Development and Preliminary Evaluation of an Android Based Heart Rate Variability Biofeedback System

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***Abstract*— the reduced Heart Rate Variability (HRV) is believed to be associated with several diseases such as congestive heart failure, diabetes and chronic kidney diseases (CKD). In these cases, HRV biofeedback may be a potential intervention method to increase HRV which in turn is beneficial to these patients. In this work, a real-time Android biofeedback application based on a Bluetooth enabled ECG and thoracic electrical bioimpedance (respiration) measurement device has been developed. The system performance and usability have been evaluated in a brief study with eight healthy volunteers. The result demonstrates real-time performance of system and positive effects of biofeedback training session by increased HRV and reduced heart rate. Further development of the application and training protocol is ongoing to investigate duration of training session to find an optimum length and interval of biofeedback sessions to use in potential interventions.**

I. Introduction

It is well known that the heart is not working as a metronome; the instantaneous heart rate varies around the mean heart rate. Heart rate variability (HRV) is the variation of heart rate between two consecutive heartbeats and hence higher HRV means less regularity of heartbeats. The sinus-atrial (SA) node, pacemaker cells of heart, has an intrinsic HR around 100-120 beat per minute (BPM) but the actual instantaneous heart rate is a result of feedback from autonomic nervous system (ANS), related to respiration, blood pressure, thermoregulation etc. However, for simplification we can assume that sympathetic activity —fight and flight— increases the SA node intrinsic HR while parasympathetic activity —rest and digest— decreases it. Depressed HRV, monotonously regular HR, is a sign of lowered regulatory function of ANS which may lead to lower ability to keep homeostasis and cope with requirements of a challenging environment.

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Several studies have reported a relation between reduced HRV and different diseases, such as poor outcome and sudden death in chronic congestive heart failure [1], general inflammation [2, 3] and asthmatic reaction to concentrated ambient coarse particles [4] etc. However, HRV reduction can be the cause or a product of disease. In the special case of systematic inflammation, reduced HRV is a sign of less vagal activity, which leads to an inefficient anti-inflammatory pathway. Therefore, it is desirable to study different methods to increase HRV as a potential non-invasive intervention method in diseases associated with reduced HRV. Vagal nerve stimulation [5] and HRV biofeedback [6] are reported as such prospective methods to increase HRV.

The aim of this study was to develop and evaluate a user friendly biofeedback system based on Android devices. This system will be beneficial for using as intervention method in clinical studies especially for patients with chronic kidney disease whom are suffering from systematic inflammation and reduced heart rate variability.

II. Method

A. System Overview

The designed biofeedback system consists of a Bluetooth device and an Android application running on a Sony Xperia Tablet Z. The device, is designed by *Z-Health Technologies AB* and has used in ATREC project [7], it measures both Electrocardiogram (ECG) and respiration (Thoracic electrical bioimpedance measured by tetra-polar electrode placement across the thorax). The Android application processes the data and provides a graphical user interface (GUI), presenting the parameters of interest back to the user. Implementation of different signal processing algorithms in Android has been evaluated by comparison to a MATLAB prototype.

B. HRV Biofeedback and Resonant Frequency

A number of methods for HRV biofeedback exist, but the most promising approach seems to be resonant frequency training (RFT) [8]. The typical procedure for HRV biofeedback involves encouraging subjects to first put themselves in a relaxed and positive state of mind before actual training begins. Procedure inspires subjects to breathe at a specific respiratory rate called resonant frequency. It has been shown that due to the nature of the baroreflex, each person has a resonance frequency for breathing where blood pressure and heart rate oscillates in synchronization which maximizes HRV [9]. The baroreflex is a reflex that regulates blood pressure through a negative feedback loop to the heart. A rise in blood pressure will be signalled to the brain, and the brain will then, mediated via the ANS, decrease the HR thus lowering the blood pressure again. And vice versa, a drop in blood pressure will lead to an increase in heart rate, restoring the blood pressure; all through the same reflex involving the ANS. This effect of increase or decrease in HR, because of baroreflex feedback, is occurring with a delay of about 5 seconds due to inertia in cardiovascular system. The HR is also constantly affected by respiration; each inhalation increases and exhalation decrease the HR; this phenomenon is called respiratory sinus arrhythmia (RSA). It is a common believe that RSA is the result of cardiac vagal efferent modulation created by respiration [9, 10]. By breathing at pace of oscillations in blood pressure, heart rate and blood pressure will oscillate at the same frequency with 180 degree difference in phase. This will enhance amplitude of blood pressure variations and thus increase HRV. The period of blood pressure oscillation is around 10 seconds, which corresponds to a frequency of approximately 0.1 Hz and a respiration rate of 6 breaths per minute [11].

