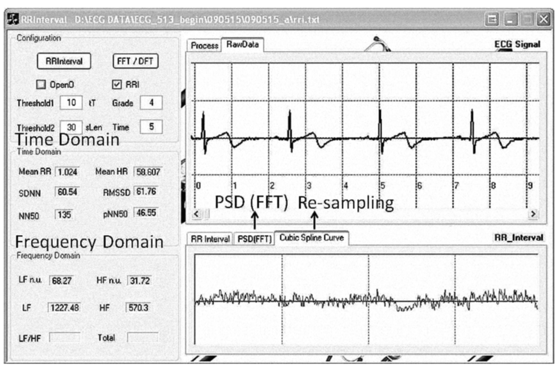

Figure 9. Waveform display module of ECG Viewer

III. METHODS

A. Participants

Fifteen healthy, right-handed volunteers between 18 and 25years (female 5, male 10) participated in experiment. All participants had normal auditory function; none had neurological disorders and asked to be free of coffee and alcoholic drinks at least three hours before each experiment. All of them were given written informed consent to complete the questionnaires and the psycho-physiological protocols. Limb lead II and III of ECG signals were acquired simultaneously for each subject under the controlled conditions. Only those high-quality signals with lasting over one minute are adopted for further analysis.

B. Procedures

In this experiment, IAPS (International Affective Picture System) was used to evoke emotion [10], and some images were selected by valence (ranging from pleasant to unpleasant). We collected the variance of ECG and EMG signal according to the change of emotion when pleasant or unpleasant images were presented. Fig.10 shows the experimental sequences. The experiment consists of three steps which are as follows: eyes-open, pleasant images, unpleasant images, pleasant and unpleasant emotion was induced for 5 minutes respectively by presenting 15 seconds per image. Moreover, a rewards-punishment stimulus was exerted to verify that there are significant differences between positive and negative emotion. After the emotional induction session, the subjects were asked to fill out an emotion questionnaire, which was used to rate their emotional status. The scales had end-points of 1= “extremely negative” to 5= “extremely positive”, as shown in Figure 11.

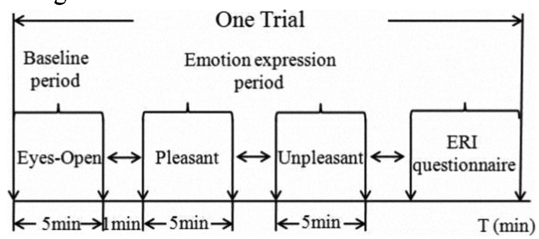

Figure 10. The flowchart of experiment

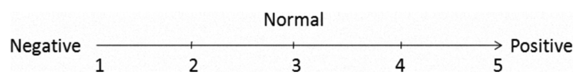

Figure 11. Score of emotion questionnaire

IV. RESULTS AND ANALYSIS

A. Reponses to the emotional stimulus

Both the positive and negative stimulus was effective for all subjects. Self-ratings made during the emotional stimulus are illustrated in Table 2, which shows that our emotion-induction protocol was effective. Subsequently, we could analyze SEMG signals as planned.

TableII. Responses to emotional induction.

	Positive	Negative
Mean Score	4.38	1.5
Grade	0.46	0.5

*Grade=(Mean Score-3)/3

B. Time Domain Analysis

Fig.12 shows the RRI series of a subject during different stimulus states, we can see clearly that RRI series is more regular during unpleasant state which means that the HRV decreased under the negative emotion. Correspondingly, RRI series is more irregular during pleasant state which indicates that the HRV increased.

SDNN is the primary measure used to quantify HRV change, since SDNN reflects all the cyclic components responsible for variability in the period of recording. Low SDNN is a risk factor and might indicate a worse prognosis. We can see clearly that SDNN has evident trend and variation (Table IV) referred to baseline period (eyes-open), the results demonstrated an increase in

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pleasant-induced positive emotion state and during unpleasant session, there was a significant decrease in SDNN. Comparison of the time domain traces revealed that there was greater heart rate variability during positive emotion, compared with negative emotion or baseline (eyes-open).

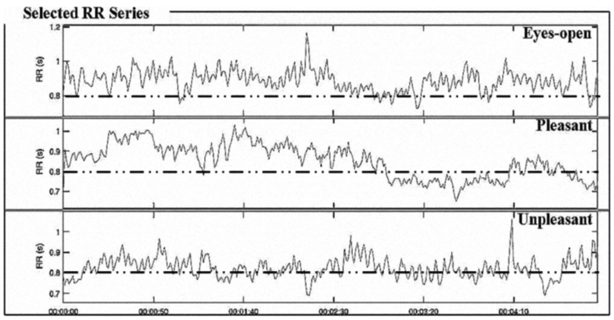

Figure 12. Different emotion stimulus' RRI series

C. Frequency Domain Analysis

There was similar trend in frequency domain. Referred to baseline period, results show that the 2 emotional states produced different effects on sympatho-vagal balance. Positive emotion resulted in a significant increase in LF power with decrease in HF power, because of the increase in LF power, the LF/HF ratio was increased during pleasant state. Correspondingly, negative emotion produced a decrease in LF and HF power, as well as LF/HF ratio. In short term analysis of HRV, these results might indicate that positive emotion caused an increase in autonomic activation, and negative emotion exerted inverse effect to autonomic nervous system.

