EFFECTIVENESS OF MUSIC-BASED RESPIRATORY BIOFEEDBACK IN REDUCING STRESS DURING VISUALLY DEMANDING TASKS

A Thesis

by

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Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

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May 2015

Major Subject: Computer Engineering

ABSTRACT

Biofeedback techniques have shown to be effective to manage stress and improve task performance. Biofeedback generally can be divided into two steps (i) measuring physiological functions (e.g. respiration, heart rate) via sensors and (ii) conveying the physiological signals to the user to improve self-awareness. Current systems require costly and invasive sensors to measure physiology, which are not comfortable and are not readily accessible to the general population. Additionally, current feedback mechanisms may be physically unpleasant or may hinder multitasking, especially in visually-demanding environments. To overcome these problems, we developed two tools: a music-based biofeedback tool that uses music as the medium of feedback, and a tool to measure breathing rate using a smartphone camera.

The music biofeedback tool encourages slow breathing by adjusting the quality of the music in response to the user's breathing rate. This intervention combines the benefits of biofeedback and music to help users regulate their stress response while performing a visual task (driving a car simulator). We evaluate the intervention on a 2×2 design with music and auditory biofeedback as independent variables. Our results indicate that music-biofeedback leads to lower arousal (as measured by electrodermal activity and heart rate variability) than music alone, auditory biofeedback alone, and a control condition. Music biofeedback also reduces driving errors when compared to the other three conditions.

While our results suggest that the music-based biofeedback tool is useful and enjoyable, it still requires expensive physiological sensors which are intrusive in nature. Hence, we present a second tool to measure breathing rate in real-time via smartphone camera, which makes it easily accessible given the pervasiveness of smartphones. Our algorithm measures breathing rate by obtaining the

photoplethysmographic signal and performing spectral analysis using Goertzel algorithm. We validated the method under a range of controlled breathing rate conditions, and our results show a high degree of agreement between our estimates and ground truth measurements obtained via standard respiratory sensors. These results show that it is possible to accurately compute breathing rate in real-time using a smartphone.

ACKNOWLEDGEMENTS

I thank my advisor, Dr. Ricardo Gutierrez-Osuna, for his immense support and encouragement throughout my graduate studies. His advice and guidance have been of great help in shaping this thesis. I admire his commitment and enthusiasm.

I would also like to thank Dr. Thomas Ferris and Dr Tracy Hammond for their interest in my research and for their feedback. Lastly, I would like to thank my lab mates, Avinash Parnandi, Sandesh Aryal, Anshul Gupta, and Chris Liberatore, for their help in editing this thesis. I would also like to thank all my lab mates and friends for being a great support and making my graduate life fun.

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LIST OF ABBREVIATIONS

Abbreviation	Meaning
BPM	Breaths per minute
BR	Breathing rate
EDA	Electrodermal activity
EPC	Electrodermal Positive Change
HR	Heart rate
HRV	Heart rate variability
PPG	Photoplethysmography
RR	Respiration rate
SCL	Skin conductance level
SCR	Skin conductance response

1 INTRODUCTION

Psychological stress is a significant risk factor in cardiovascular diseases, the leading cause of mortality in the developed world (DeVries and Wilkerson 2003). Stress causes major mental health problems such as depression, post-traumatic stress disorder, pathological aging (DeVries and Wilkerson 2003), and also economic problems due to significant loss of productivity (Leiter and Maslach 2011). As a result, different relaxation techniques involving meditation, deep breathing, imagery, and music, and biofeedback, physical and mental exercises are practiced to tackle stress.

Biofeedback techniques have been effectively used to manage stress (Varvogli and Darviri 2011) and treat anxiety (Sutarto, Wahab et al. 2010, Wells, Outhred et al. 2012). Biofeedback works by measuring physiological variables (e.g., heart rate, electrodermal activity), then displaying them to the user to improve self-awareness and self-regulation. Most biofeedback interventions generally use visual displays of physiological information, which demand visual attention from the user and make them incompatible with many routine activities such as driving. Other interventions utilize audio and haptic channels to convey information, but are monotonous and can lead to frustration (Henriques, Keffer et al. 2011). In order to overcome the above problems, this work is the first to implement and empirically evaluate a combination of music, deep breathing, and biofeedback for stress reduction during visually demanding tasks. Our intervention consists of monitoring the respiration rate of the user and adapting the quality of the music (e.g., signal-to-noise ratio) to promote slow, deep breathing, an exercise with known therapeutic benefits (Vaschillo, Vaschillo et al. 2006).

A secondary objective of this thesis is motivated by a current limitation of biofeedback systems, in that they require the use of costly or invasive sensors To address this issue and enable a wider adoption of biofeedback interventions, this thesis proposes the use of smartphones to measure physiological variables. In particular, we describe an approach to measure respiration rate in real-time using the Goertzel algorithm (Goertzel 1958) on a photoplethysmographic (PPG) signal obtained via a smartphone camera.

The two specific aims of this thesis are:

(1) To evaluate the effectiveness of music-based respiratory biofeedback in the context of a visually-demanding task (driving a car racing simulator), and compare it against auditory biofeedback and music in terms of its ability to lower arousal levels and improve driving performance.

(2) To evaluate the proposed algorithm to measure breathing rate using a smartphone and compare the results with standard chest-strap respiratory sensor.

The rest of the document is organized as follows. Chapter 2 summarizes theory related to stress and its physiological measures; it also discusses previous work on biofeedback, music interventions on driving, and measurement of respiration rate. Chapter 3 describes the proposed music-based respiratory biofeedback tool and the user studies to evaluate the tool during driving. Chapter 4 presents the tool to measure breathing rate using smartphone camera and the experiments to validate our new algorithm to measure breathing rate. Finally we provide directions for future work in Chapter 5.

2 BACKGROUND AND RELATED WORK

In this chapter we review various topics concerning stress including physiological measures of stress, effect of music on driving stress, and biofeedback tools (specifically audio biofeedback) to manage stress to motivate our choice of using music as means of feedback. Finally, we also review the measurement of breathing rate via photoplethysmography techniques, which are relevant to the second part of this thesis.

2.1 Stress

Psychological stress arises when an event is interpreted as undesirable or taxing on personal resources (Lazarus and Folkman 1984). Selye viewed stress as a response to environmental stressors to attain homeostasis, which refers to the stability of physiological system (Selye 1956). Stress can be positive, motivating force which is termed is eustress or debilitating which is termed as distress. Eustress is beneficial as it keeps us alert in dangerous situations and focused to meet challenges. Yerkes-Dodson Law (Cohen 2011) provides the relationship between arousal and health/performance. It states that increased arousal can help improve health and performance till a certain point, termed as the optimal stress level, beyond which it become harmful to the organism (see Figure 1). Negative stress can be acute or chronic: acute stress is the short term, whereas chronic stress is long term and can last for days or longer. Chronic stress can lead to severe health consequences e.g. obesity, depression, posttraumatic stress disorder, pathological aging and cardiovascular diseases (DeVries and Wilkerson 2003). About 60-80% of outpatient visits may be related to stress (Avey, Matheny et al. 2003). Apart from the health consequences, stress has become the most prevalent economic concern for many countries. In the US alone, loss of productivity associated to stress is in the order of $300 billion per year (Leiter and Maslach 2011).

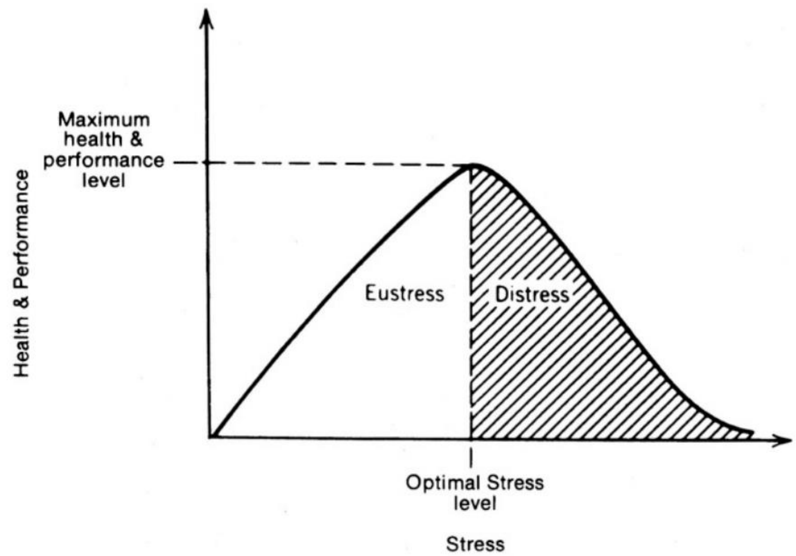


Figure 1. Yerkes-Dodson curve as described in (Everly Jr and Lating 2012)

2.2 Physiological measures for stress

Stress disrupts the balance between sympathetic and the parasympathetic branches of the autonomic nervous system (ANS), with the sympathetic nervous system (SNS) being dominant (fight-or flight response). This leads to changes in our physiological conditions such as increased muscle tension, heart rate, pupil dilation, adrenaline production, secretion of hormones such as cortisol, and difficulty in breathing. These physiological manifestations of the stress response can therefore be studied by monitoring variables including electrodermal activity (EDA), heart rate (HR), heart rate variability (HRV), blood pressure (BP), muscle tension (EMG), pupil dilation, cortisol levels, electrical activity in the brain (EEG) and respiration (Smyth, Ockenfels et al. 1998, Vrijkotte, Van Doornen et al. 2000, Healey and Picard 2005, Choi, Ahmed et al. 2012). However, in order to gain acceptance the stress monitoring/measurement tool must be minimally cumbersome to allow users to carry out routine activities/activities of daily living without hindrance. Some of these physiological variables are difficult to measure (e.g. cortisol) while some others are limited to laboratory settings (e.g. EEG). Taking usability concerns into consideration, we chose HRV, EDA, and BR as indicators of stress.

2.2.1 Heart rate variability

Heart rate variability is the phenomenon where the time interval between consecutive heartbeats changes as a result of autonomic regulation. HRV can be measured from the inter-heart beat intervals and it provides useful information about the state of the autonomic nervous system. SNS activation increases the HR and decreases HRV to prepare the body for action in response to a potential stressor (fight or flight response). In contrast PNS activation reduces HR and increases HRV so as to bring the body back to homeostasis. Therefore by analyzing fluctuations in beat-to-beat interval we can separate the contributions from both branches and infer stress levels. Vaschillo et al. have showed that HRV is maximized at breathing rates around 0.1Hz (6 breaths/min); see Figure 2. Breathing at this pace increases the baroreflex gain, leading to a resonance in the cardiovascular system (CVS) resulting in high HRV. Higher HRV is linked to better functioning of human body, such as enhanced immune system, improved cognitive abilities, reduction in high blood pressure and better hormonal functioning (Berntson, Bigger et al. 1997). It also improves creativity and mood for better emotional regulation leading to various health benefits.

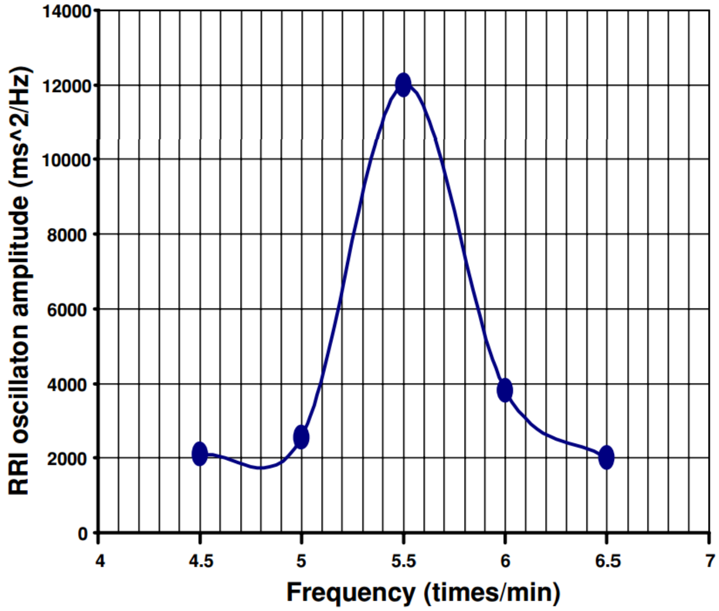


Figure 2. Resonance characteristics of the cardiovascular system for a participant;, the resonant frequency is 5.5 times/min or 0.092 Hz as described in (Vaschillo, Vaschillo et al. 2006)

2.2.2 Electrodermal activity

EDA (also known as galvanic skin response or skin conductance) measures are also strong indicators of autonomic activity, particularly the sympathetic branch. This is because the skin is innervated exclusively by the SNS, making the EDA response highly sensitive to emotional arousal e.g. startle, fear, anger etc. A stress stimulus elicits a sympathetic response by the sweat glands, which increases perspiration to flush waste and cool down the body. This increases the skin conductance due to increase in water and electrolytes. EDA consists of two components: a slow changing tonic skin conductance level (SCL) and phasic changes (spikes) known as skin conductance responses (SCRs) (Boucsein 2012). Under stress, SCL increases gradually while each stress stimulus creates a new SCR. The characteristics of each SCR like latency, amplitude, rise time and recovery time depending on the period and intensity of the stress point. SCLs are highly subject-dependent and measurement of baseline SCL is difficult in the presence of SCRs. Also the characteristics of each SCR (frequency and amplitude) strongly reflect stress response to new and unexpected events. For this reason SCRs are a better EDA measure of arousal.

