2017 Seventh International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW)

Deep Breaths: An Internally- and Externally-Paced Deep Breathing Guide

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***Abstract*—Deep breathing is a simple and intuitive technique for reducing stress, but requires familiarity with breathing exercises and suitable breathing parameters. We present Deep Breaths, a mobile tool that allows users to experiment with various respiratory pacing signals in order to maximize relaxation. Deep Breaths provides a stationary (i.e., clock-based) pacing signal as well as an adaptive pacing signal that follows fluctuations in the users heart rate. Deep Breaths also provides real-time visualizations of various standard measures of relaxation. This demonstration aims to illustrate how our system can be used for relaxation training.**

1. Introduction

Chronic stress contributes to obesity and is a risk factor for a host of diseases, including cardiovascular disease – the leading cause of death worldwide [1]. To combat high stress, a number of relaxation techniques have been developed, including mindfulness practice, deep breathing, and biofeedback [2]. Deep breathing (DB) is a simple and intuitive evidence-based method for reducing stress [3]; practitioners focus on breathing slowly, sometimes guided by a visual or auditory pacing signal. While DB is easily deployed, finding the ideal breathing parameters for each user is difficult and depends on their momentary arousal levels, their physiology (e.g., health, age), and their familiarity with breathing techniques [4].

Previous research [5] has investigated visual designs for breathing guides. However, to the best of our knowledge, a direct comparison of various DB relaxation techniques does not exist. To address this gap, we present Deep Breaths, a mobile tool that delivers multiple DB interventions. Deep Breaths uses a wrist-based photoplethysmograph (PPG) to derive the users instantaneous heart rate as well as various physiological indicators of relaxation. The tool allows practitioners to experiment with various breathing parameters (e.g., respiration rate, inhalation/exhalation ratio) and observe their effect in real time. Deep Breaths also allows the user to synchronize their breathing cycle with rhythmic fluctuations in their heart rate, a form of biofeedback that has been shown to be effective for relaxation [6]. With these features, Deep Breaths enables users to subjectively and objectively evaluate DB techniques and parameters to find the one most conducive to relaxation.

2. Background

The breathing cycle induces fluctuations in heart rate through a process known as respiratory sinus arrhythmia (RSA): heart rate increases during inhalation and decreases during exhalation. The functional role of RSA is not well understood. Some researchers hypothesize that RSA serves to preserve cardiac energy while optimizing gas exchange [7] (i.e., higher heart rate while the lungs are filling with oxygen), whereas others argue that RSA is caused by differing energy requirements for inhalation and exhalation [8] (i.e., inhalation is an active process that requires muscle activity, while exhalation is a passive process where the muscles relax). RSA is a major contributor to heart rate variability (HRV), a commonly used measure of arousal. High levels of HRV are associated with higher levels of relaxation, whereas low HRV is a risk factor for heart disease. Previous work [9] has identified a resonant frequency, typically around 0.1 Hz (6 breaths/min), at which breathing maximizes RSA. The inhalation/exhalation (I/E) ratio also plays a major role [8]: a short inhalation period followed by a long exhalation period can is more effective at inducing relaxation than the opposite.

A number of studies have also examined the synchronization between heart rate and the respiratory cycle. A technique known as voluntary cardio-respiratory synchronization (VCRS) has been used to control for respiratory-induced variations on the cardiac cycle [10]. In VCRS, the user follows a pacing signal for inhalation and exhalation cycles that is phase-locked with their heart beat: the user breathes in for a set number of heart beats and breathes out for another set number of heart beats. However, VCRS has not been used as a relaxation training tool. Synchronization between HRV and respiration is the basis for two commercial devices: the StressEraser (Helicor, Inc.), and the emWave (HeartMath Institute). The StressEraser is a portable HRV biofeedback device that guides users to inhale until the heart rate peaks and then exhale as their heart rate slows down [11]. However, following the StressEraser guide is non-intuitive because the visualization provides a rapidly changing curve that

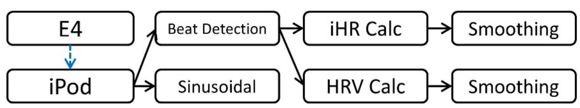

Figure 1. System diagram of Deep Breaths

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the user is supposed to use loosely until their HRV becomes regular. As such, users generally require significant practice before they can successfully use the device. The emWave is also based on HRV biofeedback, but instead uses the concept of cardiac coherence, which is measured as the amount of HRV energy in a narrowband centered on the respiratory frequency [12].