TableIII. Comparisons of HRV parameters in different states

State / Variable	unit	Eyes-open (REF.)	unpleasant	pleasant
$SDNN_{mean}$	ms	55.4±15.4	51.58±17	63.9±17.7
LF_{mean}	ms^2	1157±944	1019±716	1472±1567
HF_{mean}	ms^2	927±886	881±758	787±824
LF/HF_{mean}		2.0±1.9	1.3±0.9	2.3±1.3
Total Power	ms	2083±1824	1728±1522	2259±2461

Examining the results presented above, we can see that under the negative emotion, the activation of autonomic nervous system(ANS) were decreased compared to positive emotion and eyes-open, higher SDNN and LF power might devote as an indicator for ANS activation.

V. CONCLUSION AND DISCUSSION

In this study, we proposed an improved HRV methodology from hardware design to software analysis for positive/negative emotion assessment. Firstly, we designed a non-invasive ECG acquisition system, and then a computer-based module (ECG viewer) was developed for waveform display, signal processing, and HRV analysis. Finally, we investigated the relationship between HRV and positive/negative emotion. As we reported that emotional experiences play an important role in determining activation of autonomic nervous system. Although we only examined a few subjects over a short period of time, result support our previous work and suggest that psychological interventions that minimize negative reaction (such as stress, anxiety) and enhance positive emotional state could significantly impact cardiovascular function.

In the next, we are planning to measure the ECG and EEG and EMG simultaneously with respect to positive and negative emotion, which can help us to understand the interaction between centre nervous system (CNS) and autonomic nervous system which can help us for self-emotion management and regulation, as well as determine the clinical utility of psychological intervention.

REFERENCES

[1] U. Rajendra Acharya, K. Paul Joseph, N. Kannathal, Choo Min Lim and Jasjit S. Suri, "heart rate variability: a review", Medical and Biological Engineering and Computing, Vol. 44(No.12),Dec.2006,pp.1031-1051,doi:10.1007/s11517-006-0119-0

[2] Lee Lipsenthal, MD, "Heart Rate Variability and Emotional Shifting: Powerful Tools for Reducing Cardiovascular Risk", Holistic Primary Care, Vol.5(No.4),Retrieved April, 13, 2005.

[3] Ying-Chien Wei, Yu-Hao Lee, Ming-Shing Young. "*A Portable ECG Signal Monitor and Analyzer*", Proc. IEEE ICBBE2008.The 2nd International Conference on Bioinformatics and Biomedical Engineering, 16-18 may,2008, pp. 1336-1338.

[4] Friesen, GM, Jannett, TC, Jadallah, MA, Yates, SL, Quint, SR, and Nagle, HT. (1990): 'A comparison of the noise sensitivity of nine QRS detection algorithms',IEEE Trans. Biomed. Eng.,Vol.37, pp. 85–98, doi: 10.1109/10.43620

[5] Fei Zhang, Yong Lian. "Electrocardiogram QRS Detection Using Multiscale Filtering Based on Mathematical Morphology". Proc.IEEE Conf. Engineering in Medicine and Biology society, France,August 23-26, 2007, pp. 3196–3199.

[6] T. Y. Ji, Z. Lu, Q. H. Wu and Z. Ji, "Baseline normalisation of ECG signals using empirical mode decomposition and mathematical morphology", Electronics Letters vol. 44, pp. 82-83, Jan. 2008.,

[7] CHEE-HUNG HENRY. CHU, E.J. Delp, Impulsive noise suppression and background normalization of electrocardiogram signals using morphological operators, IEEE Trans. Biomed. Eng. Vol.36 (No.2) (1989) 262-273.

[8] Yun-Chi Yeh, Wen-June, Wang, "QRS complexes detection for ECG signal: The Difference Operation Method", Computer Methods and Programs in Biomedicine., Vol.91,pp. 245-254,doi: 10.1016/j.cmpb.2008.04.006.

[9] Ali Doruk1, Tumer Turkbay, Zekeriya Yelbo.a, Muzeyyen Ciyiltepe, Atilla iyisoy, Levent Sutcigil, Aytekin Ozflahin. "Autonomic Nervous System Imbalance in Young Adults with Developmental Stuttering", Bulletin of Clinical Psychopharmacology, Vol. 18, pp. 274-281, April 2008

[10] Lang,P.J.,Bradley,M.M.,AND uthbert,B.N.1995.NIMH Center for the Study of Emotion and Attention, international Affective Picture System(IAPS), Technical Manual and Affective Ratings.

Digital Object Identifier: 10.4108/ICST.COLLABORATECOM2009.8296
http://dx.doi.org/10.4108/ICST.COLLABORATECOM2009.8296