2.2.3 Breathing rate

Along with these, we also use breathing rate as an indicator of the physiology. Breathing rate or respiration rate is the frequency of ventilation, which includes an inhalation and exhalation of air in each cycle. During a stress episode, triggered SNS increases muscle tension and dilates bronchi, allowing more air in the lungs, resulting in shallow and faster breathing cycles to supply more oxygen to the muscles and tissues. It also increases the irregularity in breathing, and may even stop breathing momentarily in extreme cases. In contrast, deep breathing (high volume) at low pace addresses the autonomic imbalance by recruiting the PNS and inhibiting the SNS leading to relaxation. Respiration rate comparatively easier to measure and is also one of the few physiological variables which can be modified voluntarily, this is utilized to our advantage in our biofeedback tool to manage stress levels by modifying respiration rate.

2.3 Music and driving

High stress impairs decision making, decreases situational awareness and degrades performance, all of which affect driving capabilities (Hennessy and Wiesenthal 1999). In addition, stress experienced during commuting has negative impact on health and work life (Hennessy 2008). Extreme stress can result in car accidents, and potentially property damage, medical costs, insurance costs, loss of work productivity, and loss of human life. The National Highway Traffic Safety Administration estimates that the US economy incurs over $230 billion of annual losses due to car accidents (Groene and Barrett 2012).

The effects of music to reduce stress during driving have been studied extensively given that listening to music while driving is a popular activity: according to a 2014 report by Nielsen (Co. 2014), nearly a quarter of all music listening in the United States happens behind the wheel. Zwaag et al. (van der Zwaag, Dijksterhuis et al. 2012, van der Zwaag, Janssen et al. 2013) showed that music can positively influence driver mood and driving performance. Studies have also shown that music lowers driver aggression (Wiesenthal, Hennessy et al. 2003) and improves defensive driving (Ünal, de Waard et al. 2013), which directly reduces road rage –one of the main causes of fatal accidents. The extent of relaxation depends on the user's music preference, music genre (generally classical or instrumental) (Dillman Carpentier and Potter 2007, Grewe, Nagel et al. 2007), music properties (tempo, rhythm, volume, lyrics), age and type of intervention (Pelletier 2004). Music also improves performance during long monotonous driving sessions, where the driver may lose focus and become fatigued (Ünal, de Waard et al. 2013). In particular, non-vocal and slow tempo music has been used in studies to relax drivers and improve their performance by helping them focus (North and Hargreaves 1999, Dibben and Williamson 2007, van der Zwaag, Dijksterhuis et al. 2012).

2.4 Biofeedback

Biofeedback helps people control their stress response by employing relaxation techniques like deep breathing to calm an individual. Recent studies have looked at the combination of biofeedback techniques with games and music to promote regular practice. As an example, Parnandi et al. (Parnandi, Ahmed et al. 2014) presented a relaxation game that adapts game difficulty based on the players' breathing rate, in this way motivating players to relax so they can improve their score on the game. Zwaag et al. (van der Zwaag, Janssen et al. 2013) created an affective music player that learned the user's physiological response to various music genres then, at a later time, played the appropriate music to match the user's desired mood. Bergstrom et al. (Bergstrom, Seinfeld et al. 2013) compared three techniques for modulating the user's heart rate: prerecorded music, sonification of heart-rate (i.e., auditory biofeedback), and an algorithmically-modulated musical signal conveying the user's heart rate; their results show that music biofeedback was as effective as auditory biofeedback, and both superior to just listening to music. Epstein et al. (Epstein, Hersen et al. 1974) developed an intervention that allowed hypertensive patients to listen to music only if their muscle tension was low, as measured with electromyography. Weffers (Weffers 2010) developed a system to calm individuals by guiding their breathing rate via musical, haptic and visual cues. Similarly, Henriques et al. (Henriques, Keffer et al. 2011) presented a computer application to calm college students by guiding their heart rate variability via visual and audio cues. Reynolds et al. (Reynolds 1984) showed that combining autogenic training phases and music is more effective at promoting calm meditative states than using each treatment in isolation. In a similar study, Robb et al. (Robb 2000) showed that combining progressive muscle relaxation and music led to lower anxiety levels than practicing each technique separately. Wells et al. (Wells, Outhred et al. 2012) showed that audio based biofeedback on musicians leads to lower anxiety during musical performances. Siwaik et al. (Siwiak, Berger et al. 2009) developed an interactive biofeedback system with audio and visual channels of feedback to regulate breathing rate and reduce motion based artifacts during 4D CT scans. Finally, Harris et al. (Harris, Vance et al. 2014) developed a tool to modify music based on the user's respiration rate using audio layering and noise addition techniques.

In the context of driving, Edmonds et al. (Edmonds, Tenenbaum et al. 2008) showed that biofeedback training prior to driving has strong effect on driving performance. Other studies have looked at changes in human physiology (Filho, Di Fronso et al. 2014) and detection of stress (Healey and Picard 2005) during driving using physiological sensors. To the best of our knowledge, however, ours is the first study to present a biofeedback intervention during driving to reduce stress.

2.5 Photoplethysmography

Photoplethysmography (PPG) is widely used to measure vital signs due to its simplicity and non-invasiveness. PPG is based on the principle that blood absorbs more light than the surrounding tissue, so variations in blood volume affect transmission and reflectance accordingly. The resulting changes in the optical signal provide valuable information about heart rate due to its direct influence on blood flow. Research groups have developed tools to measure heart rate (HR) (Jonathan and Leahy 2010, Lakens 2013, Jiang, Wittek et al. 2014) and heart rate variability (HRV) (Lenskiy and Aitzhan 2013) via PPG.

Due to the phenomenon of respiratory sinus arrhythmia (RSA) (Hirsch and Bishop 1981), the breathing rate (BR) also modulates the PPG waveform. Thus, detecting these RSA-induced fluctuations may be used to derive breathing rate from PPG (Johansson 2003, Orini, Peláez-Coca et al. 2011, Karlen, Raman et al. 2013). The feasibility of this approach has been demonstrated in a number of studies. Initially, researchers tested different optical sensors to acquire the PPG signal to measure BR such as wrist sensors (Kagawa, Kawamoto et al. 2013), webcams (Jin, Dong et al. 2013) and different optical sensor based biosignals (Shamim, Atul et al. 2010). Lately, studies have been more focused on obtaining the data via pulse oximeters, smartphones or tablets, and utilize frequency based methods such as wavelet-based filtering and variable-frequency complex demodulation (VFCDM) technique to perform offline analysis (Dash, Shelley et al. 2010) as these methods are computationally very expensive. Lee et al. (Lee and Chon 2010), Fleming et al.

(Fleming and Tarassenko 2007) and Nam et al. (Nam, Lee et al. 2014) have applied Auto Regressive (AR) models which are computationally faster than the prior methods and have potential for computing breathing rate in real time on mobile devices. Karlen et al. (Karlen, Lim et al. 2012) has discussed hardware issues to measure breathing rate via a smartphone. Prior studies have been able to successfully obtain PPG data from smartphones but compute breathing rate measurements on different platforms. Our work is computationally more efficient by using Goertzel algorithm for frequency analysis and can estimate breathing rate using the smartphone resources.

3 MUSIC-BASED RESPIRATORY BIOFEEDBACK IN VISUALLY DEMANDING TASKS

In this chapter we describe a music-based biofeedback tool that promotes deep breathing by modifying the music based on the user's breathing rate. We evaluated our tool in the context of driving a car racing-simulator, and compared it against auditory biofeedback and music in terms of its ability to lower arousal levels (primary objective) and improve driving performance (secondary objective).

In the following subsections, we first discuss the proposed tool in detail. Then we describe the user studies to evaluate the tool during visually demanding tasks and provide the system details for the studies. Next, we present the physiological results, task performance and subjective results. Finally we discuss the results and provide our conclusions about the tool.

3.1 Music-based respiratory biofeedback tool

The Music-based respiratory biofeedback tool encourages slow breathing by modifying the quality of the music recording in proportion to the user's respiration rate. In the following subsections, we discuss the biofeedback mechanism, the breathing range considered calm, and the relationship between breathing rate and noise to change the quality of the music. Finally we provided the implementation details of the existing tool.

The proposed tool is illustrated in Figure 3. The music biofeedback tool manipulates the noise level in music to convey the users breathing rate. We use a chest strap to measure the user's respiration rate and send it to an audio modification application, where it is compared against a target breathing rate BR_0. The system adds white noise to the music proportional to the positive deviation from the target breathing rate. In terms of classical control theory model, the control loop consists of (i) user as the plant we wish to control, (ii) respiratory sensor that measures the user's breathing rate and (iii) audio modification which acts as a controller to minimize the difference between the desired and actual output. This system is based on a positive feedback control law where states of non-relaxation (breathing rates > $\mathbf{BR_0}$ breaths/min) are penalized by increasing the noise in the music while breathing rates lower than $\mathbf{BR_0}$ are not penalized.

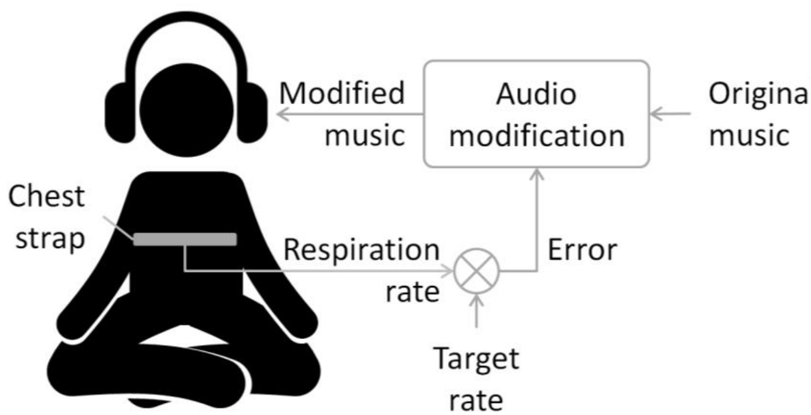


Figure 3. Biofeedback mechanism as described in (Harris, Vance et al. 2014)

3.1.1 Target breathing rate (BR_0)

We choose a target breathing rate of 8 breaths/min based on prior studies (Vaschillo, Vaschillo et al. 2006) showing that heart rate variability –a physiological indicator of relaxation, is maximized at breathing rates around 0.1Hz (6 breaths/min). Reaching this breathing rate requires familiarity with deep breathing practice, and for this reason we choose a slightly higher rate (8 breaths/min) to ensure our study participants would be able to achieve it yet enjoy the calming benefits of slow breathing.

3.1.2 Music modification

As shown in Figure 4, if the user's respiration is below the target rate the musical piece is played without applying any modification. However, if the user's breathing exceeds the target rate (8 breaths/min), the audio modification application adds white noise to the musical piece according to a piece-wise linear function as per the following set of equations (1) and (2):

$$m(t) = s(t) + n(t) \quad \textbf{(1)}$$

$$n(t) = \begin{cases} 0, & b(t) \leq 8 \\ \left[\dfrac{(b(t)-8)}{8}\right] \times s(t), & 8 < b(t) \leq 12 \\ \left[\dfrac{(b(t)-12)}{16} + 0.5\right] \times s(t), & 12 < b(t) \leq 20 \\ s(t), & b(t) \geq 20 \end{cases} \quad \textbf{(2)}$$

where $m(t)$ is the modified music's sound intensity, $s(t)$ is the original music's sound intensity, $n(t)$ is the white noise's sound intensity and $b(t)$ is the current breathing rate. Namely, at 12 breaths/min, the noise amplitude is 50% the average amplitude of the music track; at or above 20 breaths/min, noise and music have the same amplitude. The rate at which noise is added between 8-12 breaths/minute is double than the rate between 12-20 breaths/minute. The sharp rise in noise between 8-12 breaths/minute is to help the user perceive the low intensity of noise and also help them understand that their breathing rate is slightly deviated from the target breathing rate.

