Ambulatory Stress Monitoring with Minimally-Invasive Wearable Sensors

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***Abstract*——Chronic stress can have serious health consequences, and is a leading risk factor for heart diseases, diabetes, asthma and depression. This article presents a minimally-invasive and wireless wearable sensor platform that can be used to monitor a number of physiological variables known to correlate with stress. We discuss the system design and sensor selection, both of which were guided as a tradeoff between information content and wearability. The platform is thoroughly evaluated through a battery of tests that elicit mental workload and physical activity, as well as through subjective assessments of comfort. Our results indicate that the sensor system is responsive to three broad types of factors: mental workload, posture and physical activity. We also describe a system-identification method that improves detection of mental stress by removing respiratory influences on heart rate.**

***Index Terms*— Wearable sensors, electrodermal activity, heart rate variability, mental stress**

I. Introduction

Stress is a catch-all term that describes bodily reactions to perceived physical or psychological threats [1]. Stress can reveal itself in both positive and negative ways. Positive stress can motivate us to finish an upcoming deadline. However, negative stress can cause anxiety and fear, and is a leading risk factor for heart diseases, diabetes, asthma and depression. Although stress management is important, it is unfeasible for physicians to continuously monitor our stress levels throughout a day. Nor is it practical (or objectively possible) to keep logs of our internal states as they vary in relation to daily events. In some cases, we may not even be aware of own psychophysiological state. Thus, there is a critical need for systems that can monitor stress over periods that extend over weeks or months. Such information would allow physicians to assess precisely how stress is affecting our health and determine the most appropriate interventions.

A wearable system suitable for ambulatory stress monitoring must strike a balance between two criteria: information content and comfort. First, the sensors must measure variables that are relevant to the domain problem. Second, the sensors must do so without interfering with the daily life of the user. Here, we present a wearable sensor system that has been designed with the above two criteria in mind. The platform employs minimally invasive sensors, hardware miniaturization, and wireless technologies, and can record uninterruptedly for periods of up to thirteen hours a number of physiological variables known to be influenced by stress.

The paper is organized as follows. Section II provides a brief background review of physiological signals and prior wearable platforms. Section III describes our wearable platform, including physiological sensors, hardware configuration, and wireless communications. In Section IV, we validate the physiological sensors against other commercially-available sensors. Section V evaluates the system under a number of psychophysiological conditions, including various forms of mental workload and physical activity. Section VI describes a system-identification method that improves the detection of mental stress by removing respiratory influences on heart rate variability. Section VII provides comfort ratings of the system, as experienced by the 29 users in these studies. The article concludes with directions for future work.

II. Background

A. Stress and health

Stress is a state of psychological or physical strain caused by the perception of threatening situations [1]. Historically, stress has been defined as a reaction from a calm state to an excited state triggering a cascade of physiological reactions aimed at preserving the integrity of the individual [2]. Once the threat is averted, the body's physiological condition returns to normal. However, stress in modern life tends to be pervasive, as it results mainly from psychological rather than physical threats. As physiological responses to stress are repeated over and over, the result can have adverse long-term effects on our health. Stress can be mental, emotional, or physical, which makes it difficult to assess.

If chronic, stress can have serious health consequences, e.g. chronically elevated blood pressure can stimulate thickening of the arterial walls, resulting in the blockage of blood flow through the narrowed arteries and potentially leading to a heart attack. Studies have linked work stress with increased risk of coronary heart disease [3], elevated ambulatory blood pressure [4], and increased risk of myocardial infarction [5]. In the

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long-term, stress can damage the body [6] as it results in suppression of the immune system [7], inhibition of the inflammatory responses, increased blood pressure, damage to muscle tissue, infertility, and diabetes [8]. Suppression of the immune system can increase the severity of the common cold [9], and the susceptibility to infectious disease [10] and possibly many types of cancer [11]. Inhibition of the inflammatory response makes it more difficult for the body to heal itself after injury [12]. In addition, stress has been found to have long-term effects in brain damage [13]. Finally, stress has indirect harmful effects that provoke behavioral and lifestyle changes, such as cigarette smoking, alcohol abuse, drug abuse, domestic violence, eating high-fat foods, and decreasing exercise [14].

B. *Physiological variables for mental stress*

A number of physiological markers of stress have been identified in the literature, including electrodermal activity (EDA), heart rate (HR), various indices of heart rate variability (HRV), blood volume pressure (BVP), pupil dilation, muscle tension, and respiration [15-18]. EDA measures changes in the electrical conductivity of the skin and is highly sensitive to emotional arousal (e.g., startle response, fear, anger) [19]. BVP can be measured through photo-plethysmography, and provides an indication of blood flow and arteriolar tone, which are physiological correlates of stress [20]. Respiratory signals can be captured by monitoring changes in the thoracic cavity [21]: when stressed, respiratory rate increases, and breathing patterns become irregular.