C. *Signal Processing*

ECG and thoracic electrical bioimpedance (TEB) signals are recorded in this work. The TEB signal is simply band passed and used as a direct feedback to user while feedback from ECG involve calculating power spectrum and HRV time and frequency domain indexes according to European Task Force for HRV analysis [12].

The first step is R peak detection and calculating RR intervals, tachogram, which can be challenging due to noise of different origin such as muscle activity, electrode motion, baseline wander and T waves with high-frequency characteristics similar to QRS complexes. During the last three decades different approaches based on derivate, digital filters, wavelets, neural network and genetic algorithm have been introduced for QRS detection [13]. However for the sake of simplicity a derivative QRS detection algorithm known as Pan-Tompkins [14] is used. QRS detection includes simple steps of band-pass filtering, calculating derivative function, squaring, moving average and adaptive thresholds follow by finding QRS points based on specific decision rules. Thus, after the tachogram is obtained from RR time series, HRV indexes are calculated in time and frequency domain.

The tachogram is not evenly sampled and hence Fast Fourier Transform (FFT) cannot be used directly. A trivial solution is to interpolate the tachogram and resample it and then use FFT or any spectral estimation method e.g. welch periodogram. Lomb periodogram is another spectral estimation method which is suitable for unevenly nature of tachogram and is reported to perform well for estimating HRV frequency-domain parameters [15]. The Lomb periodogram require less computation compare to other approaches (interpolation, resampling and FFT), hence it is used in this work. Power in each frequency band; VLF (0-0.04 Hz), LF (0.04-0.15) and HF (0.15-0.4) and time domain measures such as the standard deviation of NN intervals (SDNN) and the number of pairs of successive NNs that differ by more than 50ms (NN50) are calculated as specified by the applicable guidelines [12].

D. *Android App Development*

The launch of an Android application will create a main thread, also called UI thread, which handles user interface events such as drawings and buttons etc. Implementing a heavy operation in main thread can lead to poor performance and it can even block UI [16]. Therefore, real-time processing and visualization of signals is accomplished by use of four working threads and one specific android thread called *intentservice [17]* in addition to UI thread. They are called UI thread, BLUETOOTH thread, TEB thread, ECG thread, PLOT thread and PSD intent service.

UI in this application is mainly built up of plots, text views, progress bars and buttons. The plots are implemented using an open source library AndroidPlot. The BLUETOOTH thread as the name implies establish the communication with the device; sends different commands (start, stop, set sampling etc.) and receives and decodes samples from received data frames. The TEB and ECG threads are performing the preprocessing of signals. The ECG thread also finds R-Peaks and calculates RR intervals. Creating a pacer based on target breathing rate is also managed by TEB thread. The PSD is an intentservice initiated by ECG thread and it terminates after calculating power spectrum of

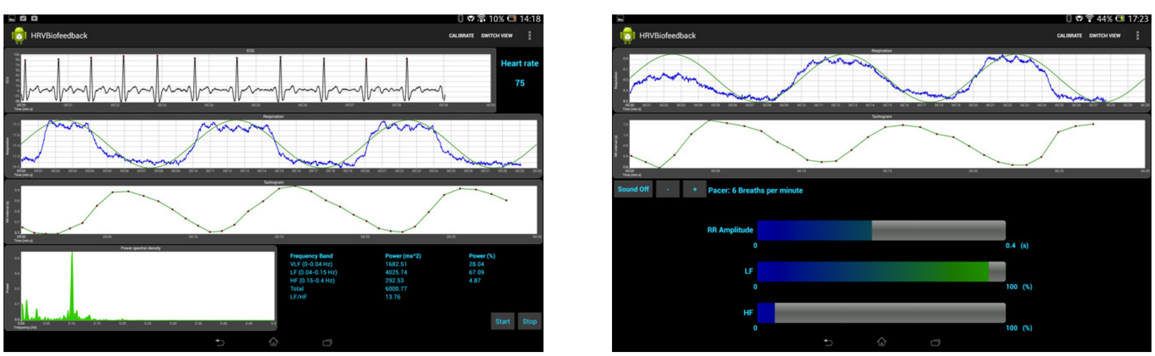

Figure 1. The first view (to the left) is the default view when launching the application, showing from top to bottom: ECG, respiration, tachogram and power spectral density. The bottom right corner shows the power in different frequency bands. The maximum peak in the power spectrum at 0.1 Hz corresponds to a respiration rate at 6 breaths per minute. The second view (to the right) is mainly used for biofeedback training, user is asked to follow the pace of metronome, the green sinus, and blue plot is the user actual respiration pattern. Tachogram shows the same desired frequency but with 180 phase delay and hence power spectrum shows a peak at 0.1 Hz corresponds to 6 breath per minute.

tachogram using the Lomb periodogram.