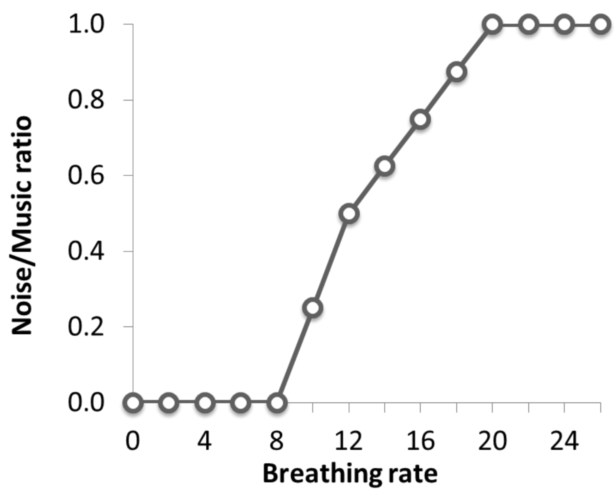
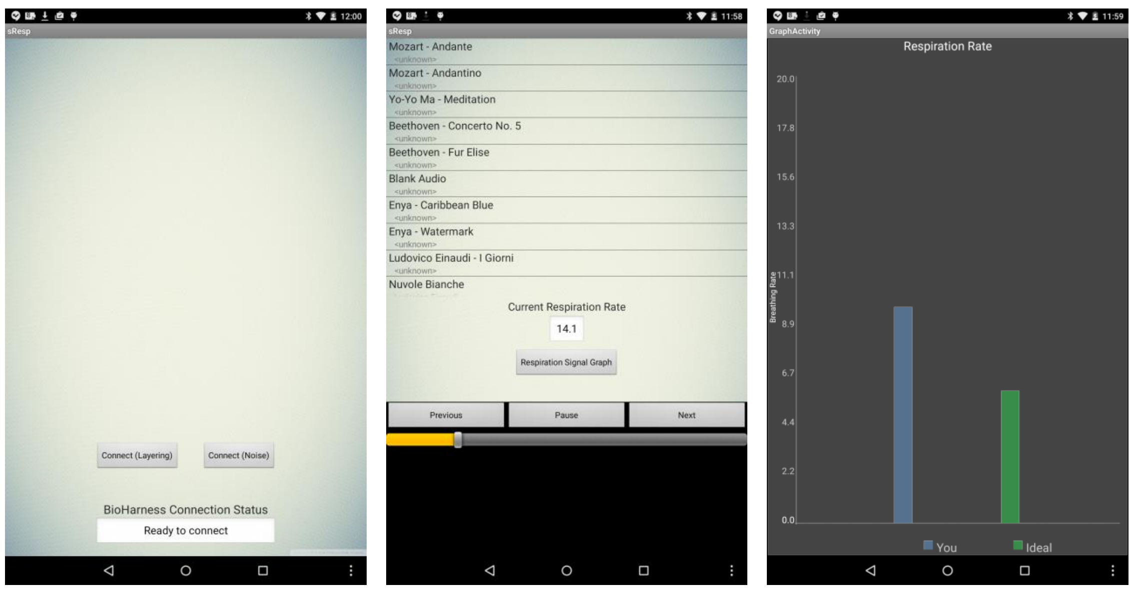


Figure 4. Relationship between breathing rate and the ratio of noise amplitude to music amplitude

3.1.3 Tool description

The initial prototype of the music-based biofeedback tool was developed by Harris et al. (Harris, Vance et al. 2014) as part of a senior design project. The tool had two different techniques to modify music: track layering and white noise addition. Track layering technique phases out audio channels from a multi-track recording based on the amount of deviation from the target breathing range (0-8 breaths/min) while noise addition technique adds noise based on the amount of deviation from the target breathing range (0-8 breaths/min). We utilize the noise addition approach for further evaluation as the study by Harris et al. (Harris, Vance et al. 2014) suggested that track layering technique is less effective since it requires familiarity with the song in order to determine if all tracks are being played and users are practicing deep breathing. Also audio layering techniques require multi-track recordings which are not commonly available.

We modified the *noise/music ratio vs breathing rate* curve based on the feedback we received during the pilot studies. We also modified other aspects such as the visual interface to suit the requirements for our user study; see screenshots in Figure 5. The tool is implemented as a mobile app on a Nexus 5 smartphone running Android 4.4 (KitKat). We measure breathing rate from a Bluetooth thoracic respiratory sensor (Bioharness BT, Zephyr Tech.) which sends the breathing rate to the smartphone app via Bluetooth communication protocol. Once a song is selected the app will modify the audio as described in Figure 4.



(a) (b) (c)

Figure 5. Visual Interface of the music biofeedback tool: (a) initial screen to connect to the respiratory sensor, (b) music player with songs playlist, current respiration rate and player controls, (c) respiration signal graph displaying the current respiration rate with the ideal value (6 breaths/min)

3.2 User studies

We evaluated our intervention on a 2×2 study design with music and auditory biofeedback as independent effects. Participants (N=28; 23 males; 22-36 years) were required to have prior driving experience. For detailed information about the participants, refer to APPENDIX B. The protocol consisted of three phases, each lasting 5 minutes:

- *Driving*: participants played the car racing simulator to measure physiological baseline during driving
- *Treatment*: participants were randomly assigned one of the four conditions in Table 1 (N=7 participants per condition)
- *Driving+treatment*: participants repeated their assigned condition while driving the simulator

Participants in the MBF condition used the mobile app to practice deep breathing while listening to music during the *treatment* and *treatment+driving* phases. ABF participants used the mobile app similarly[1], except the music track was replaced with silence; thus, ABF participants heard white noise if their breathing rate was higher than the target, and silence otherwise. MUS participants listened to music

[1] In both biofeedback cases (MBF, ABF) the level of noise guides participants towards reducing their breathing rate.

without biofeedback, and control participants received no assistance (app or music). Music was delivered with stereo headphones, and the app's GUI was not visible during the experiment to avoid visual distractions from driving.

	No Biofeedback	Biofeedback
No Music	Control (CTRL)	Auditory Biofeedback (ABF)
Music	Music only (MUS)	Music Biofeedback (MBF)

Table 1. 2 x 2 study design

Prior to the experiments, participants in the MBF and MUS condition were asked to select two songs of the same composer from a predetermined music library; see Table 2. All songs had a slow tempo (50-80 beats/min) and were instrumental –such compositions have been associated with lowering physiological responses (Pelletier 2004, Dillman Carpentier and Potter 2007, Grewe, Nagel et al. 2007, Ünal, de Waard et al. 2013). Subjects also filled a questionnaire pre and post experiments for qualitative analysis; see APPENDIX A. The study was approved by our Institutional Review Board.

Composer	**Song 1**	**Song 2**
Beethoven	Concerto No. 5	Fur Elise
Mozart	Andante	Andantino
Enya	Caribbean Blue	Watermark
Einaudi	Nuvole Bianche	I Giorni
Yo Yo Ma	Cell Suite No. 1	Meditation

Table 2. List of pre-selected musical compositions

3.2.1 Visual task: Driving

To simulate a visually-demanding task, we used an open-source car racing simulator (Parnandi and Gutierrez-Osuna 2014) , displayed on a 22" LCD and integrated with a racing wheel as shown in Figure

6. To reduce variance across participants and experimental conditions, we modified the game so players were only required to steer the car, its speed at each position in the track being predetermined. The nominal speed profile for the track was obtained by recording game runs of a proficient player in a prior study. To measure task performance, we recorded the number of crashes during the race.

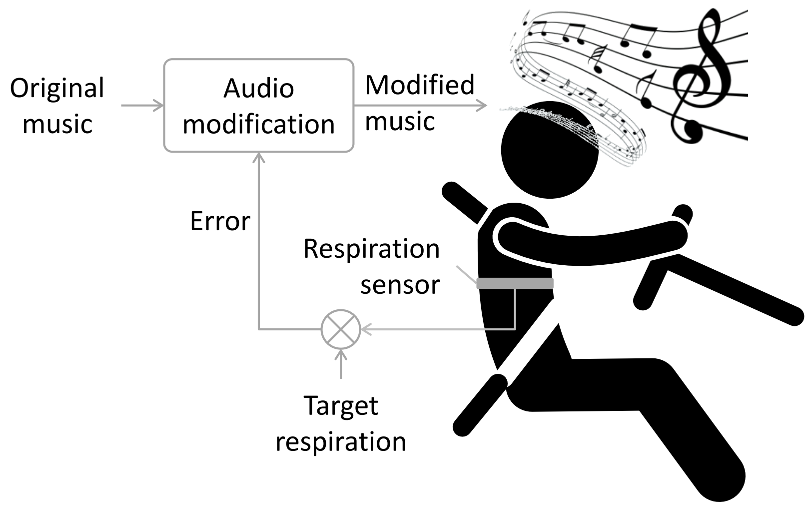


Figure 6. System overview

3.2.2 Physiological arousal

We measured arousal with two well-known physiological indices: electrodermal activity (EDA) and heart rate variability (HRV). We extract two components from the EDA response: SCL and SCR. Specifically, we estimate SCL as the average skin conductance during each phase. We computed two features based on SCR's: the number of SCRs and the electrodermal positive change (EPC) (Leiner, Fahr et al. 2012). To extract the number of SCRs, we used *Ledalab*[2], *an* open source software written in Matlab (Benedek and Kaernbach 2010, Bach 2014). To extract SCRs, Ledalab decomposes the skin conductance signal into distinct phasic and tonic components using nonnegative deconvolution to obtain a zero baseline signal, then measures SCRs via standard trough-to-peak analysis (Benedek and Kaernbach 2010). The second feature, electrodermal positive change (EPC) sums the amplitude of each SCR over time (Leiner, Fahr et al. 2012). We measured EDA using a FlexComp Infinity encoder (Thought Technology Ltd.) with disposable AgCl electrodes attached on the palmar region of the subject's non-dominant hand.

The second physiological index to measure arousal is heart rate variability (HRV). We computed HRV as the root mean square of successive differences (RMSSD) in R-R intervals over a 30s window sliding by 1s (Parnandi and Gutierrez-Osuna 2014). We measured HRV with the same Bioharness BT chest strap from which we measure respiration rate.

It is important to note that these two physiological measures were collected for monitoring purposes and were not used in any way for biofeedback purposes. When used in combination, EDA and HRV provide a robust index of arousal: changes in EDA and HRV are generally in opposite direction with increasing arousal (e.g. EDA increases while HRV decreases), so simultaneous increases (or decrements) in both variables can be dismissed as noise or motion

[2] http://www.ledalab.de/

artifacts.

3.3 Results

In the context of driving, we evaluated music biofeedback (MBF) with auditory biofeedback (ABF), music (MUS) and control (CTRL) conditions in terms of its ability to lower arousal levels and improve driving performance. We compared physiological arousal based on changes in breathing rate, heart rate variability and electro dermal activity. We also present the driving performance under each condition based on collisions and speed values. Finally we share the subjective results obtained via the survey filled by the participants.

3.3.1 Breathing rate

Figure 7 shows the average breathing rate for the four conditions at each stage in the protocol. Breathing rates for participants in the non-biofeedback conditions (CRTL, MUS) decreased moderately during *treatment*, but returned to the original levels during *driving+treatment*. In contrast, breathing rates for participants in the biofeedback conditions (ABF, MBF) dropped below the 8 bpm target during *treatment* and, more importantly, remained at that level during *driving+treatment*. 2-way ANOVA shows a main effect for biofeedback during *treatment* ($F(1,24) = 148.45,\ \mathrm{p} < 0.05$) and *driving+treatment* ($F(1,24) = 107.10,\ \mathrm{p} < 0.05$), but no music or interaction effects for either phase. It clearly demonstrates that participants under biofeedback conditions are able to reduce their breathing rate during *treatment* and maintain a low RR during the *driving+treatment* phase indicating the transfer of deep breathing skills

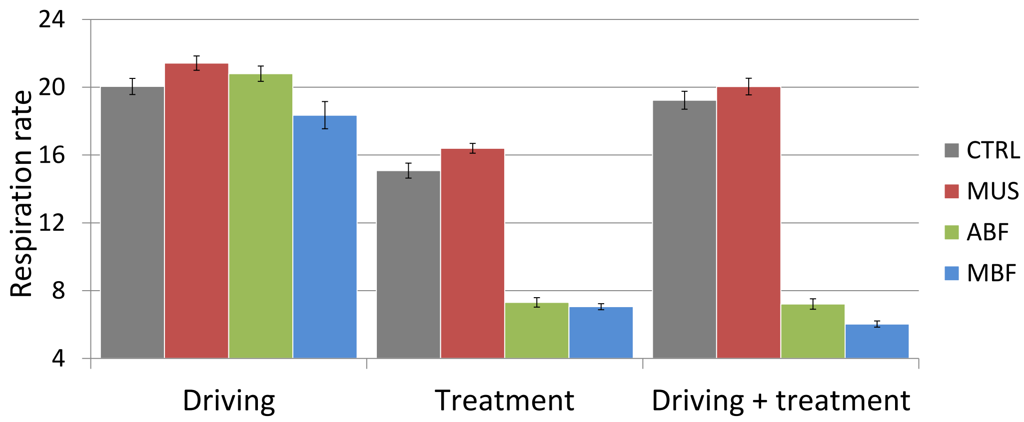


Figure 7. Average respiration rate (across all participants) during driving, treatment, and driving+treatment. Error bars indicate standard deviation.

Next, we analyze the temporal evolution of respiration rate to gain a better understanding of the difference between the four conditions. Figure 8 presents the average respiration rate for participants under each condition over the course of the experiment. These plots corroborate the results discussed above. Both biofeedback interventions are more effective at encouraging slow breathing during visually-demanding tasks (*driving+treatment* phase) compared to the other two groups.

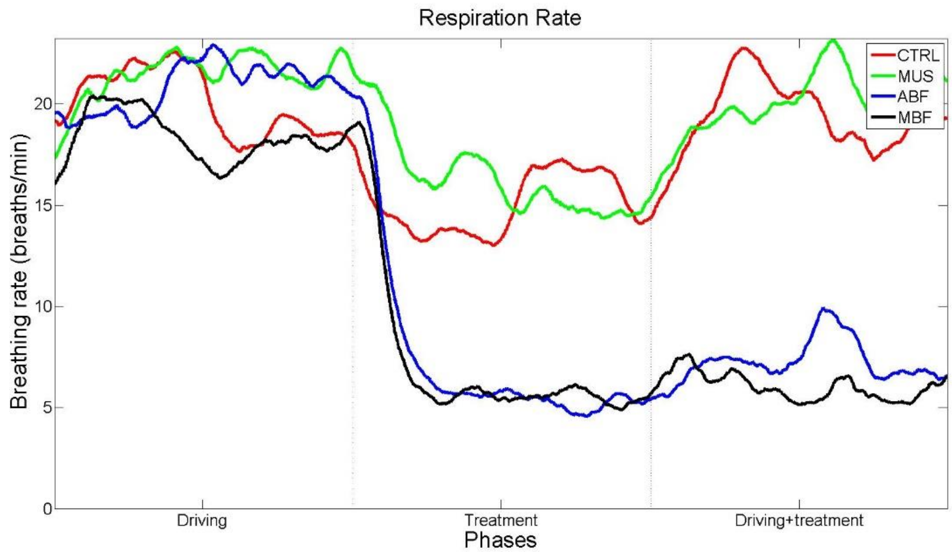


Figure 8. Average respiration rate for the four conditions (MBF,CTRL,MUS,ABF) over the entire protocol.