However, in order to gain acceptance as a method of stress management in the workplace and during activities of daily living, wearable sensors must be minimally cumbersome, so that workers can perform their tasks with complete freedom [22], and inconspicuous, to avoid anxieties associated with wearing medical devices in public [23]. These usability considerations preclude some of the above measures from being considered as a long-term solution for stress monitoring. As an example, changes in blood volume can be monitored non-intrusively through photoplethysmography [24, 25], but the sensors must be worn on a translucent part of the body–usually a fingertip or an earlobe–which interferes with daily activities. Another indicator of work 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, impractical, and inaccurate.

Fortunately, relatively simple and unobtrusive measures of inter-beat intervals can provide a wealth of information about stress through the interaction between the heart and the autonomic nervous system (ANS). The ANS is composed of two main branches: the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). The SNS branch increases heart rate and 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, reduces heart rate and is most active under unchallenging or relaxing situations, bringing the body back towards a rest state. PNS influences on heart rate tend to occur at a much shorter time scale than SNS influences. Hence, by analyzing fluctuations in beat-to-beat periods, commonly referred to as heart rate variability (HRV) analysis, one can separate the contributions from both branches and infer stress levels.

C. *System considerations for wearable sensors*

Our design for a wearable sensor platform for stress monitoring was guided by the need to balance information content of the sensors and overall comfort and long-term wearability. Our design choices not only included sensing modalities but also system-level issues such as embedded architecture, communication protocol, and energy awareness[1].

In the early era of wearable systems, sensors were often wired into a data recording unit which was responsible for signal digitization and data storage. MIThril [26], one of the best-known and pioneering systems, wired physiological sensors into a Linux based PDA. Wired connections are robust and reduce the need for separate power supplies, but the user must deal with dangling wires, which hinders mobility. Alternatively, custom e-textiles may be used to connect sensors [27, 28]; however, e-textiles generally require users to wear specially designed clothing. Instead, we turned our attention to wireless technologies [29] .

A wide variety of technologies are available for wireless communication, from wide area networks (i.e., cellular) to short-range protocols (i.e., Bluetooth, ZigBee). Cellular networks may be used to transmit data to remote servers, and provide a high degree of freedom and mobility to the user. As an example, Anliker et al. [30] developed AMON, a wearable system that transmits a patient's electrocardiographic and pulse oximetry data to a remote server using a cell phone. However cellular networks are too expensive to continuously transmit physiological data. Bluetooth is an alternative communication protocol that can handle multiple sensors simultaneously. However, the power requirements of Bluetooth limit its usability for long-term data collection (e.g., continuous recording for several hours) with the small power source that is required for usability (i.e., coin cell batteries). Recently, the ZigBee protocol has become a popular alternative for wireless communication due to its power efficiency. For example, CodeBlue [31] integrated a custom physiological sensor board with commercially available ZigBee motes (Micaz and Telos; XBow Inc.) However, ZigBee was designed for field sensor network deployments, so it contains a number of functions that are not necessary for body-area-network applications. Instead, our proposed system employs SimpliciTI (Texas Instruments Inc.), a connection-based low-power lightweight sensor network protocol that is best suited for small RF networks

Network topology is another important factor. One possible approach is for each sensor node to transmit data to a remote

[1] Several systems have recently become available in fitness and healthcare markets that achieve a higher degree of miniaturization by focusing on a small set of sensors. A tiny accelerometer-based system allows a user to monitor their sleep (Fitbit; Fitbit Inc., WakeMate; Perfect Third Inc.) or workout (Nike+; Nike Inc., miCoach; Adidas Inc.). These systems are relatively affordable and small, but unfortunately are not viable options for research purposes since they are closed platforms with limited access to raw data and make it difficult to combine and synchronize with other third-party sensors.

