On Optimal Biofeedback Parameters for Heart Rate Variability Improvement Using Breathing Entrainment

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***Abstract*— Slow breathing techniques and breathing entrainment represent promising approaches to stress reduction, autonomous nervous system improvement and improved cognitive function. The most frequently used techniques use predefined breathing rates and the resonant characteristic of heart rate variability at ~0.1Hz, the frequency of the blood control loop. We present a new method of evaluation of the personal resonant breathing frequency for the maximum heart rate variability and implementation of a real-time breathing entrainment system that automatically adjusts to the current optimal breathing frequency of the user. We demonstrate the existence of the personal optimal breathing rate, and demonstrate the change of the optimal breathing rate during the session. In our pilot experiment, we found that the magnitude of the respiratory sinus arrhythmia (RSAM) represents a promising parameter for optimization of the breathing entrainment rate, and demonstrated increase of RSAM power by continuous tracking of the optimal personal breathing rate from 100 ms^2 to more than 500 ms^2.**

Keywords—Breathing, Respiratory Sinus Arrhythmia, Heart Rate Variability, Entrainment, Real time

I. Introduction

Slow-paced breathing techniques can be highly effective for stress reduction, and effective adjunct treatment for a large range of psychological and medical conditions [1]. Deep breathing has significant physiological effects, such as activation of the parasympathetic nervous system, decrease of stress hormones, and improved blood flow. Physiological parameters, such as heart rate, breathing rate, and heart rate variability, are frequently presented to the user as biofeedback to optimize the effect of physiological changes. Heart Rate Variability (HRV) represents the variation of time between successive heart beats, commonly referred as interbeat intervals (IBI) in photoplethysmogram (PPG) or RR intervals in electrocardiogram (ECG). However, optimum methods of assessment of the effectiveness of breathing techniques and selection of optimal parameters for biofeedback treatments are still an open research issue. Breathing techniques can be highly effective for stress reduction, capitalizing on the connection between the mind and body.

Different parameters of HRV have been shown to be an effective metric for assessing the health of the cardiovascular system, the autonomic nervous system (ANS), and the parasympathetic nervous system (PNS) [2], [3]. During inhalation, the diaphragm moves down, causing a decrease in inter-thoracic pressure, decreasing blood return to the heart and increase in heart rate. Exhalation increases the inter-thoracic pressure and slows down the heart rate. The changes in heart rate are modulated by the PNS and activity of the vagus nerve represented as a vagal tone [3].

Changes of heart rate caused by breathing are called Respiratory Sinus Arrhythmia (RSA), and illustrated in Fig. 1 as changes in heart rate, blood pressure, and sympathetic activity as a function of lung volume. Heart Rate Variability (HRV) is a marker of impaired cardiovascular regulation of the Autonomic Nervous System (ANS) [4]. HRV has also been shown to effectively correlate with the emotional state of a person [5]. Thus it can be used as a quantitative measurement on how an action or event has on someone's emotional state.

This paper presents a method of real-time evaluation of the optimal breathing rate for maximum heart rate variability of the user. We present the algorithm, methods, and preliminary results of the pilot study.

II. Breathing Entrainment

Slow breathing techniques, such as yogic pranayama techniques demonstrate significant change of function of the autonomous nervous system and increase of heart rate variability [6]–[8]. E. Vaschillo analyzed resonant properties of HRV around LF oscillations (~0.1Hz) generated by baroreflex activity [9]. Vaschillo's two closed-loop model explains how HRV biofeedback procedures like slow paced breathing and rhythmic skeletal muscle tension can stimulate the baroreflex and amplify RSA [10]. Vaschillo describes the vascular tone and heart rate baroreflexes as closed loops and propose that stimulating one closed loop activates its counterpart [10], [11]. Lehrer et al. proposed resonant breathing technique at the breathing rate around naturally occurring resonance [4]. This resonant breathing rate is subject dependent and ranges between 4.5 and 6.5 BPM [4]. Song et al. investigated the nature of optimal breathing rates for high HRV, and found a resonant curve with HRV decreasing when the breathing rate is either too low or too high [12]. The study investigated HRV in women of different age. According to Song, the subjects also had approximately the same Heart Rate for each of the tested breathing rates.

