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# Using Heart Rate Monitors to Detect Mental Stress

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***Abstract*— This article describes an approach to detecting mental stress using unobtrusive wearable sensors. The approach relies on estimating the state of the autonomic nervous system from an analysis of heart rate variability. Namely, we use a non-linear system identification technique known as principal dynamic modes (PDM) to predict the activation level of the two autonomic branches: sympathetic (i.e. stress-inducing) and parasympathetic (i.e. relaxation-related). We validate the method on a discrimination problem with two psychophysiological conditions, one associated with mental tasks and one induced by relaxation exercises. Our results indicate that PDM features are more stable and less subject-dependent than spectral features, though the latter provide higher classification performance within subjects. When PDM and spectral features are combined, our system discriminates stressful events with a success rate of 83% within subjects (69% between subjects).**

***Keywords-autonomic nervous system; heart rate variability; mental stress; wearable sensors; principal dynamic modes***

## I. INTRODUCTION

Stress is a catch-all term that describes bodily reactions to a range of perceived threats, both physical and psychological. Once essential for survival, the pace of modern life and its myriad demands has turned stress itself into a major threat. If chronic, stress can have serious health consequences, and is a leading risk factor for heart diseases, diabetes, asthma and depression. Despite its impact on health, however, it is unfeasible for physicians to continuously monitor our stress levels, not is it practical (or objectively possible) for us to keep logs of our internal states throughout the day. Thus, a device that could monitor stress over extended periods (from weeks or months) would provide individuals and their caretakers with hard data with which to monitor progress and determine the most appropriate interventions.

A number of physiological markers of stress have been identified, including electrodermal activity (EDA), heart rate (HR), various indices of heart rate variability (HRV), blood pressure (BP), muscle tension, and respiration [3-6]. However, in order to gain acceptance as a method of stress management in the workplace, wearable sensors must be minimally obtrusive, so that workers can perform their tasks with complete freedom, and inconspicuous, to avoid anxieties associated with wearing medical devices in public [7]. These usability considerations preclude some of the above measures from being considered as a long-term solution for stress monitoring. As an example, EDA is one of the most robust physiological indices of stress [8], but electrodes must be placed in the fingers or the palm of the hand, which severely limits dexterity; electrodes can be placed in the feet, but the resulting measurements are then dependent on posture. Another indicator of stress, arterial blood pressure, is equally unsuited for long-term monitoring; accurate measurements are invasive (e.g. a needle must be inserted in an artery), whereas non-invasive methods (e.g. inflatable cuffs) are cumbersome and inaccurate.

Fortunately, a wealth of information can be extracted from the heart. Measurements of cardiac activity are robust and, with the advent of consumer-grade heart rate monitors (HRM), relatively unobtrusive and affordable. To this end, this article explores the possibility of detecting mental stress using the R-R time series (interval tachogram) from an HRM that has gained wide acceptance in the exercise-management area. In section 2, we provide background material on the autonomic nervous system and its regulatory function on the heart. Section 3 describes a non-linear system identification method that can estimate the activation level of the two autonomic branches. Section 4 describes the experimental protocol and wearable sensor system we used to validate the method. Experimental results are provided in section 5, followed by a final discussion.

## II. BACKGROUND

### *A. Stress and heart rate variability*

The autonomic nervous system (ANS) is the part of the peripheral nervous system that serves as a control mechanism to maintain the body under stable conditions (homeostasis). The ANS contains two main branches, the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). The SNS branch helps prepare the body for action in response to potential threats –the so-called "fight or flight" response. The PNS branch, on the other hand, is most active under unchallenging situations; it tends to work in the opposite direction (but not always, as we will see), bringing the body back towards a rest state.