3.3.2 Heart Rate Variability (HRV)

Figure 9 shows the percent increase in HRV (relative to their levels during *driving*) for the *treatment* and *driving+treatment* phases. Participants in the non-biofeedback conditions showed similar HRV during *treatment* and *driving+treatment* as observed during *driving* suggesting that music alone was unable to reduce arousal. In contrast, participants in the two biofeedback conditions had a large increase in HRV during *treatment* indicating a lowering of arousal, and these levels were sustained during *driving+treatment*. As with breathing, 2 way ANOVA shows a main effect in HRV for biofeedback during *treatment* ($F(1,24) = 15.85,\ \mathrm{p} < 0.05$) and *driving+treatment* ($F(1,24) = 10.75,\ \mathrm{p} < 0.05$), but no music or interaction effects for either phase.

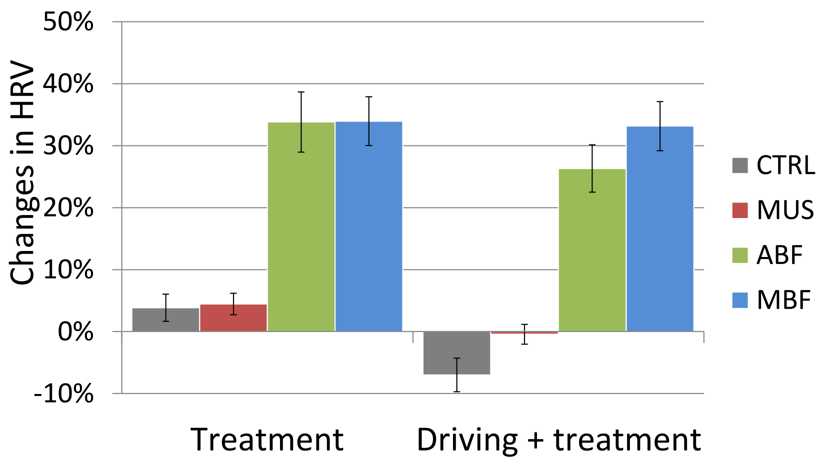
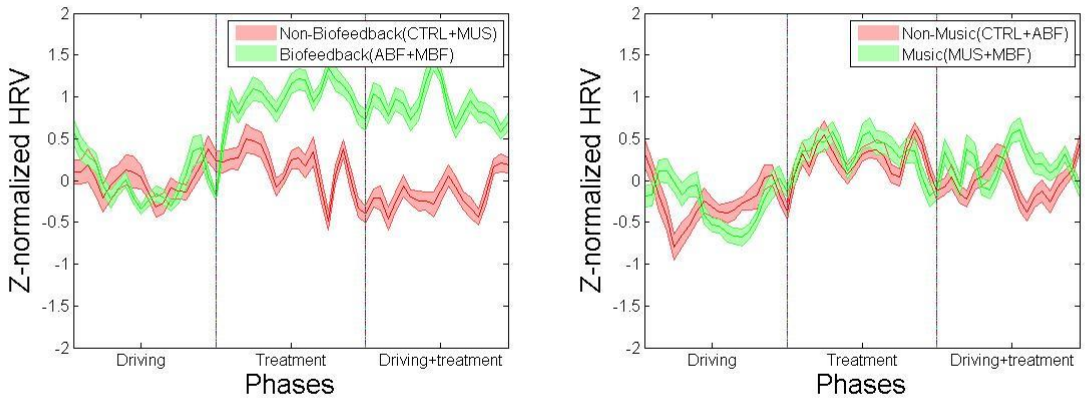


Figure 9. Percentage change in HRV (high HRV indicates relaxation). Error bars indicate standard deviation.

To understand the effects of the independent variables (music and biofeedback), we next assess the temporal evolution of the HRV signal over the course of the experiment. Figure 10(a-b) show the z-score normalized HRV over time averaged over all participants in biofeedback vs biofeedback conditions and music vs non-music conditions respectively. Figure 10(a) shows that participants under biofeedback conditions have a higher HRV throughout the *treatment* and *driving+treatment* phases in comparison to non-biofeedback conditions. As per Figure 10(b), there is no visual difference between music and non-music conditions in all the three phases.



(a) (b)

Figure 10. Z-score normalised HRV(a) Comparing HRV for biofeedback vs non-biofeedback conditions over time. (b) Comparing HRV for music vs non-music conditions over time.

3.3.3 Electrodermal Activity (EDA)

We extracted three features via the EDA signal: Skin Conductance Response (SCR), Skin conductance level (SCL) and Electrodermal positive change (EPC). Figure 11 shows the percent reduction in SCR's (relative to its level during *driving*). Here the SCRs were computed using the *ledalab*[3] software. Participants in all the four conditions show a large reduction in SCR's (greater than 50%) during *treatment* phase. Arousal levels during *driving+treatment* return close to their initial values observed

[3] http://www.ledalab.de/

during *driving* for all conditions except for MBF, which still shows a large (47%) reduction in SCR's. This result suggests that music biofeedback is more effective than auditory biofeedback at lowering arousal during visually-demanding tasks. 2-way ANOVA shows a main effect in EDA for biofeedback during *treatment* ($F(1,24) = 5.50,\ \mathrm{p} < 0.05$), a strong effect for biofeedback during *driving+treatment* ($F(1,23) = 12.06,\ \mathrm{p} < 0.05$) after outlier removal by residual analysis using SPSS software[4] and no music or interaction effects for either phase.

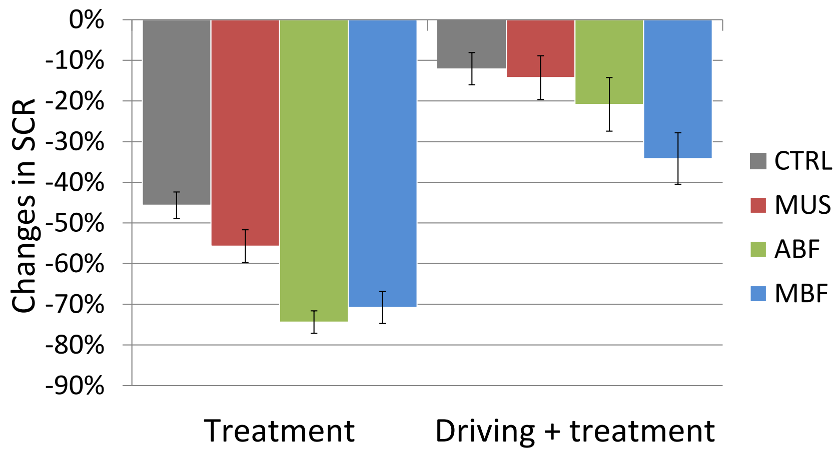


Figure 11. Percentage change in SCR (low SCR indicates relaxation). Error bars indicate standard deviation.

[4] http://www-01.ibm.com/software/analytics/spss/

Figure 12 shows the percent reduction in SCL (relative to their levels during *driving*) for each of the four conditions. Participants under all conditions showed decrease in SCL during *treatment* than during *driving* phase but the amount of reduction relatively is larger in biofeedback conditions. Participants in the biofeedback conditions showed lower SCL during *driving+treatment* than during *driving* (especially MBF condition), suggesting that biofeedback alone was able to reduce arousal more effectively. Participants under MBF condition had the largest reduction in SCL during *driving+treatment* phase which indicates that they were more relaxed. 2 way ANOVA shows a main effect in SCL for biofeedback during *treatment* ($F(1,24) = 4.50,\ p < 0.05$) and a marginal effect during *driving+treatment* ($F(1,23) = 4.00,\ p = 0.05$) after outlier removal by residual analysis using SPSS software but no music or interaction effects for either phase.

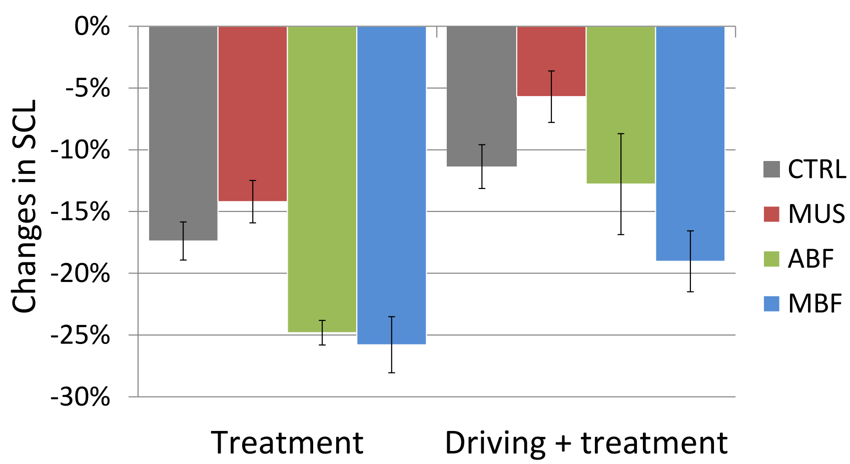
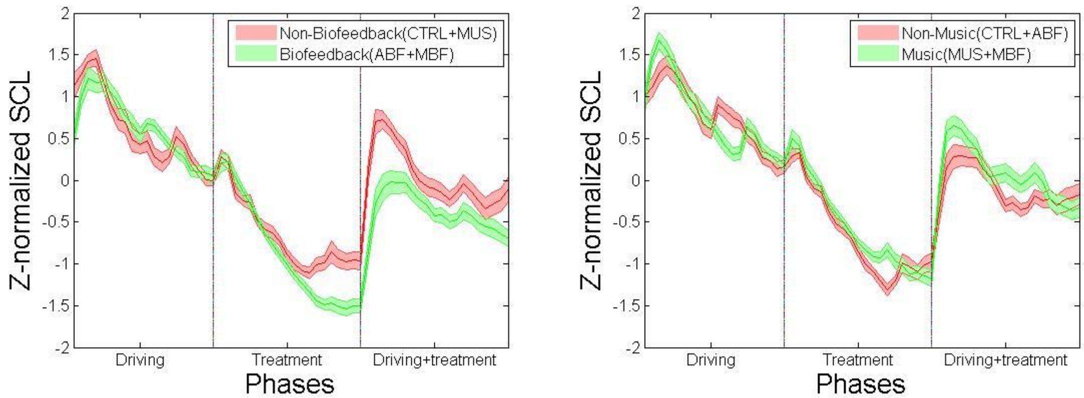


Figure 12. Percentage change in SCL (low SCL indicates relaxation). Error bars indicate standard deviation.

Figure 13 shows the z-score normalized SCL over time averaged over all participants in biofeedback vs biofeedback conditions and music vs non-music conditions. Figure 13(a) shows that participants under biofeedback conditions have a lower SCL than non-biofeedback conditions during *treatment* and *driving+treatment* phase. Visual comparison between music and non-music conditions shows no such trend.



(a) (b)

Figure 13 Z-score normalised SCL(a) Comparing SCL for biofeedback vs non-biofeedback conditions over time. (b) Comparing SCL for music vs non-music conditions over time.

Figure 14 shows the percent reduction in EPC (relative to its level during *driving*). Participants in all four conditions showed a large reduction in EPC during *treatment*, suggesting that the four conditions were effective in reducing arousal. This was especially evident for the two biofeedback groups (MBF and ABF). During *driving+treatment* phase, both biofeedback conditions show higher reductions (MBF has 1% higher reduction than ABF) than non-biofeedback conditions. This result suggests that biofeedback is effective at lowering arousal during visually-demanding tasks. 2-way ANOVA shows a main effect in EPC for biofeedback during *treatment* ($F(1,24) = 17.50,\ \mathrm{p} < 0.05$), a weak effect for biofeedback during *driving+treatment* ($F(1,24) = 1.250,\ \mathrm{p} = 0.274$) and no music or interaction effects for either phase adjustment.