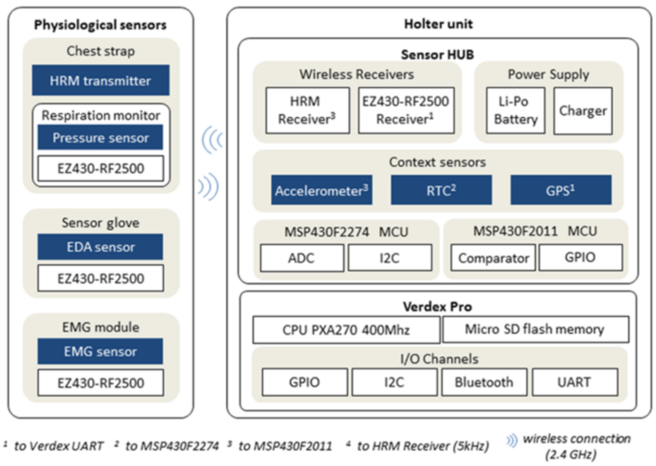

Fig. 1. Architecture of the wearable sensor platform based on 2.4 Ghz wireless sensor network and an embedded Linux platform

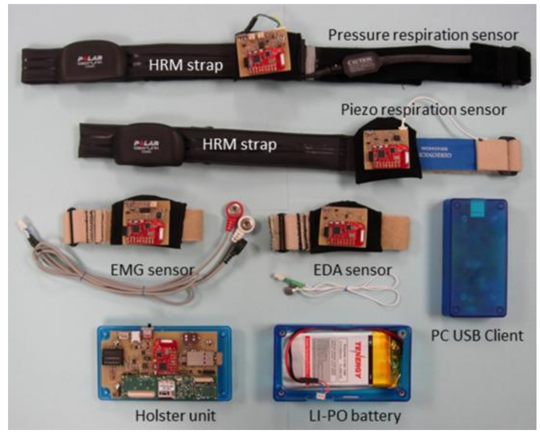

Fig. 2. Holster unit, Li-Po battery, chest straps which combines HRM and respiration sensor (Piezo and/or pressure), wireless EMG and EDA nodes, and USB transceiver

server using ad-hoc networks. iCalm [32] uses this ad-hoc network approach to connect EDA and PPG sensors to a remote base station. This approach enables building smaller unobtrusive wearable sensors, but is impractical for ambulatory data collection since the sensor network must remain within reach of a remote base station. Therefore, the most logical configuration for ambulatory applications is based on a body area hub. The hub records data transmitted from the sensor nodes while being worn by the user. This configuration is known as a star topology network and it has been used in several body sensor networks such as UFC [33] and BAN [34].

III. Wearable System Description

The long-term goal of this research is to monitor mental stress in ambulatory environments and daily living scenarios. For this purpose, we have designed and built a wearable sensor platform that follows the design factors discussed in the previous section. First, we have focused on a set of physiological variables known to be correlates of mental stress. Second, the system uses a star topology whereby physiological sensors wirelessly communicate with a hub within a holster unit. Finally, the system is power efficient, small, lightweight, and inconspicuous enough to be worn in regular daily activities.

A. *Choice of physiological sensors*

Several sensors may be used to monitor heart rate variability. Electrocardiography (ECG) is considered the gold-standard but requires electrode wiring, which we deemed impractical. HRV can also be estimated through pulse oximetry, but these measurements are very sensitive to motion artifacts. For these reasons, we decided to use a heart-rate-monitor strap (Polar® WearLink+®; Polar Electro Inc.) that has gained wide acceptance for fitness monitoring.

Monitoring breathing activity is often neglected despite the fact that respiration has a dominant influence in HRV. Several sensing technologies can be used to capture breathing patterns. In respiratory inductive plethysmography (RIP), changes in cross section of the thorax or abdomen are monitored by measuring changes in a magnetic field generated by coils embedded in a chest/abdominal strap. However, RIP requires frequent recalibration after changes in body position [35], and are sensitive to motion artifacts. In impedance pneumography (IP), an alternating current is applied between two electrodes in the rib cage, which allows the system to measure impedance changes during respiration. However, IP is also prone to motion artifacts [36]. With this in mind, and considering our objective of long-term ambulatory monitoring, we focused our design on two candidate respiration sensors: a piezoelectric respiratory effort sensor (ultra piezo strap sensor 480420; Gereonics Inc.), and a pressure-based respiration sensor (SA9311M; Thought Technology Ltd.).

Changes in electrodermal activity (EDA) can be monitored by applying a low-level electrical voltage to the skin. Skin conductivity increases with sweat, and eccrine sweat glands in specific body locations (palms and fingers [37]) respond mostly to psychological stimuli ("cold sweat"). Although the palms provide a good site for EDA monitoring, electrodes can be easily detached during ambulatory data collection. For this reason, we monitor EDA activity with two electrodes on the index and middle finger of the non-dominant hand. Small AgCl electrodes (E243; In Vivo Metric Systems Corp.) are used for this purpose.