Both autonomic branches innervate the sinoatrial node, the primary pacemaker site in the heart: SNS activation increases heart rate, whereas PNS activation decreases it. This suggests that heart rate can be used to estimate the activation level of both branches. Unfortunately, changes in SNS versus PNS activation are potentially indistinguishable

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based solely on changes in heart rate, e.g. an increase of heart rate could be the result of increased SNS input and/or decreased PNS input. Instead, one must rely on one important difference between both branches: PNS influences on heart rate tend to occur faster. Hence, by analyzing fluctuations in beat-to-beat periods, one can begin to separate the contributions from both branches. This is known as heart rate variability (HRV) analysis. Spectral analysis of HRV shows several frequency bands, two of which are important here: a low-frequency component (LF; 0.04-0.15Hz) mediated by both PNS and SNS, and a high-frequency component (HF; 0.15-0.4Hz) mediated by PNS activation [9]. As a result, the ratio of LF to HF power is sometimes used as an index of autonomic balance [9].

### *B. Autonomic state estimation*

The notion of autonomic balance suggests that autonomic state is a one-dimensional continuum, where SNS and PNS branches are under reciprocal control, e.g. when one increases, the other decreases. However, it has been shown that reciprocity is just one of several modes of autonomic control: coactivation and uncoupled activation are also possible. Thus, autonomic state is better described as a two-dimensional continuum [1]; see Fig.1(a). More recently, Backs [2] has suggested that these different modes of autonomic control (e.g. reciprocity, coactivity, and uncoupled control) map onto psychological states in a context-dependent one-to-one fashion, i.e. what Cacioppo and Tassinary [10] defined as a marker. Back's work shows that, in the context of mental workload assessment, the psychophysiological relationship is many-to-one if only heart rate is used as a physiological index; a decreased heart period cannot be used to discriminate among the three psychological processes on the left-hand side of Fig.1(b). However, by expressing the physiological response in terms of the autonomic response (degree of PNS and SNS activation), the relationship becomes a marker. What is required, then, is a method capable of decoupling the activation level of both branches.

Several signal-processing methods have been proposed to decouple SNS and PNS influences on HRV. Vetter et al. [11] proposed a blind-source-separation technique to estimate SNS and PNS activation from measures of heart rate and arterial blood pressure. Their method assumes that SNS and PNS exert independent influences on HRV, and extracts their relative contribution by means of independent components analysis. Unfortunately, this independence assumption is known to be invalid since, as we saw, SNS and PNS activation are often reciprocally coupled. In addition, their method relies on measures of arterial blood pressure (which are impractical for long-term monitoring), and ignores respiratory influences by imposing controlled breathing (also unfeasible). A later study [12] used only ECG measurements, but the method was only tested using pharmacological blockade (i.e. infusion of Phenylephrine, which increases SNS and inhibits PNS, and infusion of Nipride, which has the opposite effect); pharmacological blockade studies are useful to isolate SNS and PNS activation, but they are not relevant when the goal is to

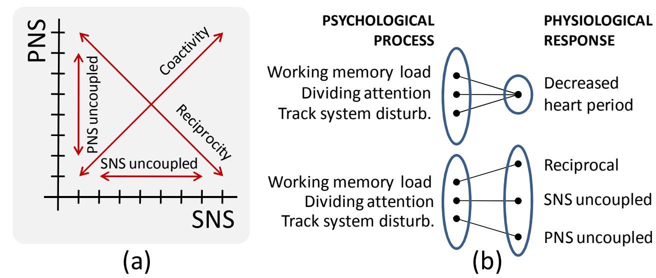


Figure 1. (a) Autonomic state as a two-dimensional continuum with four distinct ANS control modes [1]. (b) When examining mental workload, the psychophysiological mapping is many-to-one if using heart rate, but one-to-one in terms of ANS control [2].

measure PNS/SNS activation in ambulatory scenarios. More recently, Chen and Mukkamala [13] proposed a system-identification approach to estimate SNS and PNS influences on HRV. Their approach uses linear-time-invariant (LTI) techniques to model the transfer function between respiration and heart rate, and between arterial blood pressure and heart rate. Knowing that SNS influences are sluggish and PNS influences are rapid, the authors extract the slow and fast components of the transfer functions and use them as estimates of SNS and PNS activation, respectively. Unfortunately, the technique requires blood pressure measurements and has only been tested using pharmacological blockade; furthermore, the use of LTI techniques implicitly assumes that the underlying signals are stationary. Instead, our approach to estimating SNS and PNS activation is based on a nonlinear system-identification technique known as principal dynamic mode (PDM), which was originally developed as a general method for modeling nonlinear biological systems [14]. Using pharmacological blockade and electrocardiographic (ECG) measurements, Zhong et al. [15] have shown that PDM may be used to predict the activation level of both autonomic branches. What remains to be seen is whether the PDM method may be used to detect mental stress (rather than autonomic changes induced through pharmacological blockade) using inexpensive heart rate monitors (rather than ECG monitors).