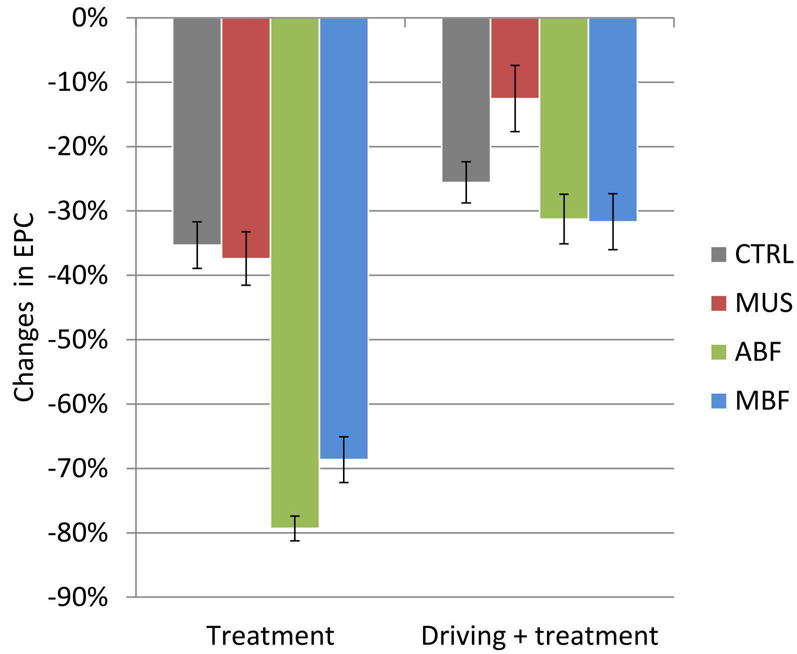
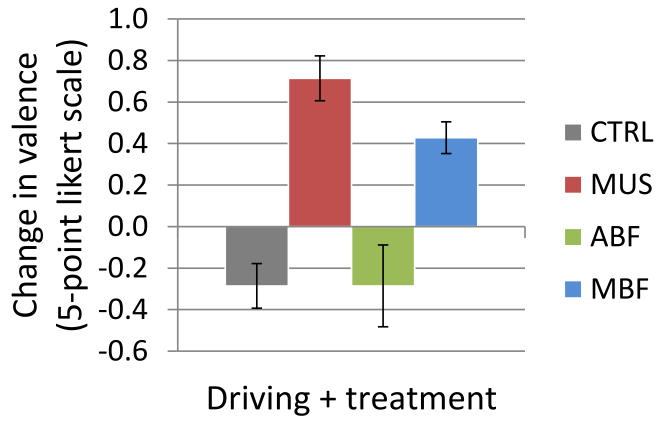


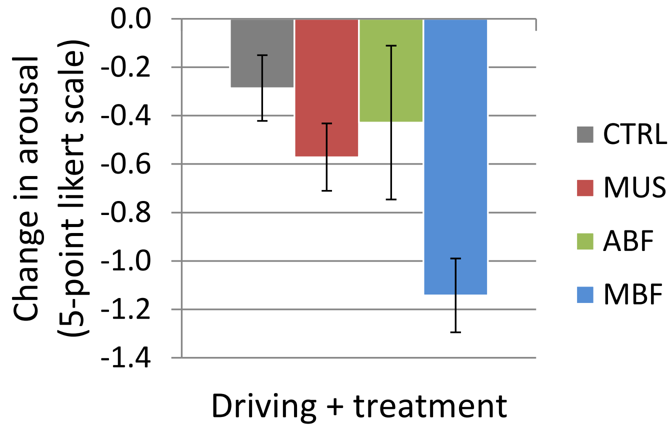
Figure 14. Percentage change in EPC (low EPC indicates relaxation). Error bars indicate standard deviation.

3.3.4 Subjective results

We also obtained subjective assessment from the participants for a qualitative analysis; refer APPENDIX A. When asked "*how negative (unhappy) or positive (happy) do you feel after listening to the music?*" on a 5-point Likert scale (1: unhappy; 5: happy) participants in the two music interventions (MBF, MUS) reported being happier after listening to music during *driving+treatment* relative to only *driving*, while participants in the non-music interventions (ABF; CTRL) reported a decrease in their happiness level; see Figure 15(a). A 2-way ANOVA shows a main effect in valence (happiness) for music during *driving+treatment* ($F(1{,}24) = 6.17,\ p < 0.05$), but no biofeedback or interaction effects. Though participants in the four conditions reported a reduction in arousal level, the reported reduction was largest for those in the MBF condition; see Figure 15(b). This result suggests that music biofeedback is more effective at lowering arousal during visually demanding tasks than music or auditory feedback alone.



(a)



(b)

Figure 15. Subjective ratings (a) Change in valence, measured using a 5-point Likert scale (1: unhappy; 5: happy). Error bars indicate standard deviation. (b) Change in arousal , measured using a 5-point Likert scale (1: calm; 5: excited)

When asked "*do you feel the music helped you reach a calmer state?*" the average rating for MBF and MUS participants was 3.4 (1: not at all; 5: extremely). Similarly, when asked "*how much did you like or* *dislike the songs?*" MBF and MUS participants provided an average rating of 4.57 (1: strongly dislike; 5: strongly like). A t-test for the likability ratings provided by participants for MBF and MUS conditions (MUS: 4.28; MBF: 4.85) showed a statistical difference ($p < 0.05$). We also found significant differences between ABF and MBF in terms of usability ratings: when asked "*would you use this app if it were available to you?*" all MBF participants responded in the positive, compared to three out of 7 among ABF participants. When asked *"how often would you use the app?"* the average answer for MBF and ABF participants was 3.28 and 2.42, respectively (1:not at all; 2:weekly; 3:several times/week; 4:daily; 5:several times/day) Finally, when asked *"how often were you able to listen to the music without any noise?"* MBF participants felt they were in better control over the quality of music and listened to the music devoid of noise more often than ABF participants (MBF: 3.71; ABF: 2.57) (1:never; 2:seldom; 3:about half the time; 4:usually; 5:always).

3.3.5 Driving performance

We compared task performance for each of the four conditions in terms of number of collisions and average speed for each phase. Figure 16 shows the reduction in the number of collisions during *driving+treatment* (relative to their values during *driving*). Participants in the two music conditions had fewer collisions than those in the non-music conditions (2 way ANOVA; marginal effect after outlier removal:$F(1,22) = 3.391; p = 0.07$). Note, however, the large error bar for the MUS condition, which indicates that the effects of music-biofeedback are more consistent across subjects than music alone.

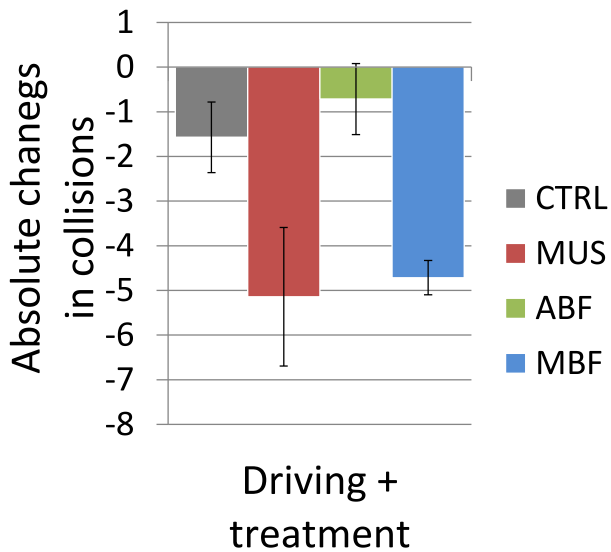


Figure 16. Absolute change in number of collisions to measure task performance. Error bars indicate standard deviation.

We also evaluated driving speed as another indicator of participant's task performance. Results in Figure 17 show an increase in speed for participants under all conditions during *driving+treatment* (relative to their values during *driving*). Participants in the two music conditions have a higher speed than the non-music conditions but the differences are not statistically significant (2 way ANOVA; weak effect: $p = 0.28$) due to high variance in all conditions. These results are similar to the results obtained for collisions as the average speed is predetermined over the track and is only affected by the number of crashes and the duration of each crash.

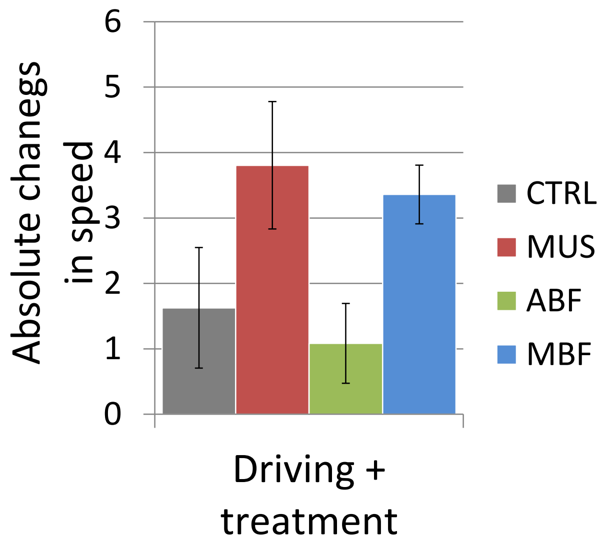


Figure 17. Absolute change in speed to measure task performance. Error bars indicate standard deviation

3.4 Discussion

We have presented a tool which combines the benefits of music and biofeedback to practice relaxation exercises during visually demanding tasks. The tool allows the user to listen to their favorite music, and adapts it to encourage slow, deep breathing. We compared this music-biofeedback tool against auditory biofeedback, music and a control condition, with four physiological measures and driving performance on a car-racing simulation as dependent variables. When compared to the two non-biofeedback conditions, music biofeedback lead to lower arousal levels across the four physiological measures. While music biofeedback and auditory biofeedback were comparable in terms of respiration and HRV, music biofeedback did lead to lower EDA levels (i.e., lower arousal) than auditory biofeedback in terms of Skin conductance response and skin conductance level. The latter is a stronger result given that EDA (especially number of SCR's) is a more robust measure of arousal than HRV –HRV is modulated by respiration rate, whereas EDA is not. Results from subjective ratings also indicate that music biofeedback leads to a larger reduction of arousal. Interestingly, the subjective reduction in arousal reported by subjects and percentage change in EDA –Figure 15(b) and Figure 11, respectively, are consistent with each other, supporting our argument that EDA is a relevant index of arousal. In terms of driving performance, music related conditions lead to fewer collisions and larger increase in speed. While music and music biofeedback are comparable in results, music biofeedback leads to more consistent performance across participants than music based on the large error bars shown in Figure 16. In terms of usability, the music biofeedback tool was preferred over auditory biofeedback tool. Overall, this suggests that music biofeedback is a viable stress-management intervention during driving and other visually-demanding tasks.

The music based biofeedback tool has other benefits over the current existing biofeedback systems. Majority of the biofeedback tools cannot be used in conjunction to any other activity while our tool can be used while performing a visual task such as reading, exercising, etc. The mobile app allows users to select any song from their personal music library which acts as a key benefit to this system compared to other music based biofeedback systems which have special format requirements for musical compositions (Bergstrom, Seinfeld et al. 2013). Deep breathing is a proven method to reduce stress but is not enjoyable due to its monotonous nature. Our tool adds the benefits of music to make this activity an enjoyable experience; leading to low attrition rates in practice of deep breathing.

We summarize the overall results in the form of a table by ranking each condition based on the results which are beneficial to the user (results indicating stronger relaxation or better driving performance or higher happiness level are ranked higher); see Table 3. Music biofeedback tool is ranked in top two groups in each category. Auditory biofeedback is ranked second in all results related to physiological arousal but last in terms of driving performance and happiness ratings. A reverse trend is displayed by participants listening to music, where driving performance and happiness ratings are highest but poor physiological arousal rankings. Interestingly, the order of ranking is same for driving performance and subjective valence (happiness); they also have similar pattern in their results as shown in Figure 15(a) and 16. This can lead us to speculate that the driving performance and happiness are directly related.

SR No.	Independent Variable	Trend	Rank #1	Rank #2	Rank #3	Rank #4
1	Breathing Rate	↓	MBF	ABF	CTRL	MUS
2	Heart Rate Variability	↑	MBF	ABF	MUS	CTRL
3	Skin Conductance Response	↓	MBF	ABF	MUS	CTRL
4	Skin Conductance Level	↓	MBF	ABF	CTRL	MUS
5	Electrodermal Positive Change	↓	MBF	ABF	CTRL	MUS
6	Subjective Arousal	↓	MBF	MUS	ABF	CTRL
7	Subjective Valence	↑	MUS	MBF	CTRL	ABF
8	Collisions	↓	MUS	MBF	CTRL	ABF
9	Speed	↑	MUS	MBF	CTRL	ABF

Table 3 Overall results table (↑= positive change in independent variable is beneficial for the user; ↓ = negative change in independent variable is beneficial for the user)

4 SMARTPHONE-BASED MEASUREMENT OF RESPIRATION RATE USING GOERTZEL ALGORITHM

In this chapter we describe the smartphone application to measure breathing rate via photoplethysmography and the experiments conducted to evaluate the tool measurements in comparison to a medical grade respiratory sensor.

The remaining sections of this chapter are organized as follows. First, we describe our algorithm to estimate breathing rate via PPG signal extracted from smartphone camera. Then we discuss our set of experiments to evaluate the accuracy of the breathing rate measurements. Next, we present the results obtained via the smartphone application and also discuss the influence of breathing rate and other algorithm parameters on the error. Finally we interpret the results in the last subsection.

4.1 Smartphone application to measure respiration rate

Respiration modulates the PPG waveform in three ways: respiratory induced amplitude variations (RIAV), respiratory induced frequency variations (RIFV) and respiratory induced intensity variations (RIIV). We aim to detect the respiration induced intensity variations (RIIV's) in the PPG signal to measure breathing rate as it provides more accurate results (Karlen, Raman et al. 2013). Our algorithm to measure breathing rate from a smartphone camera is illustrated in Figure 18. We will describe the algorithm stepwise in the following sub-sections:

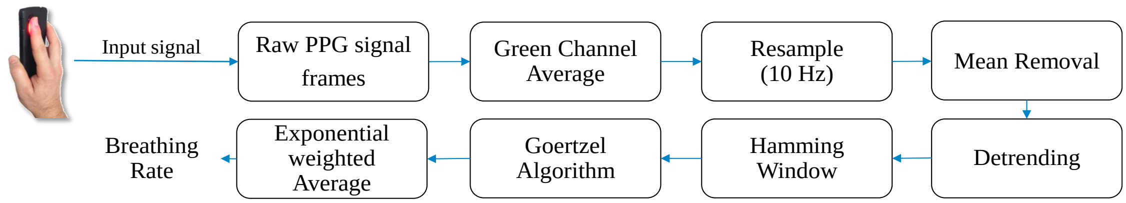


Figure 18. Steps of the algorithm to measure breathing rate

4.1.1 Algorithm

We use the built-in camera in the smartphone to collect PPG signal as shown in Figure 19. The user is required to place their index finger over the camera covering the flash light. We extract only the green channel signal due to lower absorption of green light by blood, which results in a stronger PPG signal (Wieringa, Mastik et al. 2005). At each sampling point, the PPG image is averaged to obtain a time series of PPG's after data acquisition as shown in Figure 19(d).

