Estimating Mental Stress Using a Wearable Cardio-Respiratory Sensor

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***Abstract*— This article describes a signal-processing approach to detect mental stress using unobtrusive wearable sensors. The approach addresses a major weakness of traditional methods based on heart-rate-variability (HRV) analysis: sensitivity to respiratory influences. To address this issue, we build a linear model that predicts the effect of breathing on the autonomic nervous system activation, as measured through HRV. Subtraction of respiratory effects leads to a residual signal that provides better discrimination between mental stress and relaxation conditions than traditional HRV tachogram. The method is experimentally validated on a discrimination task with two psycho-physiological conditions: mental stress and relaxation. To illustrate the effectiveness of the method, we impose a pacing respiratory signal that interferes with the main spectral band of the sympathetic branch. Our results suggest that the HRV residual signal has more discrimination power than conventional HRV analysis in the presence of respiration interferences.**

I. Introduction

A wealth of information about the state of the autonomic nervous system (ANS) can be obtained from an analysis of inter-beat intervals of the heart, commonly referred to as heart rate variability (HRV) analysis. The power spectrum of HRV shows a low-frequency band (LF: 0.04-0.15Hz) containing sympathetic influences (i.e., related to mental stress) and a high-frequency band (HF: 0.15-0.5Hz) dominated by parasympathetic activation (i.e., respiratory induced). Due to the sensitivity of the LF band to sympathetic nervous system (SNS) activation, HRV analysis has been extensively used as an indicator of psycho-physiological state. In addition, measurements of cardiac activity are robust, relatively unobtrusive, and affordable with consumer-grade heart rate monitors (HRM), which makes them suitable for long-term ambulatory monitoring.

However, the LF band can also be influenced by factors other than mental stress; when breathing slowly, energy in the HRV power spectrum that is due to respiration will overlap with the LF band. In such cases, one needs to separate respiratory contributions from those due to psychological stressors. Despite this fact, however, respiratory influences are rarely considered in studies of HRV. To address this issue, this article proposes an improved method to detect mental stress from HRV that takes into account respiratory influences. The method consists of building an autoregressive moving average model with exogenous inputs (ARMAX) model that predicts the effect of breathing on HRV. Subtracting respiration-driven oscillations from the HRV signal leads to a residual signal that is dominated by activation in the sympathetic branch. The method is validated using experimental data from two psychophysiological conditions, a mental load condition and a relaxation condition, both under paced breathing.

The paper is organized as follows. Section II provides background material on modeling of the cardio-respiratory regulatory system. Section III describes the proposed ARMAX model that can be used subtract respiratory influences. Section IV describes the wearable sensor system and the experimental protocol that was used to validate the method. Experimental results are provided in section V, followed by a final discussion in section VI.

II. Background

Modeling of the cardio-respiratory regulation system is widely accepted as a method to investigate oscillations in HRV due to respiration. Work on cardio-respiratory modeling can be traced back to Saul and Berger [1]. In this seminal work, the authors developed a transfer function model from respiratory activity to heart rate under orthostatic maneuvers (i.e., changes in posture from supine to tilt). Their result showed that gain of the transfer function from respiration to heart rate is larger at the LF band than the HF band. To estimate parameters of the transfer function between instantaneous lung volume (ILV) and heart rate, Yana et al. [2] used a linear model where current heart rate was expressed as a linear combination of past ILV; model coefficients were estimated by least squares. Their result is important because it suggests a way of using a linear model to represent the relationship between cardiac activity and respiration. Other authors have explored a way to use arterial blood pressure (ABP) as an additional input to regulatory model [3, 4]. Although those dual-input cardio-respiratory models may

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explain hemodynamic behavior of heart, measurement of ABP is invasive and impractical in ambulatory settings.

HRV can be influenced by different breathing parameters such as change of carbon dioxide, respiration frequency, and ILV [5]. However, Pöyhönen et al. [5] showed that, among those various respiratory parameters, respiratory frequency is the most dominant contributor to HRV oscillations. In their study, a decrease in respiration rate induced an increase in the LF power of HRV in all subject groups, while changes in other breathing parameters showed only partial influences in limited subject groups. This result indicates that the change of respiration frequency is important in modulating HRV (i.e., modeling of the cardio-respiratory system) rather than the change of tidal volume.

In this paper, we aim to detect mental stress using a cardio-respiratory model and minimum number of unobtrusive wearable sensors. Namely, we build a cardio-respiratory ARMAX model to estimate the influence of respiration onto HRV. Our hypothesis is that the residual signal of the model (i.e., after subtracting respiratory influences) provides better discrimination of mental stress than traditional analysis of the HRV power spectral density (PSD).