Electromyography (EMG) can be used to recognize emotions or mental stress by monitoring facial muscles [38] or the trapezius muscle [17]. During muscular activation, electrical current flows through the invoked muscles and nerves. EMG can detect this electrical potential from the skin (surface EMG) or within the muscle (needle and fine-wire EMG). However, needle EMG is too invasive for sustained use. Instead, we rely on surface EMG to monitor muscle activation. Namely, we place AgCl electrodes on the left trapezius muscle to inconspicuously monitor long-term stress responses.

B. *Holster unit*

The holster unit consists of a data processing unit, a sensor hub, and a lithium-polymer battery. The holster unit measures 114×50×28 mm, weighs 120 grams, and provides data storage (2 GB mini SD flash), real-time signal processing, ad-hoc wireless networking, and expandable graphical user interface. The system is an embedded Linux-centric platform based on a Verdex Pro motherboard (Marvell™ PXA270 400 MHz, 64

MB RAM; Gumstix, Inc.). The holster unit is connected to a sensor hub, which integrates a 3D accelerometer (LIS344ALH; STMicroelectronics), a GPS unit (RXM-GPS-SR-B; Linx Technologies Inc.), and a real time clock unit (DS1308; Dallas Semiconductor, Inc.). The sensor hub also contains a heart rate receiver module (Polar RMCM01; Polar Electro Inc.) and a wireless transceiver (Ez430-RF2500; Texas Instruments Inc.) to communicate with the wireless sensors. The sensor hub is also responsible for power management of the holster unit; it contains a built-in charging module for a 3000 mAh Li-Po battery, which allows for data to be continuously collected for over thirteen hours. The charging module also protects the battery from over charging or under discharging.

On-board analog sensors (accelerometer and HRM receiver) are connected to an MSP430 micro-controller (Texas Instruments Inc.), where they are digitized and transmitted to the motherboard. Two on-board digital sensors (e.g. RTC and GPS) are directly connected to the motherboard through digital channels (e.g., GPIO, I2C, and UART). The data processing unit stores data onto a micro SD flash memory on the motherboard. The data processing unit can further transmit data via Bluetooth onto an external system, though this option is only use sparingly to minimize power consumption. The building blocks of the wearable sensor architecture are shown in Fig. 1; an image of our current prototype is shown in Fig. 2.

C. *Wireless sensors*

Each wireless sensor node contains a transceiver module (Ez430-RF2500; Texas Instruments Inc.). To date, respiration, EMG, and EDA sensors are ready to be used as wireless nodes. The wireless nodes are programmed for power efficiency; the wireless transmitter wakes up from sleep mode, captures a sample from the connected sensor, and goes back to sleep until the next data collection cycle. Data transmission is also done in an efficient manner; several samples are transmitted as a single packet to the sensor hub. The packet length and transmission rates are configurable.

D. *Reliable wireless body sensor network*

The short range of the ad-hoc network influenced our decision about the sensor network architecture. We excluded a peer-to-peer connection between nodes, and isolated the system to prevent data from one subject being recorded on another subject's holster unit. As a result, the network is based on a star topology. As mentioned earlier, we adopted SimpliciTI, a lightweight sensor network protocol supporting two basic topologies: strictly peer-to-peer and a star topology. In our configuration, the sensor hub is the root and all other sensors are connected to the sensor hub as leaf nodes.

Message acknowledgement (ACK) is used to increase the reliability of the wireless data transmission. When a wireless sensor node sends a packet to the sensor hub, it requests an acknowledgment. If the node fails to receive ACK from the sensor hub then it will try to re-send the packet for a predetermined number of times (i.e., 5 times) or until ACK is successful. If this preconfigured limit is exceeded, the node will continue to collect data from the sensor and the failed packet will be lost.

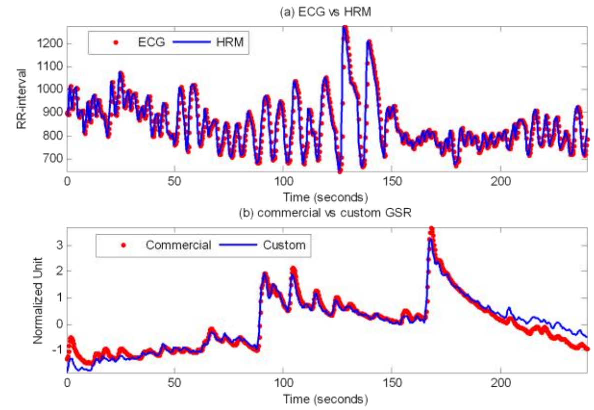

Fig. 3. Comparison of signal between (a) ECG and HRM(ρ=0.9654) and (b) commercial and custom EDA sensor(ρ=0.9851).