E. *Experimental Setup*

The physiological effect of using the developed biofeedback solution has been evaluated in a pilot study on healthy volunteers. The study population consisted of eight healthy and non-medicating adults (3 women and 5 men), in the ages of 23 to 46 (30±8) years old. All subjects were properly informed and provided a written informed consent. The biofeedback training included three consecutive sessions in sitting position; five minutes of HRV recording, twenty minutes of HRV biofeedback training and five minutes of HRV recording. The tablet user interface was not visible to user in the first and the third sessions.

During the biofeedback session, subjects were asked to breathe around 6 breaths per minute by following the pacer, a visual sine curve and an audio feedback at the target breathing rate. The feedback includes a bar that corresponds to the amplitude of tachogram and two other bars corresponding to the normalized LF (0.04 - 0.15 Hz) and HF (0.15 - 0.40 Hz) powers of tachogram. The first aim for the subjects was to fill the first two bars as far as possible to the right, i.e. to increase LF and decrease HF.

III. RESULTS

A. *Developed App and usability*

The screenshots of developed application is depicted in Figure 1. The application can execute the computation with good performance. The accuracy of the calculated indexes is validated through comparison with a MATLAB prototype. All subjects succeeded to follow instruction to use the application during training session. The second view (Figure 1) was designed to be the primary interface for training; however, the first view was also appreciated by subjects.

B. *Biofeedback Evaluation Results*

The HRV indexes before and after training session, are summarized in Table I. An increase in HRV indexes is clear for all subjects except subject 7. The box-plot of VLF, LF, HF and total power (TP) indexes are depicted in Figure 2. The figure shows power of HRV in different frequency-bands before and after training session while dash-red lines are connecting mean of each index between two sessions. The increase of variability (slope of the dash-red line) is greater in LF band and obviously because of its contribution for total power (TP) as well.

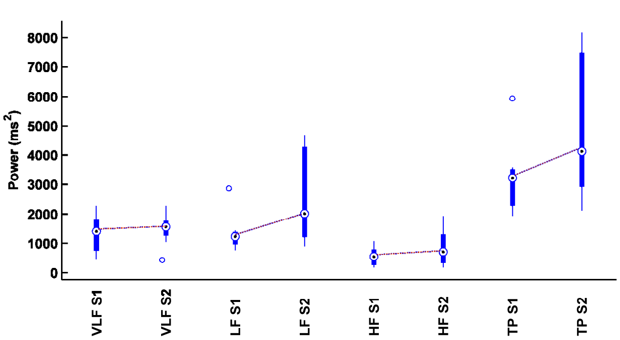

Figure 2.Boxplot of power in before (S1) and after (S2) biofeedback session is illustrated for different frequency-bands; VLF (0-0.04), LF (0.04-0.15), HF (0.15-0.4) and TP (0-0.4).

TABLE I. HRV INDEXES OF SUBJECTS BEFORE (S1) AND AFTER (S2) BIOFEEDBACK TRAINING

	HR(bpm)		Resp(bpm)		LF(ms^2)		HF(ms^2)	
	S1	S2	S1	S2	S1	S2	S1	S2
Subject 1	66	68	14	13	1179	1687	338	377
Subject 2	85	73	13	10	900	4034	816	1943
Subject 3	59	59	12	10	1025	4693	1093	1278
Subject 4	62	63	16	17	759	1085	760	886
Subject 5	84	80	12	12	1336	1330	170	288
Subject 6	67	62	13	12	2863	4543	790	1352
Subject 7	78	72	13	10	1456	903	272	169
Subject 8	87	76	12	12	1291	4343	253	543
Mean ±Std	73.5 ±11.2	69 ±7.4	13 ±1.3	12 ±2.3	1351 ±654	2577 ±1598	561 ±342	854 ±624
p-value	0.37		0.26		0,06		0.26	

The increased HRV can be noticed in both time-domain and frequency-domain, for instance HRV distribution and its power spectrum for Subject-2 before and after biofeedback session are illustrated in Figure 3-4. The HRV distribution clearly shows not just decrease in average heart rate after biofeedback session but also increase in variability of HR. The power spectrum in Figure 4 is calculated by the Lomb periodogram and clearly shows increased variability in all the frequency bands.