III. METHODS

The modeling met employed here is a special case of the ARMAX model. An ARMAX model estimates the output of the system $y(t)$ as a linear combination of previous inputs, outputs, and errors:

$$y(t) = \sum_{\tau=1}^{n_a} a(\tau)y(t-\tau) + \sum_{\tau=1}^{n_b} b(\tau)x(t-n_k-\tau+1) + \sum_{\tau=1}^{n_c} c(\tau)e(t-\tau) + e(t) \tag{1}$$

where $y(t), x(t)$ and $e(t)$ are the output, input and error at time t, and $a(\tau)$, $b(\tau)$, and $c(\tau)$ are the predictor coefficients for autoregressive (output), input, and moving average (error) term, respectively. Parameters n_a , n_b , and n_c are the respective model orders, and n_k is the number of delays that occur before an input influences the output of the system.

In our model, the system output $y(t)$ is the heart period whereas the input $x(t)$ is the respiration signal with sample delay n_k=1. If we regard the sum of autoregressive and moving average terms as a residual, our cardio-respiratory model can be represented as

$$y(t) = b(0) + \sum_{\tau=1}^{n_b} b(\tau)x(t-\tau) + r(t) \tag{2}$$

Thus, in our model, the current heart period is represented as a sum of input from past respiratory efforts and residual signal. Model coefficients can be estimated through least squares as

$$\hat{b} = \arg\min_b \sum_t r^2(t) = \arg\min_b \sum_t \left(y(t) - \hat{y}(t)\right)^2$$
$$where\ \hat{y}(t) = b(0) + \sum_{\tau=1}^{n_b} b(\tau)x(t-\tau) \tag{3}$$

In matrix form, (2) can be expressed as

$$y(t) = X_t\hat{b} + r(t)$$
$$where\ X_t = [x(t-1) \quad x(t-2) \quad \ldots \quad x(t-n_b) \quad 1] \tag{4}$$

Then the least-square estimate is given by

$$\hat{b} = (X^TX)^{-1}X^TY$$
$$where\ X = [X_1 \quad X_2 \quad X_3 \quad \ldots]^T \tag{5}$$
$$and\ Y = [y(1) \quad y(2) \quad y(3) \quad \ldots]^T$$

Taking the Z-transform of (2) yields the all-zero transfer function of the respiration to the heart period:

$$H(z) = \sum_{\tau=0}^{n_b} b(\tau)z^{-\tau} \tag{6}$$

IV. EXPERIMENT

A. *Wearable sensors*

This work is part of a long-term research program aimed at understanding the relationship between mental stress and the context of the user. This requires a wearable platform that can capture a variety of physiological and contextual information. In order to gain acceptance as a method of stress management in ambulatory environment, wearable sensors must be minimally obtrusive. To meet this goal, we have developed a wearable sensor system that combines a piezo respiratory effort sensor and a heart rate monitor into a minimally-invasive setup.

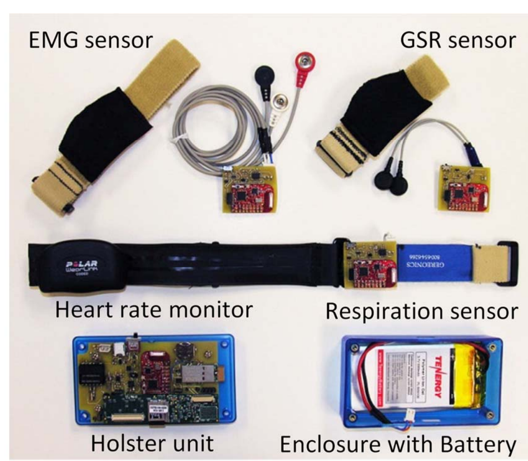

Figure 1. Prototype of the wearable wireless sensor system

Shown in Fig. 1, the wireless respiratory module is integrated into a chest strap that also holds a heart-rate-monitor in place. Two additional wireless modules (not used in this study) allow synchronized measurement of skin conductance and electromyography. Sensor signals are wirelessly transmitted (SimpliciTI protocol, Texas Instruments Inc.) and stored in a holster unit that contains an embedded Linux processor (Verdex Pro, Gumstix Inc.), and two additional sensors: a 3D body accelerometer and a GPS module. The system has a lithium-polymer battery that works for 13 hours, making it well-suited for long-term ambulatory studies.