Transmission sometimes fails due to accidental power failures at the sensor hub (e.g., the power is mistakenly turned off on the holster unit, and powered on again). To prevent permanent disconnections, each node counts the number of consecutive lost packets; if the count reaches a preconfigured limit (i.e. default is 5), the node decides that the sensor hub has experienced power failure and the node attempts to establish a new connection.

IV. Experimental: comparison to commercial sensors

A. *Comparison of cardiac sensors*

To determine whether HRMs are accurate enough to be used for HRV analysis (i.e. when compared to ECG), we simultaneously collected data from our HRM and a 3-lead ECG. Three adhesive ECG electrodes were attached to the left, right, and apex of the heart. The HRM strap was placed around the chest at the heart level. To introduce fluctuations in the RR tachogram, (n=7) subjects were asked to breathe following a pacing auditory signal which consisted of five different breathing periods, starting with a breathing period of 2s with increments of 2s every 30s. Each condition was repeated twice (total 5 min.) Signals were recorded from both devices at 2 kHz, and R peaks were identified from the EGC monitor following [39]. Good agreement was found across the tachograms in all subjects. The average Pearson's correlation coefficient between both sensors is 0.9654 with a standard deviation (σ) of 0.0204. Fig. 3(a) shows the resulting tachogram from ECG and HRM for one subject.

B. *Comparison of EDA sensors*

To test the sensitivity of our EDA sensor, seven subjects were asked to perform a Stroop color word test (CWT), which has been shown to consistently introduce an arousal response in subjects [40]. Pairs of electrodes from our EDA device and from a commercial system (FlexComp Infiniti; Thought technology Inc) were placed on the index and middle fingers of the left hand (a total of 4 electrodes). Both signals were recorded at 256 Hz. The average correlation coefficient was 0.99851 (σ=0.0175); Fig. 3(b) illustrates the high degree of agreement between both signals.

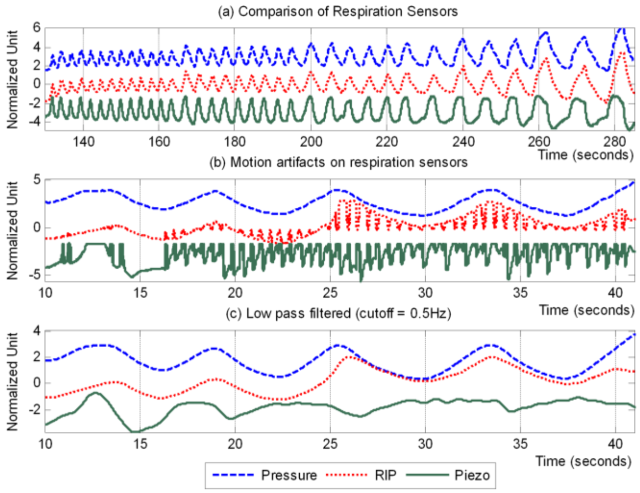

Fig. 4. (a) Comparison of signals between RIP, piezo, and pressure sensor, (b) respiration signals with motion artifacts, and (c) low pass filtered (0.5 Hz) respiration signals to reduce motion artifacts.

C. *Comparison of respiration sensors*

We compared the piezo respiratory effort sensor and the pressure-based sensor against a RIP sensor (XactTrace™; Embla systems Inc.) using the same physiological test described in section IV.A. All sensors were attached to the thorax, connected to a voltage isolator (Thought technology Inc), and sampled at 256 Hz. Fig. 4(a) shows a strong association between the normalized RIP and pressure sensor signals. The average correlation coefficients between RIP and pressure sensors were 0.9760 (σ =0.0269). Average correlation between RIP and the piezo sensor was 0.6407 (σ-=0.0637), due to the fact that the output of the piezo sensor is related to the derivative of respiration.

We also evaluated these sensors under motion artifacts; for this purpose, the subjects were asked to walk at a slow pace. Results shown in Fig. 4(b) indicate that the pressure sensor is robust to body movements. In contrast, the piezo sensor is very sensitive to motion artifacts. The RIP sensor also picks up these body movements. Most of these motion artifacts, however, can be removed by applying a low pass filter with 0.5Hz cut off; see Fig. 4(c).