Shaffer and Meehan also evaluated an individual's RSA Response to varying breathing intervals to find what breathing interval maximizes the power of the breathing frequency band. Although they were able to find the ideal breathing frequency for a person at a given time, they are uncertain how long that breathing rate will remain optimal for the given subject [10].

There are several devices and applications on the market intended for heart rate variability training. One of the most commonly used methods is the Breathe application on the Apple watch. This application provides preset routines for breathing entrainment utilizing visual pattern on the watch and watch vibration. The breathing rate can be set between 4 and 10 BPM. Additionally, the Apple Watch has been shown to provide a very good HRV assessment [13]. Custom devices, such as Inner Balance Coherence Plus from HeartMath, provide a real-time coherence score of heart rate variability [14].

Slow breathing techniques, such as yogic pranayama techniques demonstrate significant change of function of the autonomous nervous system and increase of heart rate variability [6]–[8]. The authors hypothesize that this type of biofeedback exercises the baroreflexes, and renders them more efficient.

It has also been shown that there is a large self-reported reduction of stress in those that have undergone HRV biofeedback training [15]. It is theorized that a personalized Heart Rate biofeedback training program should be able to amplify the effects of a generic biofeedback training program, and according to Shaffer and Meehan, more research needs to be done on the effect of such a program versus a universally prescribed breathing rate for entrainment [10].

We hypothesize that resonant breathing at 6 BPM is very hard for most users, and faster increase of HRV can be achieved by finding a personal optimum slow breathing rate. We believe that breathing at a personal optimum breathing rate assessed using parameters of heart rate variability can increase the effect of deep breathing techniques and psycho/physiological benefits. In this paper we present the evaluation of parameters of HRV suitable for the real time biofeedback and implementation of the real-time biofeedback system.

The goal of the authors is to perform a similar type of analysis as Shaffer and Meehan to find the ideal breathing rate of a person, but to extend this work to perform this analysis in real time and provide a visual indication of the ideal breathing rate in real time. Such that a user can continuously stay breathing at the ideal rate while using the device.

We implemented a system for real-time breathing entrainment and physiological assessment, as shown in Figure 1. The system consists of:

- System controller, implemented on a Raspberry Pi 4b single board computer,
- Physiological Monitor, is a low power microcontroller used for data acquisition and signal processing of the PPG and ECG signal. In this study we used a custom PPG board with MAX86150 PPG sensor for ease of sensor attachment.
- LED light entrainment controller, is a Teensy 3.2 controller connected to an Adafruit Jewel LED. The controller receives commands from the main controller with the breathing rate and generates light pattern to entrain breathing of the user.

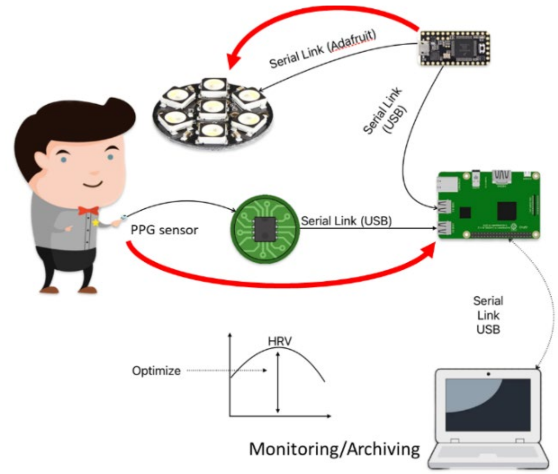

Figure 1. Organization of the breathing entrainment and physiological assessment system.

A typical setup is presented in Figure 2. The subject uses a clip with the PPG sensor connected to their finger. The monitor displays both the raw signals and calculated HRV parameters in real-time. The light controller with LEDs is sitting on the desk in front of the subject, such that they can get a clear view during breathing entrainment.

A. Signal Processing

Physiological monitor collects raw PPG using I2C communication with the PPG sensor. The controller filters the signal, eliminates baseline, and finds moments of individual heart beats using Pan&Tompkins algorithm [16], and inter beat intervals. In preparation for spectral analysis, IBI outliers were removed. The upper and lower bounds of acceptance was 1.3 and 0.7 times the last IBI respectively [16]. Signal processing on physiological monitor is implemented in C.