## III. NONLINEAR SYSTEM IDENTIFICATION

Assume a stable (finite-memory) nonlinear time-invariant dynamic system. Such system can be modeled with a discrete-time Volterra series as:

$$y(t) = k_0 + \sum_{\tau=0}^{M-1} k_1(\tau)x(t-\tau) + \sum_{\tau_1=0}^{M-1}\sum_{\tau_2=0}^{M-1} k_2(\tau_1,\tau_2)x(t-\tau_1)x(t-\tau_2) + \cdots \tag{1}$$

where $y(t)$ is the system's output, $x(t-\tau)$ is the system's input with a delay of $\tau$, $M$ is the memory of the model, and $(k_0, k_1, k_2, \dots)$ are the Volterra kernels, which describe the dynamics of the system. When modeling physiological systems, second-order series are commonly used to provide a balance between computational efficiency and expression power [14]. Using matrix notation, a second-order Volterra series can be expressed as:

$$y(t) = X^T(t)QX(t)$$
$$\text{where } X(t) = \begin{bmatrix} 1 \\ x(t) \\ \vdots \\ x(t-M+1) \end{bmatrix} \text{and } Q = \begin{bmatrix} k_0 & \frac{1}{2}k_1{}^T \\ \frac{1}{2}k_1 & k_2 \end{bmatrix} \tag{2}$$

Since $Q$ is symmetric, there always exists an orthonormal matrix $R$ such that $Q = R^T \Lambda R$, where $\Lambda$ *is* a diagonal eigenvalue matrix. This leads to:

$$y(t) = X(t)^T QX(t) = X(t)^T R^T \Lambda RX(t) = U(t)^T \Lambda U(t)$$
$$= \sum_{i=0}^{M-1} \lambda_i u_i^2(t) \tag{3}$$

Thus, the output of the system $y(t)$ can be expressed as a weighted sum of functions $u_i^2(t)$. The *ith* principal dynamic mode ( $v_i$ ) is then defined as the eigenvector of $Q$ corresponding to the largest *ith* eigenvalue $\lambda_i$ , and the function $u_i(t)$ can be computed as the convolution of the tapped-delay input $X(t)$ with $v_i$:

$$u_i^2(t) = \{v_i * X(t) + \mu_{i,0}\}^2$$
$$\text{where } v_i = [\mu_{i,1} \quad \mu_{i,2} \quad \cdots \quad \mu_{i,M}] \tag{4}$$

By selecting the most significant eigenvalues from $\Lambda$, $y(t)$ can then be approximated with a small number of components:

$$\hat{y}(t) = \sum_{i=0}^{S} \lambda_i \{v_i * X(t) + \mu_{i,0}\}^2 \tag{5}$$

Zhong et al. [15] have shown that the PDM method can be used to predict the activation of both autonomic branches using only heart rate measurements. In this case, the output signal $y(t)$ is assumed to be the heart period (i.e. the inter-beat interval time series), and the input signal $x(t)$ is assumed to be unknown. Since the PDM formulation requires knowledge of $x(t)$, an estimate $\tilde{x}(t)$ is obtained from a delayed and transformed version of the output: $\tilde{x}(t) \sim f(Y(t-1))$. Ideally, this estimated input $\tilde{x}(t)$ would be broadband [14] and related to the output. To achieve these characteristics, the delayed output $Y(t-1)$ is first used as an input to construct an initial PDM model $\tilde{y}(t) = Y^T(t-1)QY(t-1)$. By construction, the residual error from this initial model $\tilde{x}(t) = y(t-1) - \tilde{y}(t-1)$ is broadband and remains correlated with the output. This residual error becomes the final estimate of the input, and is used to construct a final PDM model $\hat{y}(t) = \tilde{X}^T(t)Q\tilde{X}(t)$.