B. *Experimental protocol*

To illustrate how respiration and cardiac activity are correlated, we first collected data from three experimental conditions with different respiration settings: regular breathing at fixed 3.5 seconds period, deep breathing at fixed 10 seconds period and broadband breathing at random periods. Signals for each condition were collected for five minutes, and each condition was repeated four times. During the fixed breathing rate conditions, subjects were asked to breathe following an audible pacing signal.

To validate the stress-detection model, we collected cardio-respiratory measurements from four subjects on two experimental conditions (relaxation and mental stress), and an additional calibration phase used to build the model. For the relaxation condition, the subjects were asked to breathe following an audible sinusoidal pacing signal with a fixed period of 6.67 seconds; this pace ensured that respiratory influences affected both the LF and the HF components of the HRV power spectra. For the mental stress condition, subjects performed a dual task [6] consisting of target tracking and memory search tasks (shown in Fig. 2) while breathing at a fixed duration of 6.67 seconds too.

During the dual-task condition, subjects were asked to keep a moving target (dot) within a small square using the mouse. At the same time, subjects were asked to memorize three letters at the beginning of the task and do a left-mouse click when one of the three letters was displayed on the screen. Distractor letters (i.e., other than three target letters) were also randomly displayed; in case of distractors, subjects were asked not to click the mouse. Subjects were provided instantaneous visual feedback about their overall performance by means of three error bars on the screen; this form of feedback was hypothesized to increase subject engagement.

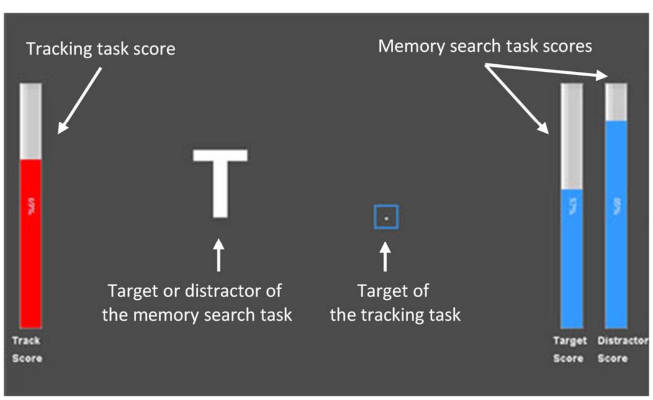

Figure 2. Screenshot of the dual-task stress protocol

Estimation of the cardio-respiratory transfer function can be done only at the frequency bands in which the breathing signal contains power. As a consequence, breathing with a broad frequency band is required to estimate the cardio-respiratory transfer function. For the calibration phase, subjects were asked to breathe following a random pacing signal whose period was drawn from a modified Poisson process [1] to have a nearly flat power spectrum over a broad range of respiratory frequencies. In a Poisson process, the distribution function describes the probability of observing k events at a given time t if the events occur i.i.d. at an average rate λ:

$$P(X=k)=\frac{(\lambda t)^k e^{-\lambda t}}{k!}; \quad k=0,1,2 \ldots \tag{7}$$

Then, the interval t between two consecutive events follows the exponential density function:

$$\mathrm{f(t)}=\lambda e^{-\lambda t} \ for\ t>0 \tag{8}$$

We used a mean breathing period $\mu=1/\lambda=3.66$ second to generate random breathing periods. As a modification to the traditional Poisson process, the minimum and maximum interval limits were set to 2 and 10 seconds respectively; breathing periods outside this range were dropped to avoid discomfort (which may have also induced stress).

Each of the three conditions (relaxation, stress, and calibration) lasted for five minutes. Each subject repeated all conditions three times on different consecutive days. Respiratory signals were recorded at a sampling rate of 10 Hz. Then, RR tachogram from the heart rate monitor and respiratory signals were uniformly re-sampled to a common 4Hz rate, and band-pass filtered between 0.04 Hz and 0.5 Hz to remove the VLF (very low frequency) component. The experiment protocol was approved by the Institutional Review Board at Texas A&M University; all subjects provided written informed consent for the study.

V. Results

A. *Correlation of breathing and heart period signal*

Fig. 3(a,b) shows the power spectra of the respiration and HRV signals for the two fixed-breathing conditions. The correlation coefficient between PSDs for regular and deep breathing is 0.99 for both fixed breathing rates. These results indicate that, when breathing occurs over a narrow frequency band, HRV and respiration have a peak at the same frequency and similar frequency content. In contrast, Fig. 3c shows the power spectra under broadband breathing; the correlation coefficient between PSDs of the respiration and HRV in this case is 0.91. Thus, even under broadband (irregular) breathing, the respiratory frequencies significantly alter the frequency characteristics of HRV.