The primary controller employs Python for signal processing and HRV analysis of IBIs. HRV parameters are calculated in a 64 second window of IBIs. Average value of all intervals is used as a mean value of IBI in the window, and subtracted from all IBIs in the window to remove the baseline. The IBIs are then interpolated at 4 Hz using a cubic spline method. The spectrum for HRV is calculated by performing a Fast Fourier Transform (FFT) on 256 interpolated IBIs contained within a 64-second time frame, with the application of a Hanning window. The effect of breathing on IBIs (RSAM), was assessed using Fourier analysis of IBIs at the breathing frequency f_b in the middle of the processing window. However, since the breathing frequency is not constant, and changes even in the 64 second window, we use Fourier analysis of the previous breathing frequency (f_{b-1}) as well as the next breathing frequency (f_{b+1}).

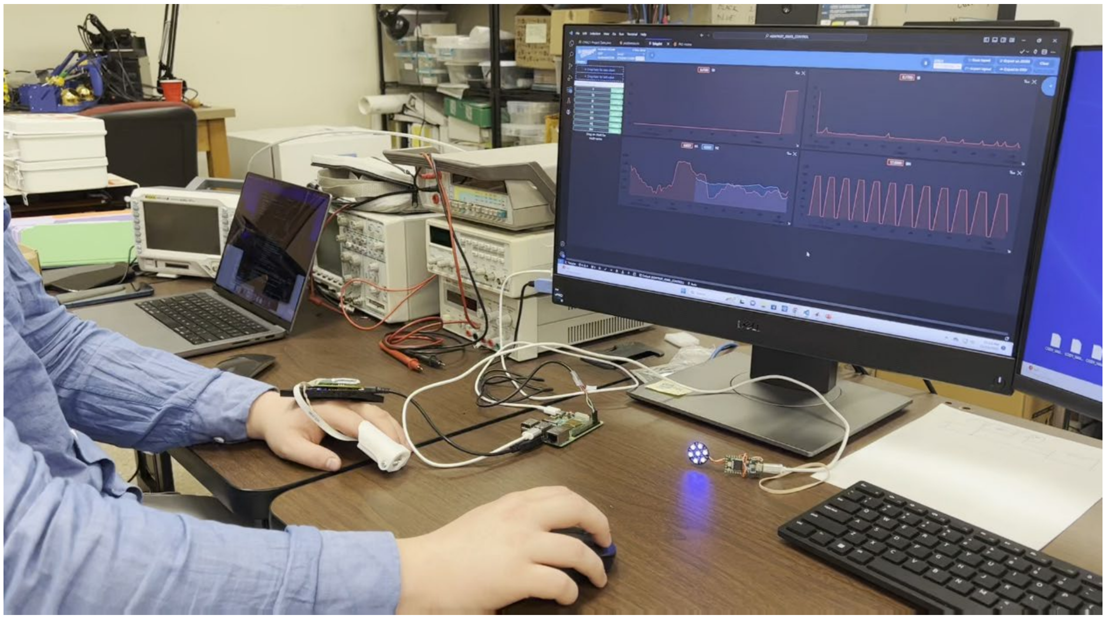

Figure 2. Real-time breathing entrainment setup

This approach compensates for spectrum leakage and variations in breathing rate. RSAM is calculated as a sum of magnitudes from all three spectral components. This methodology aims to enhance the accuracy of our results by addressing the influence of varying breathing rates and potential spectrum leakage issues.

We use root mean sum of squared differences (RMSSD) as a classical measure of HRV [2], calculated as shown in (1).

$$RMSSD = \sqrt{\frac{\sum_{2}^{N}(IBI_N - IBI_{N-1})}{N-1}} \quad (1)$$

We assess short-term and long-term variability of HRV by calculating RMSSD for two window lengths of 20 and 60 seconds. A longer window represents a more stable measure of RMSSD, while shorter window represents more recent changes of heart rate variability, as shown in Figure 3. All data, raw and processed, are saved to a CSV file for later review.