V. CLUSTERING OF PHYSIOLOGICAL RESPONSES

A. *Effects of mental workload, body posture, and breathing*

To assess whether the wearable sensor system is informative enough to detect different physiological responses, we collected data from three different conditions: mental stress, tilt table, and deep breathing. The mental stress condition consisted of a battery of tests, including dual and memory search tasks, mirror trace and Stroop CWT, and public speech [41-43]. The public speech test consists of a 3 min preparation phase, where the subject was asked to prepare a short speech about a current topic, a 4 min speech phase, and a 3 min question & answer phase. The tilt table condition measures the body's response to tilt and supine postures. In the tilt table test, PNS is dominant in a supine position, whereas SNS is dominant in an upright position [44]. During the deep breathing test, the participants were asked to breathe in for 4 sec and breathe out for 6 sec. The sequence of tests was: deep breathing 1, memory search, deep breathing 2, color word test, deep breathing 3, dual task, deep breathing 4, mirror trace, deep breathing 5, supine, tilt, public speech, and deep breathing 6.

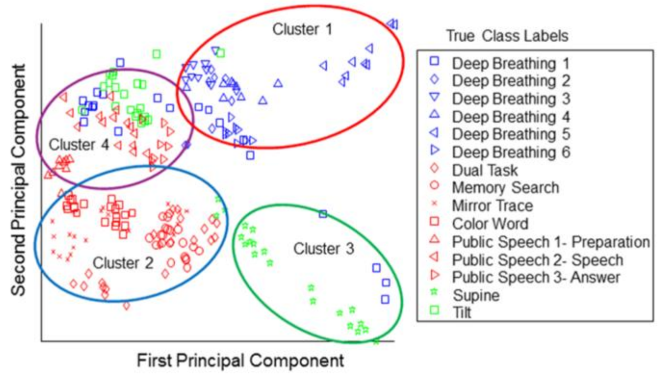

Fig. 5. True class labels vs. k-means cluster assignments from a participant.

We collected data from 22 subjects, and calculated features from HRV, EDA, and respiration sensors. Features were calculated using 90 sec windows with an overlap of 80 sec. Following [44], we computed the following HRV time-domain features: mean of R-R intervals (AVNN), standard deviation of successive R-R intervals (SDNN), the portion of the R-R interval that changes more than 15msec (pNN15), and the root mean square of successive differences of R-R intervals (RMSSD). We also computed the following HRV spectral features: high and low frequency power (HF, 0.15-0.50 Hz; LF, 0.04-0.15 Hz), and LF/HF ratio [44]. The same three spectral features (LF, HF, LF/HF) were computed from the respiration signal. Features from EDA included the mean and standard deviation of skin conductance level (SCL) and the skin conductance response (SCR) [45].

K-means clustering was applied to the above feature vector on each subject to determine if the physiological sensors could discriminate the different conditions [46]. To facilitate visualization, the 14-dimensional feature vector was reduced down to two variables by means of principal components analysis. K-means was initialized using the average value for each of four groups: deep breathing (cluster 1), mental stress (cluster 2), supine posture (cluster 3), and tilt posture (cluster 4).

Fig. 5 illustrates result from a single subject. Three of the final clusters maintain a strong association with deep breathing, supine, and stress groups. The remaining cluster is a mixture of stress, tilt, and deep breathing that exhibit similar physiological responses (i.e., more power on HRV LF). To summarize results across subjects, we computed a confusion matrix between the true class label of each instance and its cluster assignment, averaged over all participants. Results are shown in Fig. 6. Three clear clusters emerge for the deep breathing, tilt, and supine conditions. The majority of mental stress conditions can be found in the same cluster, though some instances were confounded with tilt and deep breathing conditions.

B. *Ambulatory mental stress under physical exercise*

The previous experiment indicated that the wearable sensor

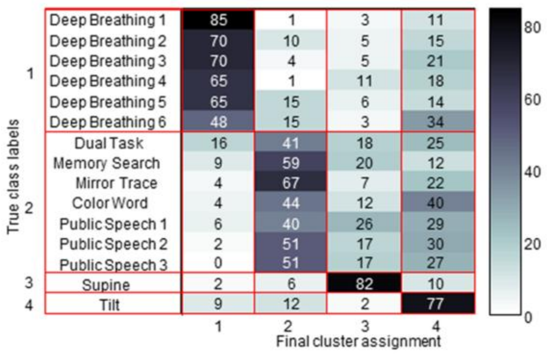

Fig. 6. Average confusion matrix of true clusters vs. cluster assignments. Each cell represents the percent of assigned points per each condition (row).