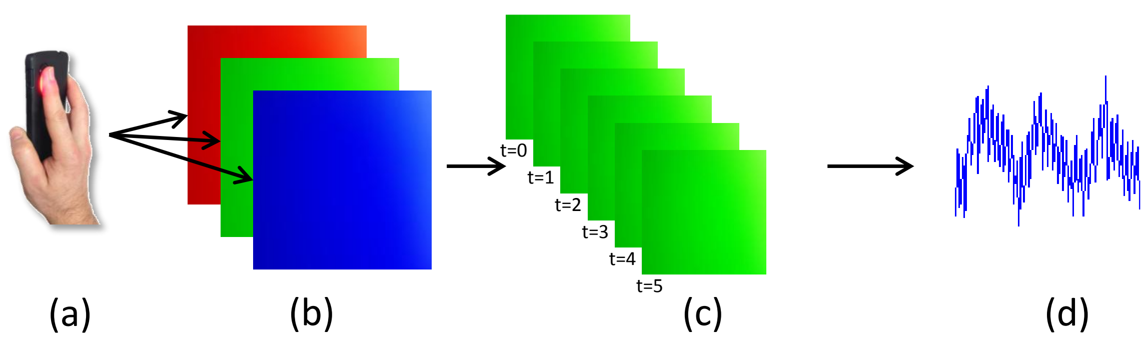


Figure 19 Data acquisition (a) Cover flash and camera with index finger (b) separate image in RGB channels (c) extract green channel data and average each time frame to a single point (d) PPG signal

As shown in Figure 20, the PPG time series data goes through several preprocessing steps before being used for BR estimation. First, we select a segment of PPG signal from a time window of certain width and resample at interval of 100 ms (10 Hz) to rectify variable camera sampling interval using cubic interpolation. We then remove the mean from the resampled signal and apply linear detrending (Fleming and Tarassenko 2007, Dash, Shelley et al. 2010, Lee and Chon 2010), which helps remove local trends before frequency analysis and reduce sensor based or subject based motion artifacts.

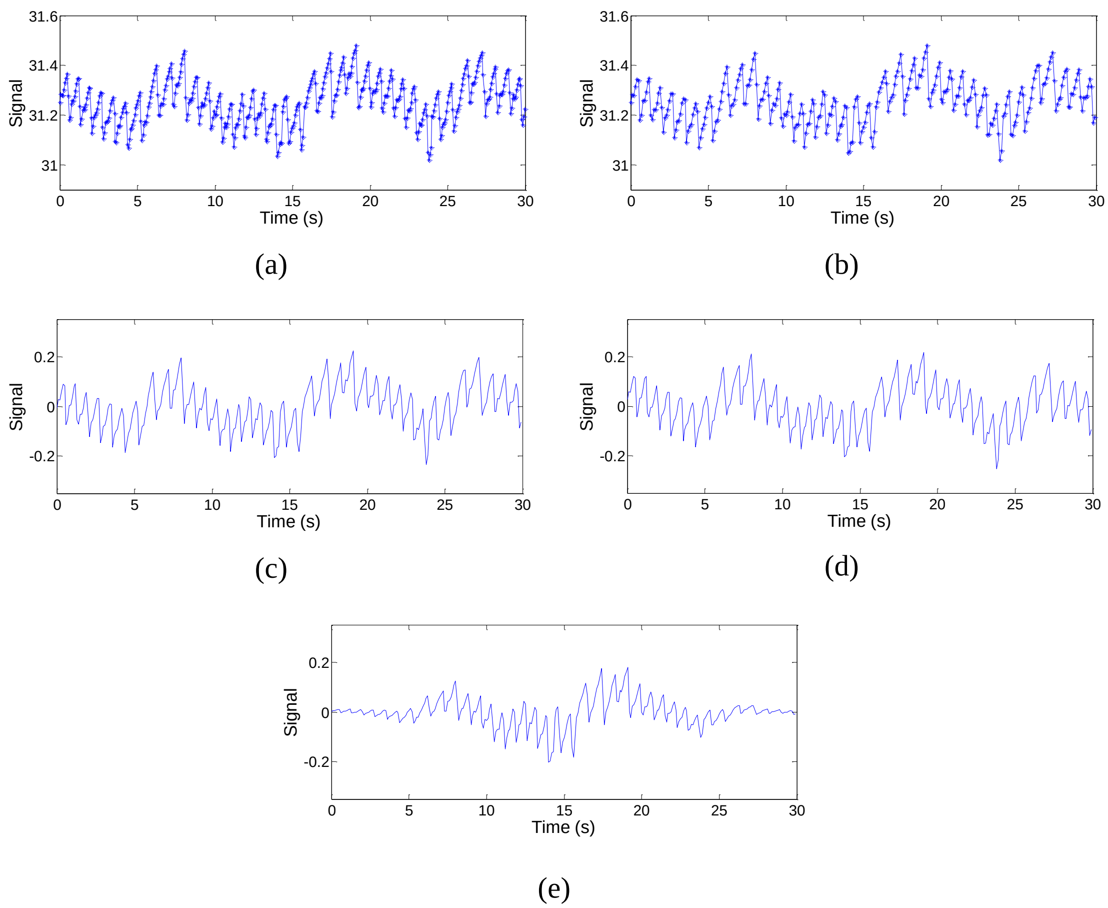


Figure 20 Pre-processing steps (a)Raw PPG signal (b) Resampled signal (10 Hz) (c) Signal after mean removal (d) Detrended signal (e) Signal after multiplication for hamming window

We estimate the breathing rate BR by obtaining frequency responses g_r for the preprocessed signal X at specific frequencies f using Goertzel algorithm and calculating the exponential weighted average as shown in Equation (3):

$$BR = \frac{\sum_f (f * g_r(f, X)^{\alpha})}{\sum_f g_r(f, X)^{\alpha}} \quad \textbf{(3)}$$

where $\alpha = 10$ is found to be appropriate exponential weighting parameter in our preliminary work. Goertzel algorithm (Goertzel 1958) returns the frequency response at specific frequencies for the input data (see Figure 21) as per equations (4) and (5) :

$$s(n) = x(n) + 2\cos(2\pi f)\, s(n-1) - s(n-2) \quad \textbf{(4)}$$

$$y(n) = s(n) - e^{-2\pi i f} s(n-1) \quad \textbf{(5)}$$

where $s(n)$ is the intermediate sequence, $x(n)$ is the input sequence, f is the given frequency, and $y(n)$ is the output sequence[5]. The final term in the output sequence is the Goertzel response (g_r) for the given frequency f. Goertzel algorithm analyses one specific frequency component from the discrete signal. It suits our purpose as it is computationally inexpensive and provides frequency response for selected frequencies. We choose frequencies which correspond to low breathing rates

[5] $s(-2) = s(-1) = 0$; $x(n) = 0$ for all $n < 0$

(4-16 at interval of 0.125 breaths/minute) as the signal is strongly influenced by RSA at low breathing rates (Hirsch and Bishop 1981). A Hamming window is used to minimize the first side lobe for frequency response.

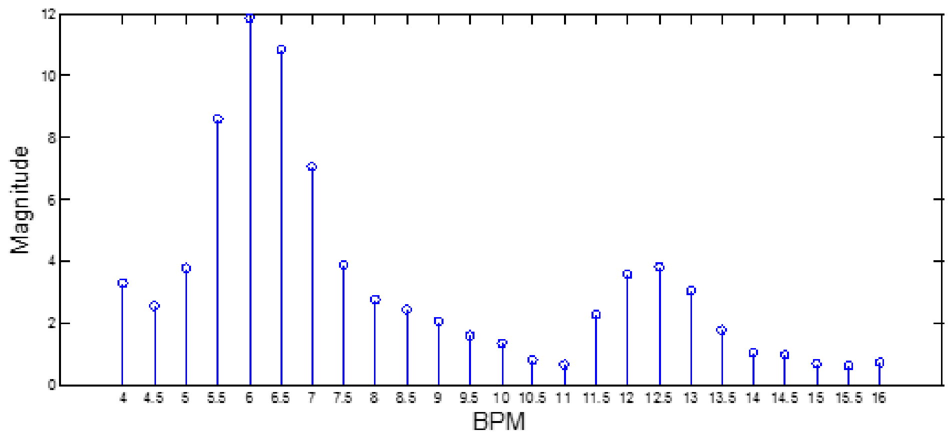
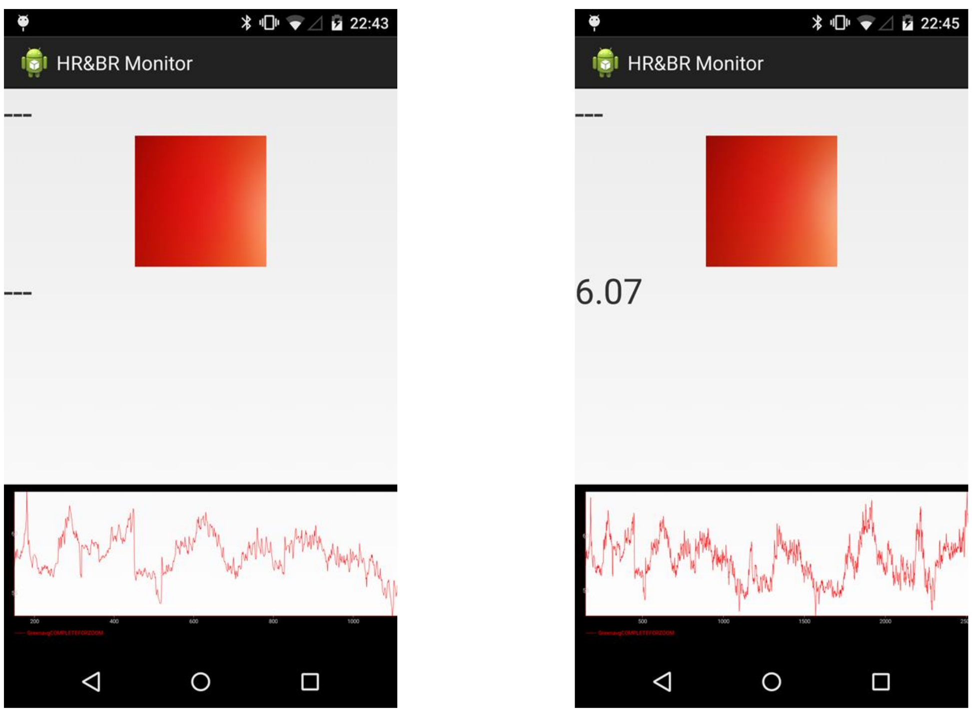


Figure 21 Goertzel response at specific frequencies for a PPG signal (30 seconds) for a participant breathing around 6 BPM (frequency correspond to 4-16 BPM at interval of 0.5 BPM)

4.1.2 Tool description

We implemented the tool as a mobile app on a Nexus 5 smartphone running Android 4.4 (KitKat). Initial version of the app also included measurement of HR using peak detection algorithms over the PPG signal, but was removed to reduce computational cost to measure breathing rate. The visual interface displays the video stream captured by the camera, the PPG signal (green channel only) and the computed respiration rate; see screenshots in Figure 22. Note that the mobile app can run on any Android smartphone with a flash based camera which acts as the source of light for PPG.

We extensively tested the accuracy of our measurements under different lighting conditions, spectral considerations (green, blue and red), region of interest in the frame, flash light intensity during our initial experiments. To utilize the tool, users are required to place their index finger on the smartphone camera (generally camera on the other side of the screen) after starting the application on the android smartphone. The app will start streaming the PPG signal on the bottom of the screen –see Figure 22(a). The streaming helps detect motion artifacts in the PPG signal visually in real-time. After a fixed time period, a breathing rate value will be displayed as shown on in Figure 22(b). To avoid inaccurate readings, users should cover the complete camera and flash while keeping their finger still until a measurement is displayed on the screen.



(a) (b)

Figure 22. Visual interface of the smartphone application to measure breathing rate : (a) screenshot during data collection, (b) screenshot after breathing rate value is estimated

4.2 User studies

To evaluate this tool, we compared the breathing rate estimated from the app with the reference values obtained by the chest strap respiration sensor. Participants (N=5; 5 males; 22-36 years) were required to have no current cardiac or respiratory problems.

Participants maintained a fixed breathing rate (6, 8, 10 or 12 BPM) for each paced breathing session. During each session, four reliable[6] datasets were collected (participants placed their index finger on the camera for each dataset). Overall, we collected 80 signals (5 subjects x 4 breathing rates X 4 repetitions), each lasting 2 minutes. To avoid ordering effects, the sequences of sessions for fixed breathing rates were randomized.

During these controlled breathing sessions, subjects were instructed to inhale and exhale by following an auditory pacing signal[7] with the inspiration to expiration ratio set to 2:3 (Strauss-Blasche, Moser et al. 2000). To measure respiratory ground truth, we used Bioharness BT chest strap sensor which provides medical grade breathing rate measurements (Hailstone and Kilding 2011). This study is approved by our Institutional Review Board.

[6] Unreliable datasets (corrupted due to motion artifacts or inconsistent breathing rate) were rejected

[7] *Paced Breathing*: Android app which provides visual and audio breathing cues, available on google play. (https://play.google.com/store/apps/details?id=com.apps.paced.breathing&hl=en)

4.3 Results

4.3.1 Online analysis

We evaluated the accuracy of the proposed method by computing the root mean square error (RMSE) between ground truth values measured by a chest strap respiratory sensor and estimated breathing rates. Figure 23 shows the RMSE for the four breathing conditions (refer Section 4.2). The average RMSE for the four breathing conditions was 0.323 BPM with the error being less than 1 BPM for all conditions. We also observed that the error and the corresponding variance was relatively higher for 8 and 12 BPM conditions.