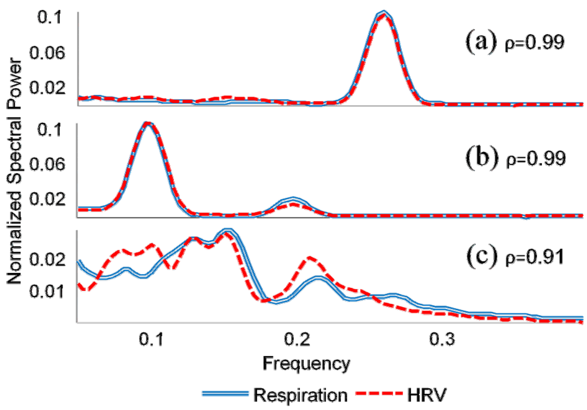

Figure 3. Power spectrum of HRV and respiration under (a) fixed breathing period of 10 seconds (b) fixed breathing period of 3.5 seconds, and (c) irregular breathing following a Poisson process

Fig. 4 shows the magnitude of the transfer function in (6), which captures the HRV response to broadband respiration. The transfer function magnitude shows a gradual roll-off from 0.04 to 0.5 Hz. This result is consistent with Saul and Berger's result [1], and it indicates that the LF band of the HRV PSD has more gain from the respiration than HF bands Also transfer gain is maximized at the breathing frequency of 0.1Hz which is widely used on HRV biofeedback because of good HRV response to respiration effort [7]. As a consequence, discrimination power of HRV PSD to mental stress can be easily influenced by respiration if breathing frequency exists at LF bands.

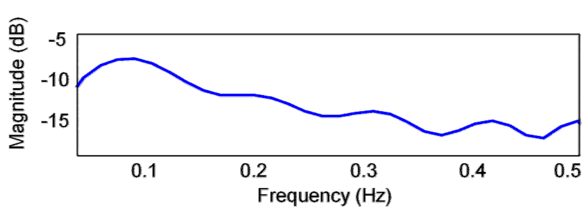

Figure 4. Magnitude of the transfer function from calibration condition

B. *Prediction using the cardio-respiratory model*

Subsequently, for each stressed and relaxed condition, the derived coefficients were used to predict the HRV signal from the respective respiratory signal. Shown in Fig. 5, HRV spectra displayed a dominant peak at 0.15 Hz, which follows the respiration pacing signal. Power spectra for the predicted respiration signal and residual signal are shown in Fig. 5c-d. Fig. 5b shows that the power spectra for the relaxed and stressed conditions are similar. In contrast, Fig. 5d shows that the residual signal of the stressed condition has more spectral power than the relaxed condition. These results suggest that the residual signal provides more discriminatory information than the HRV signal.

To confirm these findings numerically, we compared the traditional HRV analysis (5b) and residual analysis (5d) with a pattern classifier. First, we split the data recordings into 60-

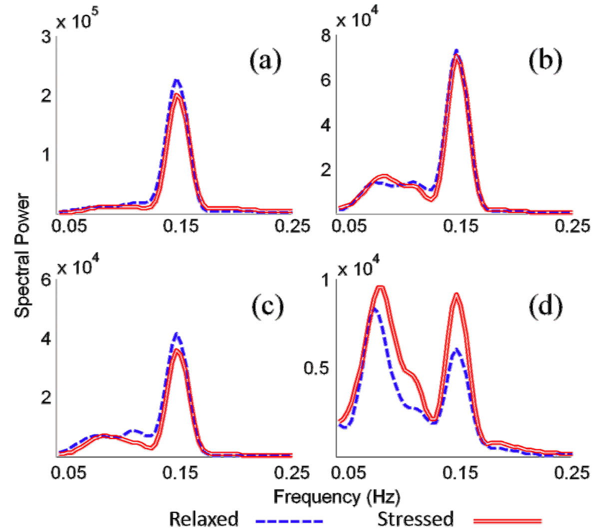

Figure 5. Power spectrum of (a) respiration signal (input), (b) HRV signal (output), (c) prediction by MA model and (d) residual signal.