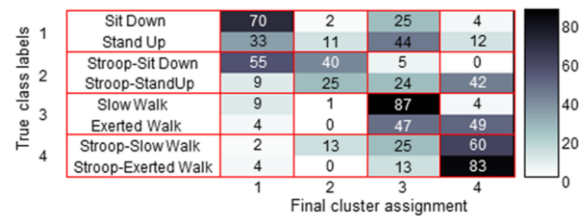

Fig. 7. Average confusion matrix of true clusters vs. final cluster assignments. Each cell represents the percent of assigned points per each condition (row).

system can discriminate among various mental stress and physical conditions. The next experiment examined whether mental stress could be detected under physical activity. Mental stress was elicited using the Stroop CWT. Four physical activity conditions were considered: two active conditions (walking on a treadmill at either 2.0 or 3.5 km/h) and two non-active conditions (sitting and standing). A total of eight conditions result by combing the two factors. Each test took 5 min, with a 3-min rest between tests. A touchscreen laptop permitted subjects to perform the CWT test while walking on the treadmill. The sequence of the tests was: sitting, CWT + sitting, standing, CWT + standing, slow walk, CWT + slow walking (2.0 km/h), exerted walking, and CWT + exerted walking (3.5 km/h). Data was collected from n=7 subjects.

As before, we performed k-means clustering. Cluster centroids were initialized as follows: rest (sitting and standing), rest-stress, exercise (two walking speeds), and exercise-stress (two walking speeds). Fig. 7 displays the final cluster assignment for all subjects. These results indicate that the system response is heavily influenced by the exercise condition. Four of the conditions were assigned to the correct cluster: sitting, slow walk, and CWT + walking (both slow and exerted). However, most of the CWT + stand and exerted walk conditions were ultimately assigned to cluster 4. Moreover, half of the CWT-sitting conditions were assigned to cluster 1.

These results indicate that ambulatory physical activity and mental stress have overlapping effect on the sensor signals, and illustrate the challenge of measuring mental stress in ambulatory conditions. Thus, in order to monitor mental stress in ambulatory settings, one must reduce the unwanted influence of physical activity on physiological signals. As an example, the LF power in HRV shows a significant difference between mental stress and relax conditions, but it can be easily affected if the respiratory frequency overlaps with the LF band. In such cases, one needs to separate respiratory contributions from those caused by the psychological stressors. The following section describes a method that provides improved detection of mental stress by subtracting the effects of respiration.

VI. Removing Respiratory Effects on Heart Rate Variability

In [47] we proposed a system identification method to compensate for respiratory effects on HRV. Our method is a special case of the ARMAX model. Namely, the method estimates the current heart period $y(t)$ as a linear combination of respiratory efforts and residual signal, where $r(\tau)$, $b(\tau)$ and n_b are the residual signal, coefficients, and model order. Model coefficients are estimated through least squares.

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

To validate the 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, subjects were asked to breathe following an audible sinusoidal pacing signal with a fixed period of 6.67 sec; 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 consisting of target tracking and memory search tasks while breathing at a fixed duration of 6.67 sec too. Each of the three conditions (relaxation, stress, and calibration) lasted for 5 min. Each subject repeated all conditions three times on different consecutive days.

Subsequently, for each stressed and relaxed condition, the derived coefficients were used to predict the HRV signal from the respective respiratory signal. As shown in Fig. 8, the HRV spectra displayed a dominant peak at 0.15 Hz, which follows the respiratory pacing signal. Power spectra for the predicted respiration signal and residual signal are shown in Fig. 8(c-d). Whereas relaxed and stressed conditions have nearly identical power spectra, the corresponding residual signals are quite different. Namely, the stressed condition has significantly more residual power, which facilitates discrimination between both conditions.

To confirm these findings numerically, we compared the traditional HRV and residual analysis in a pattern classification paradigm. Namely, 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 set up as a binary classification problem, where the goal was to discriminate the mental stress conditions from the relaxation conditions. Results are summarized in Fig. 9. 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

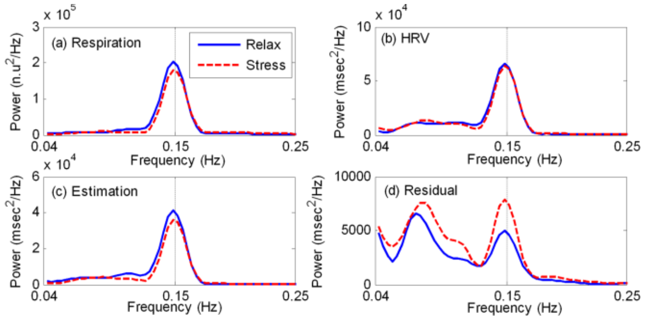

Fig. 8. Power spectrum of (a) respiration signal (input), (b) HRV signal (output), (c) prediction by the model and (d) residual signal.