B. Breathing rate and phase control

To entrain breathing, the controller generates a pattern of lights of different color and intensity to cue different breath phases: inhalation, full lung hold, exhalation, and empty lung

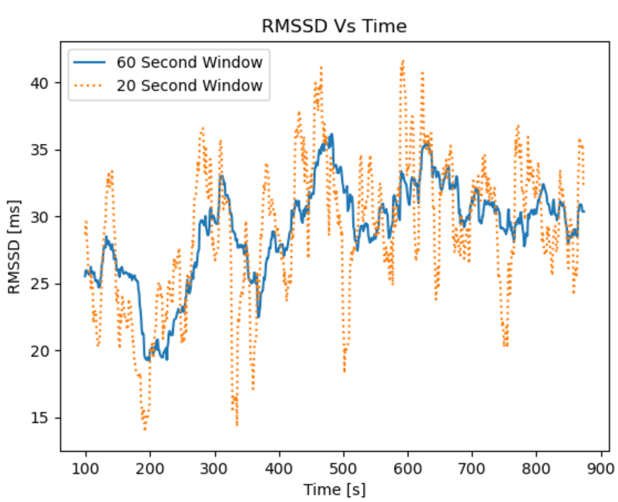

Figure 4. Changes of HRV measured using RMSSD using two window sizes.

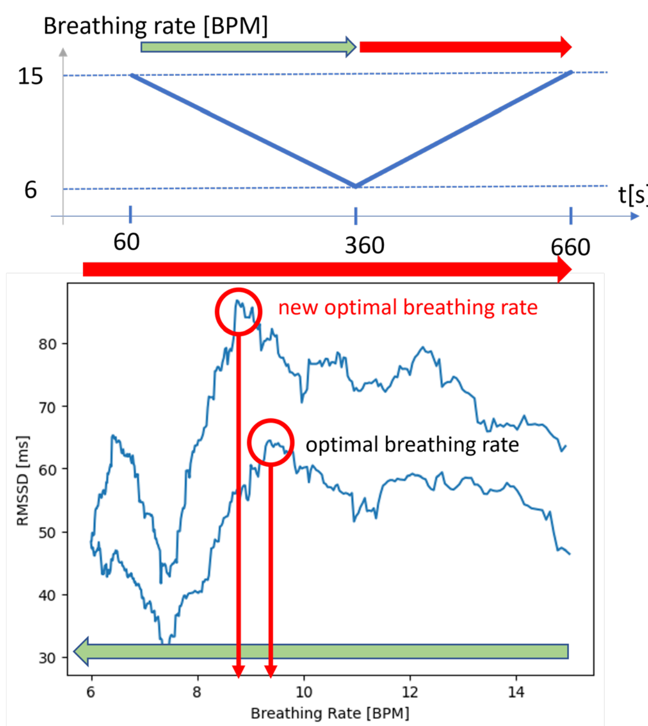

Figure 3. HRV during SCAN operation; breathing rate changes from 15 BPM to 6 BPM and back to 15 BPM.

hold. The light intensity gradually increases when breathing in, and gradually decreases when breathing out.

C. *Real-time biofeedback algorithm*

We implemented two modes of breathing entrainment operation:

- *Scan* uses predefined variation of the breathing rate to assess personal response to a range of the breathing rates,
- *Search* applies variable breathing rate in search of the maximum HRV of the user. The system collects physiological baseline information for 60 seconds, uses natural breathing rate during preliminary assessment as initial breathing entrainment rate, and proceeds with slowing down until maximum HRV has been detected. After that, the system will continue to accelerate and slow-down breathing rate around personally optimal breathing rate according to the measures of HRV.

The main controller updates system state and target breathing entrainment rate every second. The stream of IBI and time stamps is received from the physiological controller, processed every second to find next value of the breathing rate that is sent to the light controller as a command with the target breathing interval. The light controller then generates the light pattern according to the received breathing interval.

The breathing control algorithm plays a pivotal role in our system, striving to find optimum breathing rate for a user in real-time during the session. The program starts by natural breathing rate of the user, detected during the first 60 seconds of the experiment. Starting from the natural breathing rate of the user, the program than starts breathing entrainment for the remaining time of the session by using light to guide inhalation and exhalation of the user. The program deliberately slows the breathing rate and monitors heart rate variability as long as RSAM is increasing. When RSAM starts to decrease, we use it as an indication that the breathing rate is too slow for a user at the given moment, and that the user is struggling to breathe at such a low rate. Therefore, we start to increase the breathing rate. The central mechanism of the algorithm lies in its dynamic adjustment of the breathing rate based on real-time physiological feedback. The algorithm utilizes a feedback loop that assesses changes in RSAM as a critical indicator of parasympathetic activity. If the system observes an increase in RSA during the slowing phase, it interprets this as a signal to further slow down the breathing rate by incrementing the breathing period. Conversely, if RSA decreases during the slowing phase, the algorithm transitions to the accelerating phase, initiating an increase in the breathing rate.