How is the final PDM model related to PNS and SNS activity? Zhong et al. [15] noted that the first two PDMs had similar spectral characteristics as PNS and SNS activity (i.e. one mode contained both LF and HF power, and the other contained mainly HF power), and that they explained over 90% of the variance in the system dynamics. In our studies, however, the first two PDM eigenvalues only capture 60% of the variance, which suggests that additional modes are required to capture the system's dynamics. Here we propose an alternative selection criterion. First, we discard any eigenvalues whose magnitude $|\lambda_i|$ is lower than 5% of the total energy $\sum|\lambda_i|$. Second, we assign negative eigenvalues to SNS activation, since they reduce heart periods (increase heart rate), and assign positive eigenvalues to PNS activity, since they increase heart periods (decrease heart rate). Finally, we add up positive and negative dynamics separately to obtain the estimates of PNS and SNS activity:

$$\hat{y}_{PNS}(t) = \sum_{\lambda_i > 0} \lambda_i \{v_i * X(t) + \mu_{i,0}\}^2$$
$$\hat{y}_{SNS}(t) = \sum_{\lambda_i < 0} \lambda_i \{v_i * X(t) + \mu_{i,0}\}^2 \tag{6}$$

These assignments are not only theoretically-based, but also ensure that $\hat{y}_{PNS}(t)$ and $\hat{y}_{SNS}(t)$ capture a large percentage of the energy in the system's output.

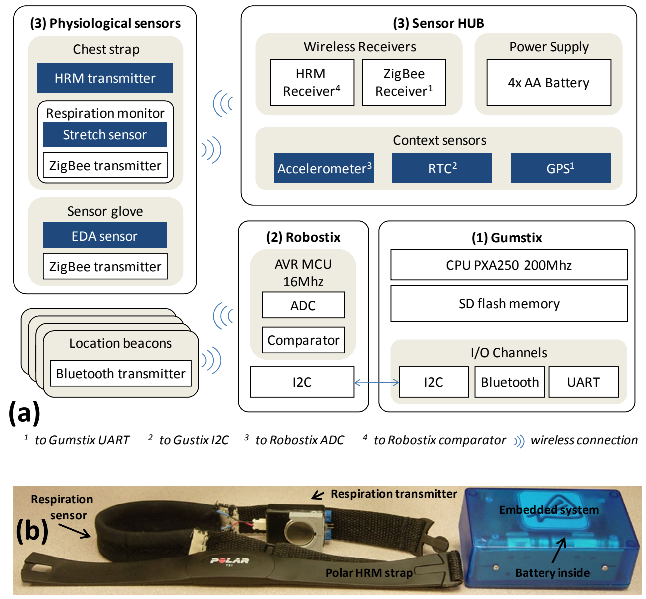


Figure 2. (a) Architecture of the wearable sensor system, and (b) current prototype

## IV. EXPERIMENTAL

The overall approach was validated through a series of experiments that tested (1) the feasibility of estimating HRV from a heart rate monitor, and (2) the extent to which HRV could be used to estimate stress.

### *A. Wearable sensor platform*

This work is part of a larger project aimed at understanding the relationship between the user's internal state and his/her environment. This requires a wearable platform that can capture a variety of physiological and contextual information. The system has to be open (e.g. to have access to raw signals and full control of data acquisition); modular (i.e. to integrate additional sensors); minimally obtrusive (e.g. no wires dangling around the user's body, lightweight, and small); power-efficient (e.g. at least 8 hours between battery charges); and low-cost (below \$500). None of the commercial ambulatory systems currently available satisfy all the above constraints, which prompted us to design a custom platform.