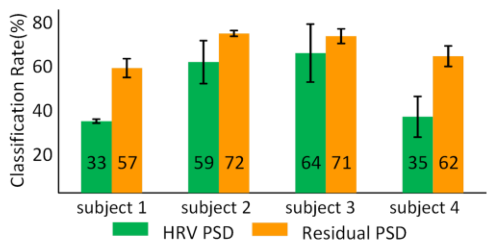

Fig. 9. Comparison of classification rates for HRV p and residual PSD

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.

VII. Comfort Rating

The previous sections evaluated the sensor system in terms of its ability to monitor mental stress. To evaluate the comfort of the prototype, we also collected user evaluations following those experiments. Comfort rating scales (CRSs) suggested by Knight [48] were used to evaluate multiple factors including: emotion, attachment, harm, perceived change, movement, and anxiety (see Table I). We used a 7 point Likert-type scale for each question: disagree completely (1), neutral (4), and agree completely (7). Evaluations were collected from 29 subjects; 21 subjects used the device in a lab setting (section V.*A*), while 8 subjects wore it in the ambulatory exercise experiment (section V.*B*). Results are shown in Fig. 10. We performed a two sample t-test for each of the comfort factors to determine if users in the lab setting ($n = 21$) felt different about the device than users in the ambulatory setting ($n = 8$). For each factor, no significant differences were found between the two settings ($df = 56$, $p < 0.05$).

VIII. Discussion

We have designed and developed a minimally-invasive wearable and wireless sensor platform which allows long-term ambulatory monitoring of a number of physiological indices of mental stress. Our design is a concerted attempt to balance information content and comfort, and focuses on four physiological modalities: heart rate, respiratory effort, electrodermal activity, and electromyography. Communication between the wireless sensors and a holster monitor is achieved by means of a lightweight communication protocol, which allows uninterrupted operation for over 13 hours.

TABLE I
COMFORT RATING SCALES

Factors	Question
Emotion	I feel worried about how I look when I wear this device
Attachment	I feel the device moving on my body
Harm	I feel some pain or discomfort wearing the device
Perceived change	I feel awkward or different wearing the device
Movement	I feel that the device affect the way I move
Anxiety	I feel in secure wearing the device

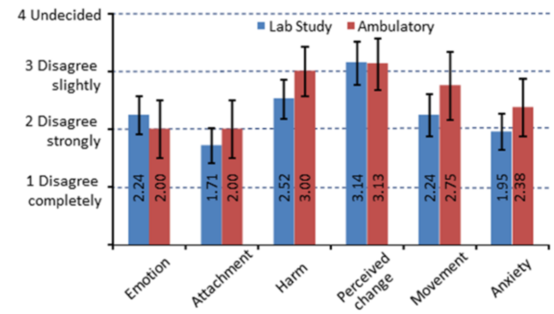

Fig. 10. Comfort rating of the wearable sensor (lower scores are better)

Individual sensors were validated against a commercially available (but wired) physiological monitoring system. The overall system was also validated through a series of tests that elicited mental workload and physical activity. Our results indicate the sensor responses naturally cluster along four broad types of psychophysiological conditions (mental workload, relaxation, supine, tilt). It is important to notice that this discrimination was performed using unsupervised techniques (i.e., principal components analysis and k-means clustering); additional improvements in discrimination performance could be obtained with supervised techniques, such as Fisher's discriminant analysis for dimensionality reduction and various types of classification techniques (e.g., neural networks, support vector machines, Bayesian classifiers). Our results also illustrate the challenge of monitoring mental stress in ambulatory settings, where the user may engage in a variety of physical activities. As a step towards minimizing these kinds of interferences, we have presented a system-identification approach to remove respiratory influences on HRV. Finally, user comfort ratings of the platform show no statistical difference between lab settings and ambulatory settings.

Several improvements to the hardware system are being considered at the time of this writing. A wireless inertial measurement unit (IMU) consisting of accelerometers, gyroscopes and magnetometers is being designed to allow monitoring of gait and body posture. Since physiological signals are affected by physical activity, mental state detection could be further improved by subtracting gait and postural influences. Second, we are developing an Android-based platform to serve as a graphical user interface for the sensor system. This addition will allow a user to observe their physiological signals in real time, manage the operation of the device, monitor the status of the sensors, and also provide useful metadata (e.g., subjective ratings of stress, activities) for ambulatory studies being designed at the time of this writing. Lastly, we are exploring an application that would perform feature extraction and system identification to fuse physiological signals and decompose the result into meaningful variables that can be understood by non-experts (i.e. stress levels, mental load).

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