second windows with a 15-second shift, then extracted LF and HF power using Welch's method [8]. Each window was treated as a different sample, resulting in 71, 67, 70, and 71 windows for each subject respectively (some windows had to be discarded due to noisy measurements). We trained a classifier for each subject using data from two days and tested it on data from the remaining day; this was repeated three times per subject, one for each day of data collection. Classification performance was measured with a quadratic classifier learned on training data. The problem was setup as a binary classification problem, where the goal was to discriminate the mental stress conditions from the relaxation conditions. Results are summarized in Fig. 6. For all four subjects, classification performance of the residual signal outperforms that on the HRV PSD. In the case of subjects 1 and 4, for whom the HRV PSD shows low classification rate, the residual signal outperforms HRV analysis by around 25%. In the case of subjects 2 and 3, who have higher performance on HRV PSD, the residual signal still shows better classification result by around 10%. In addition, the performance of the residual signal has relatively lower standard error across subjects than HRV PSD.

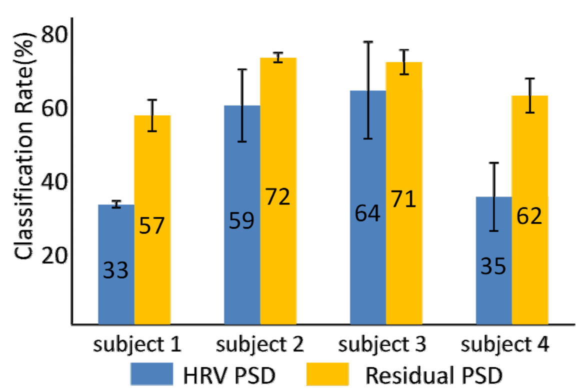

Figure 6. Classification rates for HRV PSD and residual PSD

VI. Discussion

We have presented an approach to remove respiratory influences from HRV that aids in the detection of mental stress. The approach consists of building an ARMAX model with a respiration and heart period signal to estimate a residual signal that is relevant to mental stress. We validate the suggested method using data obtained from four human subjects. The suggested method is based on a linear model where the respiration signal acts as an input and heart period signal acts as the output. Our work extends prior linear system-identification work on cardio-respiratory regulatory system in two respects that are particularly relevant to applications of wearable sensors on ambulatory environments. First, our study aims to cancel respiratory influences from the RR tachogram. This result is significant because it overcomes the limitation of traditional HRV methods; sensitivity to respiration influence. The result increases the potential of HRM to mental stress detection in ambulatory setting. Second, we focus on using minimally invasive and consumer-grade sensors. These sensors are more affordable, more robust, and less cumbersome, which increase their potential for widespread adoption in ambulatory settings. We are currently investigating the effectiveness of the approach to cancel respiratory influences under free breathing, which is required when tracking stress patterns in ambulatory settings.

References

[1] J.P. Saul, R.D. Berger, M.H. Chen and R.J. Cohen, “Transfer function analysis of autonomic regulation. II. Respiratory sinus arrhythmia,” American Journal of Physiology - Heart and Circulatory Physiology, vol. 256, no. 1, 1989, pp. 153-161.

[2] K. Yana, J. Saul, R. Berger, M. Perrott and R. Cohen, “A time domain approach for the fluctuation analysis of heart rate related to instantaneous lung volume,” IEEE Transactions on Biomedical Engineering, vol. 40, no. 1, 1993, pp. 74-81.

[3] J.P. Saul, et al., “Transfer function analysis of the circulation: unique insights into cardiovascular regulation,” American Journal of Physiology - Heart and Circulatory Physiology, vol. 261, no. 4, 1991, pp. 1231-1245.

[4] K. Chon, T. Mullen and R. Cohen, “A dual-input nonlinear system analysis of autonomic modulation of heart rate,” IEEE Transactions on Biomedical Engineering, vol. 43, no. 5, 1996, pp. 530-544.

[5] M. Pöyhönen, S. Syväoja, J. Hartikainen, E. Ruokonen and J. Takala, “The effect of carbon dioxide, respiratory rate and tidal volume on human heart rate variability,” Acta Anaesthesiologica Scandinavica, vol. 48, no. 1, 2004, pp. 93-101.

[6] D. Reeves, S. LaCour, K. Winter, K. Raynsford and K. Vogel, The UTC-PAB/AGARD STRES Battery: user's manual and system documentation, Storming Media, 1991.

[7] P. Lehrer and E. Vaschillo, “The Future of Heart Rate Variability Biofeedback,” Biofeedback, vol. 36, no. 1, 2008, pp. 11-14.

[8] P.D. Welch, “The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms,” IEEE Transactions on Audio Electroacoustics, vol. 15, no. 2, 1967, pp. 70-73.