Our design is based on a Linux embedded platform. Shown in Fig.2(a), the system consists of (1) a Gumstix motherboard (Intel XScale® PXA255, 400 MHz, 64 MB RAM; Gumstix, Inc.), (2) an add-on Robostix data-acquisition card, (3) a custom sensor hub, and (4) a suite of physiological sensors. The sensor hub bridges the Robostix data-acquisition module with sensors, and is also responsible for supplying power to Gumstix, Robostix, and sensors. A ZigBee module (XBee; Digi International Inc.) on the sensor hub allows us to configure a body sensor network using multiple sensors. Raw sensor data is stored into a flash memory on the Gumstix. Fig.2(b) shows a picture of our current prototype. To date, we have integrated a 3D accelerometer (MMA7260Q; Freescale Semiconductor, Inc.), a GPS unit (EM-406A SiRF III Receiver; USGlobalSat, Inc.), a real time clock unit (DS1307; Dallas Semiconductor, Inc.), a heart rate transmitter (Polar T31; Polar Electro Inc.) and a custom-made respiration sensor.

### *B. Experimental protocol*

To validate the proposed method, we collected heart-period measurements from three subjects on four experimental conditions: two that elicited mental load, and two that induced relaxation. In the mental workload conditions, each subject performed the Stroop color word test (CWT) [16] or a mental arithmetic test (MAT) [17], whereas in the relaxation conditions each subject was asked to rest using either fee breathing or deep breathing. On a given session, each subject was asked to perform the four tests (6 minutes 30 seconds per test) in a random sequence, with a ten-minute break between tests. These sessions were repeated five times on five different days, for a total of 20 tests per subject. The experiment protocol was approved by the Institutional Review Board at Texas A&M University; all subjects provided written informed consent for the study.

Heart period signals were sampled at 500 Hz, and processed with a peak-detection algorithm to identify the R waves [18]. The R-R period signal was then re-sampled at 4Hz. This instantaneous heart period was processed with an aperiodic trend-removal algorithm [19] and band-pass filtered between 0.04 Hz and 0.4 Hz to remove the VLF (very low frequency) component. For each test, the signal was analyzed with a four-minute window, sliding at increments of 30 seconds. Thus, each test resulted in five

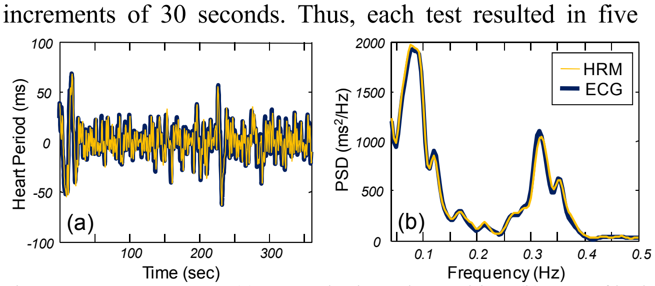


Figure 3. ECG vs. HRM: (a) R-R series in supine position; (b) PSD of both signals.

analysis windows. Each window was treated as a different sample, resulting in 98, 101, and 104 windows for subjects 1, 2, and 3, respectively (some windows had to be discarded due to noisy measurements). A separate PDM was computed for each window. Given that ANS information is located in the 0.04-0.5 Hz region, we used a Volterra kernel with a memory of M=120 samples (30 sec). For comparison purposes, we also computed the power spectral density (PSD) of each window by means of Welch's method .

## V. RESULTS

### *A. Comparison between HRM and ECG*

Are HRMs accurate enough (i.e. when compared to ECG signals) to be used for HRV analysis? To answer this question, we collected a dataset consisting of heart-rate measurements from a HRM and a 3-lead ECG monitor for two experimental conditions: a tilt body posture (70 degrees) and a supine body posture. These two conditions are standard in studies of cardiac regulation because they shift the autonomic balance: PNS being more dominant in the supine position, and SNS in the upright position [9]. Signals for each condition were collected for five minutes, and each condition was repeated five times. Fig.3(a) shows the R-R signal obtained with both monitors for the supine condition; the correlation coefficient between both signals was $\rho=0.99$. Fig.3(b) shows the PSD of both signals, which further demonstrates that HRV measures are consistent across both monitors.