Crucially, the synchronization between the user's breathing pattern and the recommended rate involves an active role for the user. The user is prompted to adjust their breathing phase in real-time to align with the dynamically changing LED indicator output. As the breathing period is adjusted based on physiological feedback, these updates are translated into corresponding changes in the light controller subsystem, providing a tangible and perceptible feedback mechanism for users.

The implemented real-time biofeedback method is represented by the following pseudocode:

```
// Breathing control algorithm
while (t<60) {          // Collect Baseline state for 60 seconds
  if (ibiAvailable()) {
    // serial message with IBI info available?
    update_IBI_and_timestamps();
    } // end if IBI available
  } // end baseline

// set initial value of the breathing rate
calculate_breathing_rate();
slowing=true;           // start by slowing the breathing rate
while (t < 660) {       // default session is 10 minute long
  if (ibiAvailable()) { // check for new messages
    update_IBI_and_timestamps();
    }
  if (t > Tupdate){     // execute once a second
    process_HRV();      // calculate RMSSD in previous window
    process_RSA();      // calculate RSA in previous window
    if(slowing) {
      if (RsaIncreasing(RSA)) {     // is RSA increasing?
        BreathingPeriod += DT;      // keep increasing period
        } else {
          // RSA decreases, change the direction
          slowing = false;          // start increasing the rate
        } // end RSA decreasing while slowing rate
      } // end slowing
    else {
      // breathing rate is accelerating
      if (RsaIncreasing(RSA)) {     // is RSA still increasing?
        BreathingPeriod -= DT;      // keep decreasing period
      }
      else {
        // RSA decreased, start slowing down the breathing
        slowing = true;
        } // end RSA decreasing while accelerating rate
      }   // end breathing rate update
    // update breathing period of the light controller
    updateLedSubsystem();
    Tupdate +=1;        // schedule next processing in one sec
  } // end update
} // end while session
```

We performed initial evaluation of the optimal breathing period using a SCAN mode. This operation collects the baseline

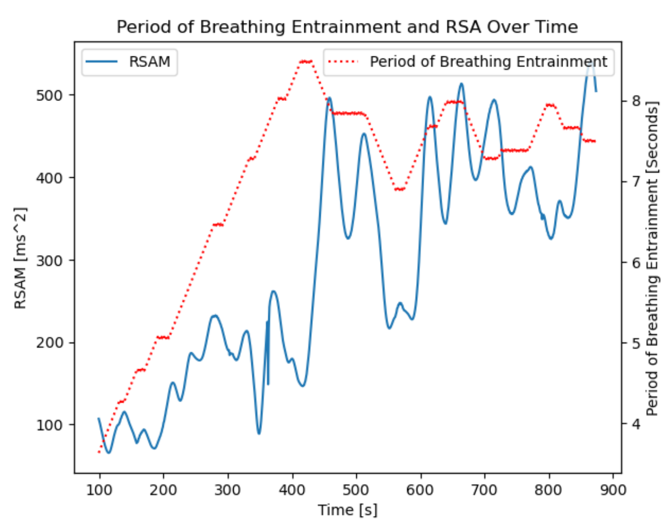

Figure 5. Change of RSA during search for optimal breathing rate.

data for 60 seconds, then proceeds to change the breathing interval from 15 BPM to 6 BPM in 5 minutes, and back to 15 BPM over 5 minutes. Change of HRV measured using RMSSD during SCAN is shown in Figure 4. Arrows represent direction of the change of the breathing rate during the SCAN, that starts from 15 BPM on the right of the lower plot. Please note local maximums of RMSSD indicate optimum personal breathing rate of the user for the maximum heart rate variability. During the slowing phase of the scan local maximum is generated at 9.4 BPM. It is also important to note that after slowing the breathing rate to 6 BPM, and acceleration of the breathing rate, we have a new optimal breathing rate that is lower than previous optimal rate, now at 8.7 BPM. We believe that the change of local maximum was generated by the change of physiological state caused by the scan.