IV. DISCUSSION

The result shows increased HRV after biofeedback sessions. The HR is reduced for five subjects when the other three subjects had similar HR or with tiny increase after biofeedback session. It can be seen that for subjects with low heart rate before training session, e.g. Subject 3, biofeedback training cannot reduce HR. The significant levels calculated by ANOVA, Table I, shows a significant ($p=0.06$) difference between low frequencies power (LF) of HRV after training session. Since there is no significant difference between respiration rate before and after training, this increase cannot be caused by sinus arrhythmia. Therefore, it could be possible to conclude that biofeedback session was efficient to increase HRV. Despite no significant difference in some

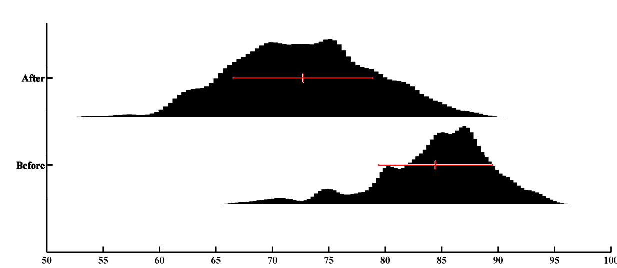

Figure 3.Heart Rate distribution plot of Subject2 before and after biofeedback sessions are depicted in bottom and top, respectively.

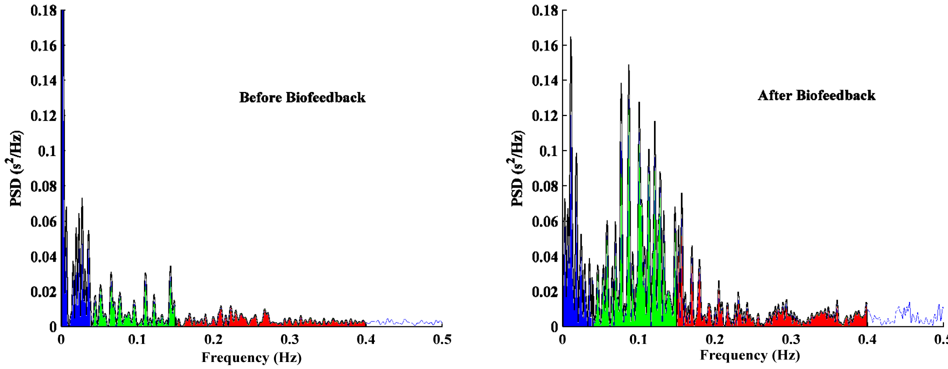

Figure 4.The Lomb periodogram of Subject2 before and after biofeedback sessions are depicted in left and right, respectively. The VLF (0-0.04), LF (0.04-0.15) and HF (0.15-0.4) frequency bands are filled by blue, green and red colors, respectively.

of HRV measures after the training sessions, a look at each individual subject reveals that all subjects except Subject-7 exhibit higher HRV after training. However, Subject-7 who has reduction in HRV has at least lower HR.

In this study, all subjects were asked to breath at six breaths per minute corresponding to resonant frequency. It could be valuable to find each individual resonance frequency at the beginning of training session. The resonance frequency can be determined by measuring HRV amplitudes while the subject breathed at 5-7 breaths per minutes for intervals of ~1–2 minutes. The resonance frequency will produce the highest peak at the respiratory frequency. Furthermore, like any other type of training, the skills improve by more training and hence, having multiple biofeedback sessions should also produce greater increase in HRV.

Regardless of the basic study protocol and small study population, the result of this brief study and comparison of the implemented algorithms in Android compared to the MATLAB prototype is sufficient for validation of the system. Further development aims to provide a more entertaining biofeedback session e.g. by integrating simple game controls by HRV and respiration indexes and the use of sensorized garment similar to textile electrode straps[18]. The study protocol will be revised to study optimum duration and interval for biofeedback sessions.

V. Conclusion

The implemented HRV biofeedback system in Android works in real-time and provides feedbacks to user during training session. A brief study for evaluation of the system shows positive effect of biofeedback as reduced HR and increased HRV and confirms the usability of the developed system. Further software development and design of new study protocol is ongoing.

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