### *B. Detection of mental stress*

For classification purposes, we extracted two features from the PSD (LF and HF power) and six features from the PDM (sum of the significant positive and negative eigenvalues, LF and HF power for $\hat{y}_{\mathrm{PNS}}(t)$ and $\hat{y}_{\mathrm{SNS}}(t)$). Classification performance was measured with a $k=7$ nearest neighbor rule operating in the Fisher's linear discriminant analysis projection computed on training data (the number of neighbors was obtained through cross-validation). The problem was setup as a binary classification problem, where the goal was to discriminate the two mental-load conditions from the two relaxation conditions.

Two classification experiments were performed: within-subject and between-subjects. In the first case, we trained a classifier for each subject using data from four days and tested it on data from the remaining day; this was repeated five times per subject, one for each day of data collection. This procedure allowed us to determine whether the classifier was able to generalize across sessions of a given subject. In the second case, we trained a classifier on data from two subjects and tested it on the third subject; this was repeated three times, one for each subject. This procedure allowed us to determine whether the classifier generalizes across subjects. Results are summarized in Table 1. In the within-subject case, the PSD outperforms the PDM on two subjects and also on average. In the between-subject case, the PDM outperforms the PSD on average, though by a narrower margin. In both experiments, the PDM has lower variance across subjects, which suggests that its features are

TABLE I. CLASSIFICATION RATES (%) FOR PSD, PDM AND A COMBINED FEATURE VECTOR

| | (a) within-subject | | | (b) between-subjects | | |
|---|---|---|---|---|---|---|
| | PSD | PDM | Both | PSD | PDM | Both |
| Subject 1 | 80 | 61 | 86 | 63 | 63 | 68 |
| Subject 2 | 87 | 74 | 93 | 74 | 69 | 78 |
| Subject 3 | 63 | 63 | 71 | 61 | 72 | 62 |
| **mean** | **77** | **66** | **83** | **66** | **68** | **69** |
| std. dev. | 12 | 7 | 11 | 7 | 5 | 8 |

more stable than those of the PSD. More interestingly, the PDM shows comparable performance within- and between-subjects, whereas the PSD performance degrades when used between subjects, suggesting that the two representations are complementary. To test this conjecture, we trained an additional classifier on a combined feature vector containing the PSD and PDM features. Results are also included in Table 1; the combined feature vector outperforms each individual method on both classification problems and for every subject, which does support the notion that the PDM and PSD capture complementary information that may be used to identify stressful events.

## VI. DISCUSSION

We have presented an approach to detect mentally stressful events using only a heart rate monitor (HRM). The method is based on the principal dynamics modes of Marmarelis [14], later extended to HRV analysis by Zhong et al. [15]. Our work extends this prior work in three respects that are particularly relevant to the wearable sensors community. First, we focus on consumer-grade HRMs rather than ECG monitors; this difference is important because HRMs are more affordable, more robust, and less cumbersome, which increase their potential for widespread adoption. Second, unlike [15], our study does not rely on pharmacological blockade to shift autonomic state towards SNS or PNS activation. Instead, we apply the method to the subtler changes in autonomic state that result from changes in mental stress. This result is significant because it supports the use of our approach on ecologically-valid scenarios, i.e. experience sampling during daily activities. Lastly, we propose an alternative criterion (one that is theoretically-based rather than empirical) to map the various dynamic modes into SNS and PNS influences. Our previous results [20] show that this modified PDM outperforms the PSD when discriminating autonomic states induced by postural changes (e.g. supine and tilt). The present study suggests that the PDM is more stable and user-independent than the PSD, and that the two methods provide complementary information that can be exploited to improve discrimination performance.

Our approach may enable greater insight to life styles when combined with context data, e.g. location or ambient. In particular, it may provide more meaningful clustering of daily events and better cues to the user's stress patterns through the day. Hence, estimates of autonomic state may not only help identify habits but could also provide feedback to users interested in developing healthier behaviors.

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