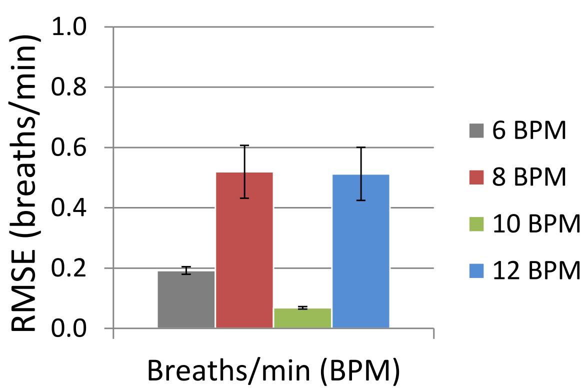


Figure 23. Root mean square error (breaths/min) for estimated BR in comparision to ground truth values for different breathing rates. Error bars indicate standard deviation.

Figure 24 shows a scatter plot with the estimated breathing rate and ground truth values for all datasets. In our assessment we noted that 91.25% of the estimated BR values were within ± 1 standard deviations of the mean values (datapoints in green region). We had only two extreme outliers: a dataset with reference breathing rate of 8 breaths/min (estimated BR=15.98, the harmonic frequency being captured) and a dataset with reference breathing rate of 12 breaths/min (estimated BR=4, no strong frequency response in applicable range). These datasets are the cause for high variance in results under 8 and 12 BPM as shown in Figure 23. The Spearman correlation coefficient between the estimated BR and ground truth was found to be $r = 0.88$ (($p < 0.01$)) indicating a strong correlation. This shows that the method measures breathing rate accurately and is robust too.

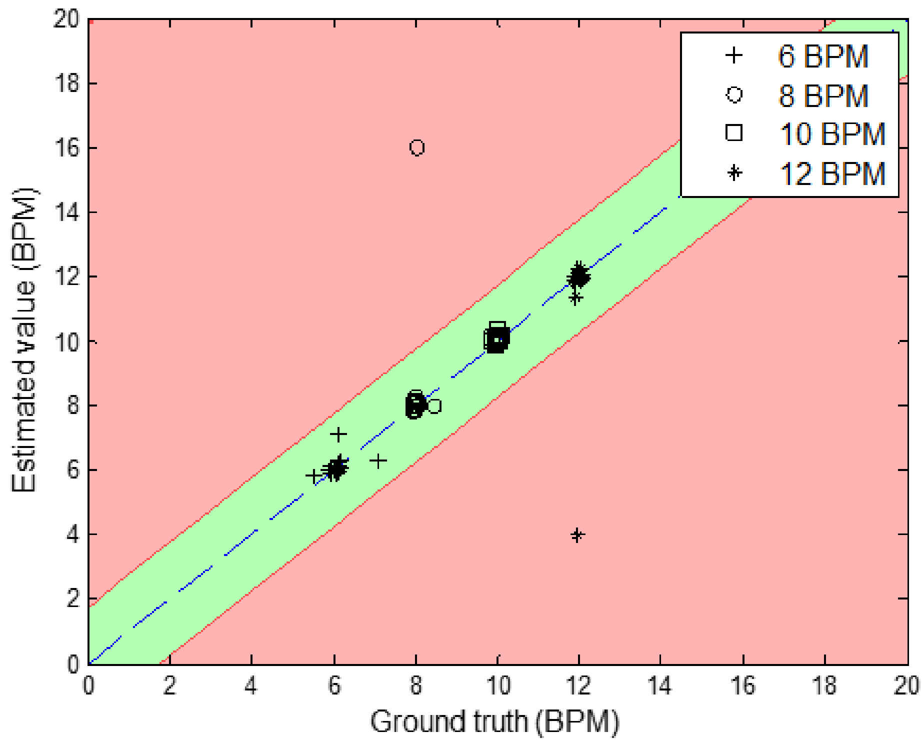


Figure 24. Scatter plot, error per subject : Scatter plot showing the estimated and mean of the reference values of RR. Blue dashed line represents the optimal performance

4.3.2 Offline analysis

We also performed an offline analysis on the PPG data obtained from the smartphone application to simulate a continuous measurement[8] of breathing rate. Continuous measurement is achieved by using a sliding window with specified window size and overlap. We completed offline analysis to tune the different parametric values used in our algorithm. We examine the accuracy of our method for the four controlled breathing rates included in the user study. Our algorithm comprises of a few variables which can be tuned to achieve higher accuracy in the estimation which include:

- Alpha (α): The exponential factor for the weightage of frequency response of Goertzel algorithm as shown in Equation (3)
- Window size (w): Data length in seconds used for each estimation
- Spacing (s): The spacing between each breathing rate used in the Equation (3)

Figure 25 shows the RMSE for different breathing rates averaged different overlapping windows. We average the results obtained using windows of size 30, 60, 90, and 120 seconds (with an overlap of 29, 59, 89 and 119 seconds respectively) for each breathing rate. The error for lower breathing rates (6 and 8 BPM) is comparatively lower than higher breathing rates (12 BPM). The error increases with increase in breathing rate. The variance of the error also increases with higher breathing rates showcasing the variability in the estimation of the breathing rates.

[8] Note that the app provides single reading for each 2-minute dataset

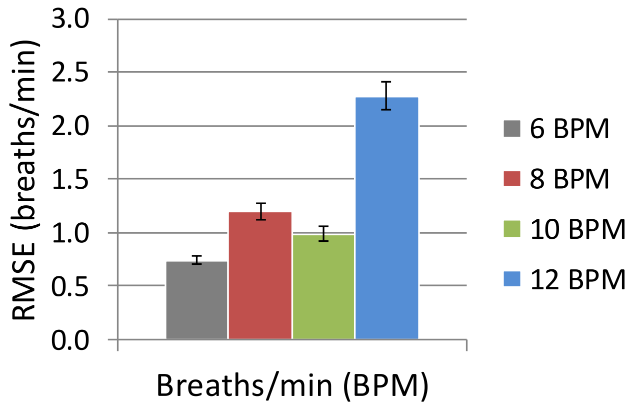


Figure 25. RMS error (breaths/min) for different breathing rates (average over different window sizes). Error bars indicate standard deviation.

Figure 26 shows the averaged RMS error for all the datasets for different alpha values (the exponential factor for the weight of frequency response as described in Equation (3)). Other parameters such as window size (*w* =120 seconds) and spacing (*s* =0.125 breaths/min) are kept constant for this assessment. We chose these parameter values since they resulted in the lowest RMSE during our preliminary studies. As the alpha value increase from 0.1 to 100, the error initially reduces after which it starts to increase. This analysis shows that α=10 led to the smallest error (RMSE=0.32 breaths per minute).

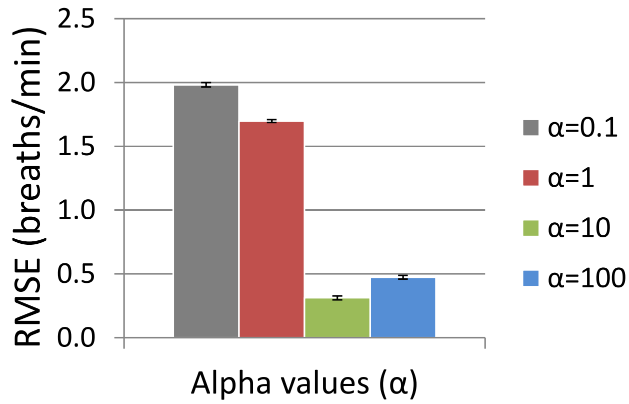


Figure 26. RMS error (breaths/min) for different alpha values (average over entire dataset). Error bars indicate standard deviation.

Figure 27 shows the averaged RMS error for the complete dataset with different data length used for breathing rate estimation. Other parameters such as alpha (α=10) and spacing (*s* =0.125 breaths/min) are kept constant across all datasets. It shows a large reduction in error with increasing window size. The error is highest (2.62 breaths/min) for window size = 30 seconds while a window size of 120 seconds led to the lowest error (0.32 breaths/ min). These results show that the error reduces with increasing window size. However, it is worth mentioning that duration required for each measurement is directly dependent on the measurement window i.e. higher the window size, longer the measurement duration,

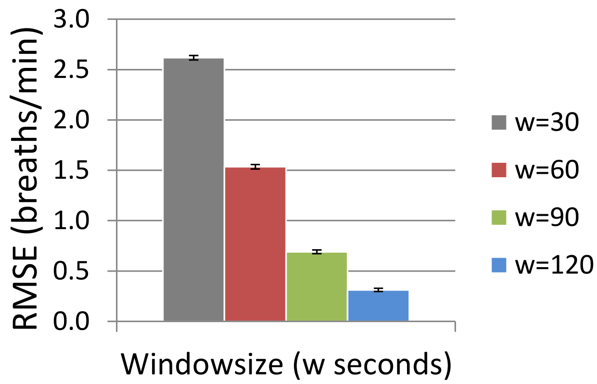


Figure 27. RMS error (breaths/min) for different window sizes (average over entire dataset). Error bars indicate standard deviation.

Figure 28 shows the averaged RMS error for the complete dataset for different spacing values (0.125, 0.25, 0.5 and 1 breaths/min) between the ranges of breathing rate queried in equation (3). Other parameters such as alpha (α=10) and window size (w =120 seconds) are kept constant. The error is least with spacing equal to 0.125 breaths/min; however the difference in RMSE for the different values of s is not significant (less than 0.1 breaths/min).

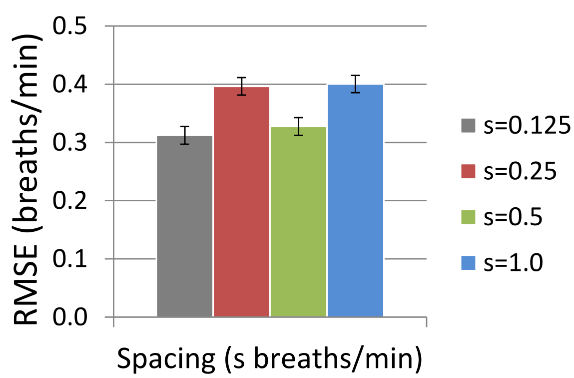


Figure 28. RMS error (breaths/min) for different spacing values (error averaged over entire dataset). Error bars indicate standard deviation.

4.4 Discussion

We presented a method to extract respiratory rates using Goertzel algorithm directly from smartphone camera recordings. We compared our algorithm performance with medical grade respiratory sensors over controlled breathing settings. The algorithm has shown high accuracy and robustness in estimating breathing rates from PPG signal when computed on the smartphone. The results also suggest that our method is more accurate for lower breathing rates. The accuracy reduces for higher breathing rates as the modulation of PPG signal by respiration reduces with higher breathing rates. Also the higher breathing rates exhibit large amount of motion corresponding to high artifact noise in the data. In addition, the error significantly decreased when longer time windows were used.

In comparison to prior methods, our algorithm can compute breathing rate over the smartphone itself while prior methods ((Kagawa, Kawamoto et al. 2013, Karlen, Raman et al. 2013, Nam, Lee et al. 2014) could not due to high computational complexity and implemented their methods offline (Matlab framework). We were able to achieve this by using Goertzel algorithm, which reduces computational cost by providing frequency response for selectable frequencies only. After obtaining the frequency responses for desirable frequencies, we tested different averaging systems to estimate the breathing rate by tuning the alpha value described in Equation (3). As per Equation (3), α=0.1 can be considered as giving no weightage to any frequency response; α=1 is the linear mean of the frequency responses obtained; α=10 represents the exponential average while α=100 is selecting the highest value amongst all frequency response values. We can conclude that exponential average provides better results than linear average or by selecting the frequency with highest response value as used by (Dash, Shelley et al. 2010). We also increased the granularity of the frequencies used for the averaging system by increasing the spacing between the frequencies. These results are not highly influenced by frequency spacing, which can be explained by the fact that our reference values are very close to integer values, hence a spacing of 1 BPM is also sufficient. Note that to reduce our computational costs, we limited the frequency spacing to 0.125 breaths/min and window size not more than 120 seconds.

5 CONCLUSIONS AND FUTURE WORK

In this thesis, we have presented two tools related to biofeedback:

- a tool for practicing relaxation exercises during visually demanding tasks.
- a tool to measure breathing rate using a smartphone camera.

The first tool aims to use music as an alternative means of feedback while the other provides a solution to measure breathing rate using a smartphone eliminating the need for any special sensor. There are several interesting research directions that arise from the work. We discuss work required to further investigate each tool and the eventual integration of these tools in the following subsections.

5.1 Music-based respiratory biofeedback tool

Our study to evaluate the biofeedback tool used slow-tempo instrumental songs, a music style that has been associated with reductions in physiological responses and better driving (North and Hargreaves 1999, van der Zwaag, Dijksterhuis et al. 2012, Ünal, de Waard et al. 2013). While our tool may in principle be used with any song in the user's personal library, additional work is needed to determine if the beneficial effects of music biofeedback hold when other music genres are used, particularly those that are designed to excite/arouse the user. Further work is also needed to measure potential interference effects on driving performance and mental workload (Dibben and Williamson 2007).

Our results are based on a modest sample size of college students (N=28), so further work is also needed to test the intervention on different demographics, particularly older adults and novice vs. experienced drivers. Further studies will also require more realistic and complex driving tasks (e.g., urban driving, unexpected events) than those possible with our car racing simulator, and more sensitive measures of driving performance than the one we used, such as lane tracing accuracy, eye tracking .