III. RESULTS

We implemented a real-time biofeedback session with the search for the local maximum of HRV caused by the current optimal breathing rate. Change of RSA during Search was illustrated in Figure 5.

During the Search, respiratory sinus arrhythmia measured as RSAM constantly increased. This increase indicates the effectiveness of real-time optimization of the breathing interval according to the changes of RSAM. Change of the RMSSD in the 60 second window during the same session is presented in Figure 6. The pattern of change of RSA and RMSSD are different; however, both parameters demonstrate increased physiological response during the *Search* for the optimal breathing rate. RSAM is much more stable and represents response to the change of the breathing rate much more accurately; therefore, we selected RSAM as the main biofeedback parameter.

The peak RSA magnitude during the entrainment session increased dramatically, the maximum value of RSAM at the end of the session was approximately 5 times higher than at the beginning of the session. The change of RMSSD during the session was significantly smaller, only 40% increase of the maximum RMSSD (~35ms) compared with the RMSSD at the beginning of the session (~25ms).

The scan mode revealed the change of the optimal breathing rate, even in a short time necessary for the *Scan* operation. This issue was raised by Shaffer and Meehan, as concern of the validity of the optimality of results in prolonged time periods [10]. As shown in Figure 4, the breathing rate which maximizes HRV can change in as little time as the 5 minutes it took to finalize slowing of the breath and start of increased breath rate. Our system allowed us to quantify the change and monitor optimum breathing rate during the session and between the sessions. We believe that the *Scan* itself represents an "exercise" that changes local physiological optimal breathing rates, but that hypothesis requires further research and testing.

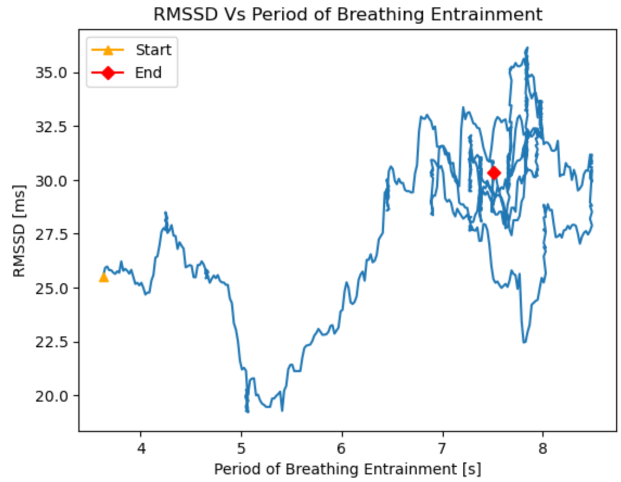

Figure 6. Change of RMSSD during search for optimal breathing rate.

IV. CONCLUSION

Breathing entrainment represents a promising approach to stress reduction, ANS function improvement, enhanced emotional regulation, and improved cognitive function. Most researchers use predefined breathing rates, or physiologically important rates, such as 6 BPM (0.1 Hz), generated by the physiological blood pressure regulation control loop. In this paper we presented a method of the real-time adjustment of the optimal breathing rate based on the magnitude of respiratory sinus arrhythmia at the frequency of breathing entrainment. This approach resolves the concerns about the length of time for which the calculated breathing rate remains optimal.

We demonstrated the effectiveness of the use of RSAM for the control of the breathing rate. Although we implemented the system in the Laboratory environment with real time visualization of all parameters, the system can work autonomously with the main controller and light controller only, which makes it suitable for portable relaxation applications for everyday use. In our pilot experiment, the RSAM was increased more than five times during the breathing entrainment session lasting only ten minutes.

In light of the findings, it is essential to acknowledge the limitations stemming from the relatively small sample size, comprising only two subjects. While the insights gained from this study provide valuable initial observations, future work will include evaluation of the proposed algorithm in larger study with diverse subject population in order to further validate our approach. We will also evaluate other parameters extracted from PPG and ECG for possible optimization of the breathing entrainment algorithm.

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