3. System description

To study the effects of DB guide timing mechanisms on relaxation, we developed Deep Breaths, a DB guide application that displays a sinusoidal breathing guide, instant heart rate, and multiple measures of HRV. The application runs on an iPod touch and currently uses an E4 sensor (Empatica, Inc) to measure PPG. The system is outlined in Figure 1.

To calculate instantaneous heart rate (iHR), the system uses a beat detection algorithm to identify troughs in the PPG signal, as those are generally easier to detect than peaks. The algorithm works as follows; see Fig. 2 for an illustration:

1) Apply a FFT over the previous 512 samples to determine the average R-R interval distance t_{RR}
2) From the most recently detected beat time t_b, look for a new beat in a window centered around $t_b + t_{RR}$
3) If a sample within the window is the minimum as determined by a five-point analysis and is less than the average amplitude of the previous 512 samples, it is marked as a beat
4) If the window passes without a beat detection, insert an artificial beat at $t_b + t_{RR}$
5) Repeat

The search window size can be adjusted to smooth the R-R intervals. However, for HRV calculations, locating the actual heartbeat is more important than smoothing R-R intervals. As such, the window size is carefully selected to avoid missing a heartbeat while still reducing the search space. The artificial beat insertion is necessary to avoid drastic changes in iHR due to missed heartbeats.

Deep Breaths is configured to deliver two deep-breathing guides: a clock-based (CB) guide, and a heart-based (HB) guide. The CB guide uses an asymmetric sinusoidal wave whose frequency and I/E ratio are set by the user, whereas the HB guide displays the users iHR as a wave. In both cases, the user is supposed to synchronize their breathing with the wave.

The CB guide is calculated with the asymmetric cosine function (1), which uses the beta function in (2) to warp

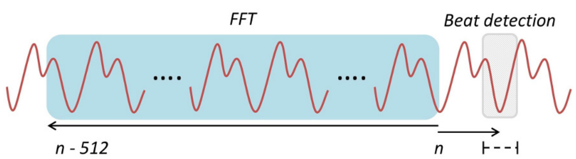

Figure 2. Beat detection demonstrated on an ideal PPG signal. A FFT is applied to the previous 512 samples to determine the average R-R interval. The algorithm then searches for a PPG minimum within a window centered on the time of the most recently detected beat plus the average R-R interval

time. In this fashion, the wave decreases from peak to trough for r_o percent of the period, and increases from trough to peak for r_i percent of the period T. We use the parameters $T = 10$ sec, $r_o = 0.6$, and $r_i = 0.4$, which causes the wave to increase for 4 sec and decrease for 6 sec, a 4:6 I/E ratio that has been shown to maximize relaxation [8].

$$v(t) = cos(2\pi\beta(mod(t, T))) \tag{1}$$

$$\beta(t) = \begin{cases} t \leq r_o T, & \dfrac{t}{2r_o T} \\ r_o T < t \leq T, & \dfrac{t - r_o T}{2r_i T} + 0.5 \end{cases} \tag{2}$$

In turn, the HB guide displays a smooth version of the users iHR. Shown in (3), the iHR is measured as the inverse of the RR period, where t_{B_i} represents the time of the ith heartbeat. To smooth this signal, we use a first-order linear filter shown in (4), which combines the most recent iHR measurement ($t_{B_{last}}$) and the previous function output.

$$iHR(t_{B_i}) = \frac{1}{t_{B_i} - t_{B_{i-1}}} \tag{3}$$

$$f(t) = \alpha f(t - \tau) + (1 - \alpha) iHR(t_{B_{last}}) \tag{4}$$

4. Experiment design

We are currently conducting a formal evaluation of our DB system. At the conference, we will have our system prepared for session attendees to try for themselves. Interested attendees can practice deep breathing with both CB and HB guides to see the differences between the two; practitioners often feel effects from DB after only a few minutes, so we can conduct multiple short demonstrations with anyone who would like to try Deep Breaths.

5. Conclusion

In this demonstration, we presented Deep Breath, a DB tool to study timing mechanisms for breathing-based relaxation. Our tool allows users to set custom breathing parameters for a CB guide or follow their own fluctuating heart rate, all the while seeing changes in their HRV in real-time. As such, Deep Breath allows users to experience multiple forms of DB, learn how their physiology responds to stress and relaxation, and find an intervention that is most effective for them. Our next steps are to improve the beat detection algorithm's robustness to motion artifacts and test these relaxation techniques in long-term, situated studies.

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