Driver fatigue and drowsiness is also a major cause for accidents apart from road rage. These problems arise due to long and arduous driving sessions or sleep deprivation. Physiological arousal can be used to detect sleepy behavior in drivers (Lal and Craig 2001) while biofeedback techniques can be used to increase their arousal level to optimize their driving performance. Our tool can be utilized with a modified biofeedback mechanism where participants listen to arousing music during drowsy state. The music used in this scenario will be high tempo music with abrupt tempo changes which has been used to increase physiological arousal (Dillman Carpentier and Potter 2007).

For this study we used a sensor chest strap, but some subjects complained that the sensor was *"not comfortable"* or *"the chest sensor was tight"*. This was one of the key motivations for us to find a less cumbersome way to measure respiratory rate. For example, respiration rates can be measured with contact-free sensors (e.g., Doppler ultrasound) or estimated from webcams or smartphone cameras. This led to the development of our smartphone application to measure breathing rate without the need of any sensor.

5.2 Smartphone-based respiration measurement tool

There are several limitations in our study to measure breathing rate via smartphone camera that present opportunities for further work. We evaluated participants under controlled breathing settings; however our future goal is to evaluate this tool in spontaneous breathing conditions. We have tested this tool for a breathing range (8-16 breaths/min) applicable for adults at rest only. Further investigation is required to measure the accuracy for higher breathing rates (20-40 breaths/min) commonly found in children (under 12 years) or in adults during physically strenuous activities.

Powerful processors, multiple sensors and wireless connectivity makes mobile phones a low cost portable option to deliver health care services, especially in the developing countries where medical trained professionals and clinical facilities are scarce but mobile phones are ubiquitous in the rural areas. It has been anticipated that smartphone based healthcare services now termed as 'mHealth' as per World Health Organization, will benefit more than 500 million people by the end of 2015 (Ciaramitaro and Skrocki 2011). Smartphones have already been used as microscopes, ultrasound systems and spectrometers to detect diseases such as malaria and sickle cell anemia (Breslauer, Maamari et al. 2009, Mertz 2012). Using PPG techniques, our tool can be used to diagnose cardiovascular diseases in impoverished countries. We can aim to detect medical problems such as atrial fibrillation (Jinseok, Reyes et al. 2013). and blood loss (Selvaraj, Scully et al. 2011) by measuring vital signs such as heart rate, heart rate variability and respiration rate.

This study was conducted in a controlled environment, but further studies can look into the measurement of breathing rate in real-life settings which have an ambulatory environment. In this scenario, the biggest hurdle is the unreliable readings obtained due to motion artifacts. Prior studies have used statistical models (Selvaraj, Mendelson et al. 2011) and independent component analysis (Kim and Yoo 2006) to remove motion artifacts in PPG signal. Other groups have tried to minimize motion artifacts by integrating mobile games with data acquisition of PPG signal and penalizing the user's gameplay for motion artifacts (Han, Shi et al. 2014). In future, we would like to incorporate these approaches and use commercially available phone attachments to suppress motion artifacts as shown in Figure 29.

Figure 29. Phone attachment to place index finger over the camera to reduce motion artifacts[9]

5.3 Integration of both tools

Our final aim is to integrate the music based respiratory biofeedback tool with the measurement of breathing rate tool. The envisioned smartphone application will measure breathing via the smartphone camera and modify the music based on the respiration rate. It will be a complete end-to-end biofeedback tool, which is a zero cost solution (except the phone cost), requires no extra

[9](www.designboom.com/design/morpholio-photoplethysmography-technology-transfer-28-04-2014)

hardware and can be practiced with any musical composition. The requirement of only a smartphone and no special sensors makes it accessible to anybody just by downloading an app. It will help wider adoption of biofeedback techniques and will be enjoyable too. Apart from driving, it can be used in parallel to other tasks such as reading, web browsing, etc.

We can experiment with different modifications of this integrated tool to suit our purpose. We can modify the biofeedback mechanism to be used in a mobile game to perform relaxation exercises as shown by Parnandi et al.(Parnandi, Ahmed et al. 2014). We can also change the means of feedback to haptic or visual channels to test the tool with auditory tasks such as public speaking or listening to a podcast. We can measure heart rate variability (Lenskiy and Aitzhan 2013) and change the quality of music based on user's heart rate variability.

In terms of implementation challenges, both tools are smartphone applications which allow seamless integration of these tools. Although the algorithm to measure breathing rate is computationally efficient (around 150 ms per measurement), we need to further improve the implementation to provide continuous measurements by using coding practices such as threading. We also need to integrate the visual interface of both applications for improved usability experience. To use the app in ambulatory conditions, we need to address the issue of motion artifacts as explained in section 5.2.

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APPENDIX A

Biofeedback Gaming Survey

Subject Number:

BACKGROUND

– Age:

– Gender:

– Occupation:

– How do you feel today?

Very tired	A bit tired	Neutral	A bit energetic	Very energetic
○	○	○	○	○

– Do you practice meditation regularly? If so, how often and for how long?

– Do you practice deep breathing regularly? If so, how often and for how long?

- Do you have any experience with biofeedback?

- Have you ever used wearable sensors (e.g., heart rate monitors, activity sensors)? If so, which ones?

MUSIC PREFERENCES

– Music experience: How often do you listen to music per week?

Not at all	0-1 days	2-3 days	4-5 days	6-7 days
○	○	○	○	○

– For how long each time?

Not at all	Less than an hour	1-2 hours	3-4 hours	More than 4 hours
○	○	○	○	○

– Does music alter your emotional state? If so, in what ways?

– Which of the following music genres do you like? Check all that apply

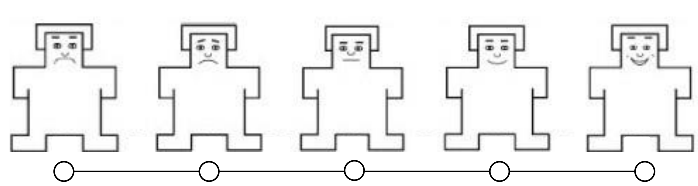
Check	Music Genre	Example Artists/Bands
	Classical	Mozart, Beethoven

	Jazz	Ray Charles, Frank Sinatra
	World	Ravi Shankar, Ali Farka Touré
	Blues	BB King, Stevie Ray Vaughan
	Country	Taylor Swift, Keith Urban
	Pop	Bruno Mars, Michael Jackson
	Rock	Pink Floyd, Queen
	Heavy metal	Metallica, AC/DC
	Hip Hop/Rap/R&B	Eminem, Usher
	Electronic	Daft Punk, Skrillex

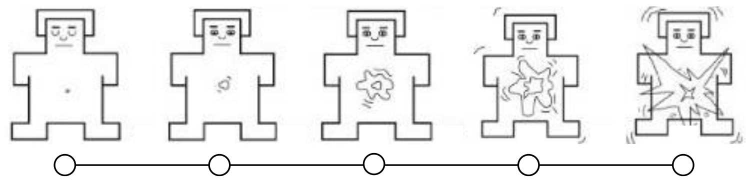
Others (please mention genre and artist/band):

Baseline emotional state

– Valence: How negative (unhappy) or positive (happy) do you feel at the moment?



– Arousal: How calm or excited do you feel at the moment?



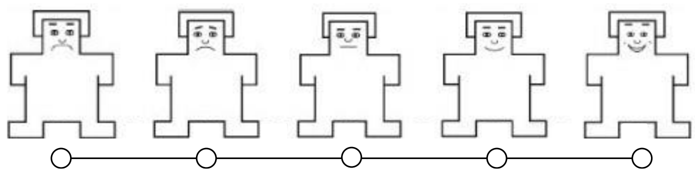
Post Paced Deep Breathing Task

– How hard was it for you to follow the breathing pace during the task?

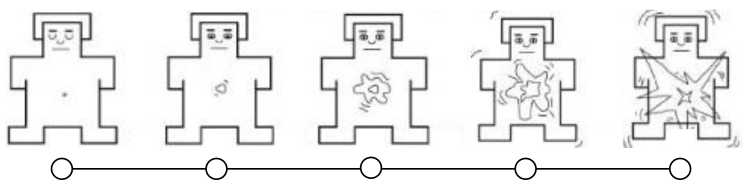
Very easy	A bit easy	Neutral	A bit hard	Very hard

Deep Breathing (Relaxation)

– Valence: How negative (unhappy) or positive (happy) do you feel after completing the deep breathing (relaxation) session?



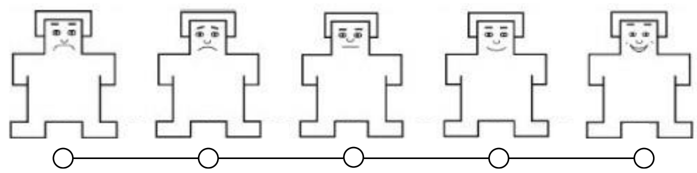
– Arousal: How calm or excited do you feel after completing the deep breathing (relaxation) session?



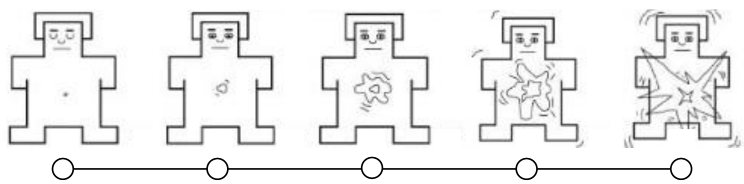
– In which situations or places would you practice deep breathing?

Music

– Valence: How negative (unhappy) or positive (happy) do you feel after listening to the music?



– Arousal: How calm or excited do you feel after listening to the music?



– Do you feel the music helped you reach a calmer state?

Not at all	A little	Neutral	A lot	Extremely

– How much did you like or dislike the songs?

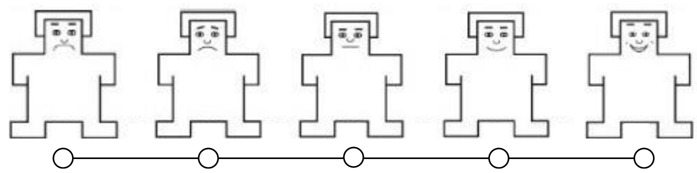
Strongly dislike	Dislike	Neutral	Like	Strongly like

– In which situations or places would you listen to music to relax?

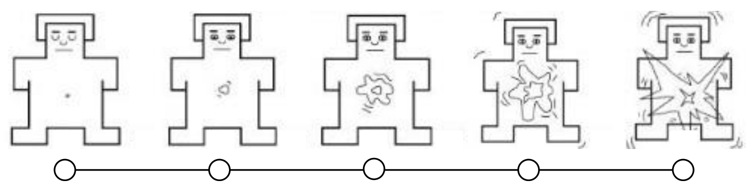
– Can you suggest other songs/artists/genres that may help you relax?

Musical Biofeedback App

– Valence: How negative (unhappy) or positive (happy) do you feel after listening to the music?



– Arousal: How calm or excited do you feel after listening to the music?



– Do you feel the music helped you reach a calmer state?

Not at all	A little	Neutral	A lot	Extremely

– How much did you like or dislike the songs?

Strongly dislike	Dislike	Neutral	Like	Strongly like

– To what extent did you feel that you were in control of the quality of the music?

Not at all	A little	Neutral	A lot	Extremely
○	○	○	○	○

– How often were you able to listen to the music without any noise?

Never	Seldom	About half the time	Usually	Always
○	○	○	○	○

– Can you suggest other songs/artists/genres that may help you relax?

– Would you use this app if it were available to you?

– In which situations or places would you use it?

– How often would you use it?

Not at all	Weekly	Several times/week	Daily	Several times/day
○	○	○	○	○

– Please list the things you liked most about this app

– Please list the things you liked least about this app

– Do you like the idea of using wearable sensors as an input to an app? Why? Why not?

– Do you have any comments or suggestions to improve the app?

Protocol design

– What was the goal of the overall experimental protocol?

– Were the instructions provided clear? Please elaborate

– Did you find the sensors comfortable? Please elaborate

– Did you notice any difference in difficulty between pre and post task (Color Word Test)? Please elaborate

– Do you have any comments or suggestions related to the overall experimental protocol?

APPENDIX B

Description of Participants Characteristics by Group

(Pre-protocol survey)

Sr. No.	Variable Name	Valid Options	Number of participants (out of 7 participants)			
			CTRL	MUS	ABF	MBF
1	Gender	Male	6	7	4	6
		Female	1	0	3	1
2	Age	<25 years	2	2	4	1
		25-30 years	4	3	3	5
		>30 years	1	2	0	1
3	Occupation	Student	6	6	7	6
		Non student	1	1	0	1
4	Practice meditation	Yes	2	1	1	2
		No	5	6	6	5
5	Practice deep breathing	Yes	2	1	1	1
		No	5	6	6	6
6	Familiarity with biofeedback	Yes	0	2	2	1

		No	7	5	5	6
7	Wearable sensors used in the past	Yes	0	2	4	1
		No	7	5	3	6
8	Listen to music (in days/week)	0-1 days	2	0	1	0
		2-5 days	2	1	1	3
		6-7 days	3	6	5	4
9	Each music listening session duration (in hours)	Less than an hour	2	2	2	3
		1-2 hours	2	3	2	3
		More than 2 hours	3	2	3	1
10	Music alter emotional state	Yes	5	6	7	6
		No	2	1	0	1
11	Preferred music genre	Classical	3	4	2	5
		Jazz	2	3	2	1
		World	2	3	2	1
		Blues	1	2	2	2
		Country	1	3	2	1
		Pop	5	5	2	2

		Rock	2	5	2	4
		Heavy Metal	1	1	1	2
		Hip Hop/Rap/R&B	2	4	3	4
		Electronic	1	2	2	3
12	Energy levels prior to experiment	Tired	3	2	2	1
		Neutral	4	3	2	5
		Energetic	0	2	3	1