Design of a Wearable System to Capture Physiological Data to Monitor Surgeons' Stress During Surgery

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***Abstract*— The mental and physiological stress experienced by surgeons during operations has been identified as an important human factor that impacts surgical performance and patient safety. It is crucial to objectively measure and quantify surgeons' stress via physiological signals in order to enhance the understanding of how stress contributes to surgical outcomes. Current clinical and consumer devices for monitoring bio signals are not well adapted for use in the operating room; therefore, we designed an unobtrusive system, that measures select signals that correlate with stress and stores the data for integration into a data processing pipeline. Herein, we present a proof-of-concept device that captures data from ECG, EMG, EDA, and IMU sensors and initial testing results.**

***Clinical Relevance*— Developing quantitative measures of stress in clinicians provides a means to understand, monitor and, potentially, mitigate situations that compromise their wellbeing and also affect the quality of patient care.**

I. Introduction

Stress can be defined as the result of an individual perceiving that the demands of a situation exceed their resources [1]. The healthcare environment places stressful cognitive and physical loads upon physicians, who present an incidence rate of burnout twice that of the general population. Surgery is the medical specialty with the highest incidence of burnout [2-5]. Stress is also a contributing factor to medical errors, which account for approximately 251,000 deaths in the US annually, the third leading cause of death [6]. The development of means to monitor stress in a comprehensive and unobtrusive manner is crucial to begin investigating better stress management of surgeons during long and complicated procedures in the operating room (OR).

The current gold standard for evaluating stress is self-reporting; however, this is subjective, affected by memory and emotional expression biases, and do not allow for continuous *in-situ* monitoring [7]. For an objective and real-time assessment, research efforts have focused on technologies that measure the physiological effects of stress. Applicable measurements include cortisol concentration in sweat [8], frontal brain electrical activity [9], muscle activity [10], heart electrical activity [11], galvanic skin response [8], respiratory activity [12] and blood pressure [13].

Individual wearable bio sensors are available, in both clinical and consumer forms; however, no single device exists that meets all the requirements in an operating room (OR) setting including: unobtrusiveness, measurement of a comprehensive set of biological signals that correlate with stress, and reliable data storage for integration into a data processing pipeline [14-18]. A device that only measures a single physiological signal lacks comprehensiveness. Due to the complexity of the stress construct, a multi-modal measurement is needed. Herein we present the design, system architecture, and initial testing of a wearable device able to collect, integrate, and transmit physiological data in order to monitor the stress levels of surgeons in an experimental OR setting. The eventual goal of this work is to identify stressful events during real surgeries and link them to specific periods or occurrences during a surgical procedure.

II. Design

Measuring the stress of a surgeon while he or she is conducting an operation requires a device that is comfortable to wear over a period of hours, unobtrusive and operates on a single charge for the duration of a surgery. The device must also maintain procedural sterility. The key requirements and approaches are summarized in Table 1.

TABLE I. Design Requirements

Functional Requirement	Approach
Infer stress	Select a subset of representative, non-invasive bio signs shown in literature to correlate with stress
Unobtrusive	Identify sensor placement that does not hinder surgeons' motion or field of view
Synchronous Acquisition	Build architecture to acquire multiple data streams in a single time-stamped data file
Storage	Minimum 4 hours of on-board recording capacity
Sterility & Cleanliness	No parts of the system may enter the sterile field and device must be cleaned between users

A. Sensor Selection

We identified that a representative data set should consist of three or more decoupled sensor readings, with a sufficient degree of sensitivity to identify acute stress. We also considered the ability to take these readings concurrently, non-invasively and comfortably from accessible body regions.

Heart rate variability (HRV) and heart rate (HR) correlate with stress [11] and can be measured from electrocardiography (ECG) and photoplethysmography (PPG) signals. For stress measurement, ECG signals are

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978-1-7281-1990-8/20/$31.00 ©2020 IEEE

preferred over PPG because they can be measured closer to the heart and offer a more accurate representation of heart activity [11, 19]. Stress has also been associated with the contraction of trapezius muscles [20] and these muscles' activity can be measured via electromyography (EMG). Sweating decreases the resistance of skin [8] and the skin galvanic response can be measured using electrodermal activity (EDA) sensors. Respiratory rate (RR) can be deduced from chest wall movement [21] and, therefore, an inertial measurement units (IMU) can provide RR.

Considering the ease of electrode placement on the upper torso, without impeding the workflow of surgeons, ECG, EMG, EDA and IMU were selected as the subset of physiological signals. For proof-of-concept purposes, off-the-shelf component sensors were employed, shown in Table 2.

TABLE II. SELECTED SENSORS

Name	Vendor	Model	Output	# chan.
EMG	SparkFun Electronics	Myo Ware	Analog	1
ECG	SparkFun Electronics	AD2832 Heart Rate	Analog	2
EDA	Seed Technology	Grove GSR	Analog	1
IMU	SparkFun Electronics	MPU 9250	Digital, I2C	6

B. Digital Architecture

The requirement of synchronous data acquisition and storage was met through the design of a digital system that integrated readings from the component sensors. The synchronization of the data set also allows identification of measurement artifacts. Artifacts from individual recording channels can be identified when their signals do not match the data from other channels, suggesting interference, potentially from motion or poor signal transduction. Fig. 1 shows a high-level schematic of the electronic architecture. A Teensy 3.2 development board was selected as the central computing unit of the system connected to an SD card breakout board, part #254 from Adafruit, through an SPI communication link. The SD card served as a storage unit for all the data collected as a single TEXT file. This minimized the risk of data loss in the storage process, since there is a direct physical link between data collection and storage. The sampling rate of the system is set as 50 Hz for all sensors, which is reasonable for the physiological signals of interest (i.e., we are interested in heart rate, not exact waveform) and within the microcontroller's processing capacity [8, 10-12].

As indicated in Table 1, the EMG, ECG, and EDA sensors provide analog output signals, hence a 4 channel Analog to Digital Converter (ADC), part #1528-1014-ND from DigiKey, was included in the architecture. The programming is based on the Arduino open source platform in C. The IMU sensor comprises a 3-axis accelerometer and a 3-axis gyroscope. The Teensy communicates using the I2C protocol with the 6 channels of digital data from the IMU as well as the ADC.Finally, a power budget was developed to select a battery that would allow for continuous operation during a 6 hour surgery. Tallying the components' power draw, the load was estimated at 163.7 mA. Using a 10,000 mAH rechargeable USB battery pack gave the system a run time in excess of 2 days.

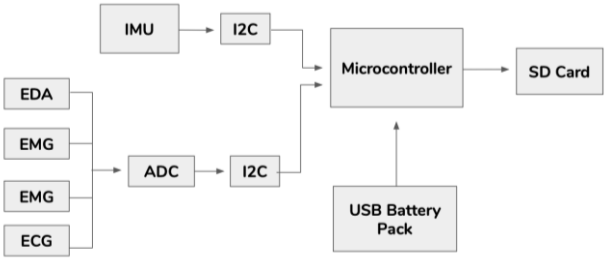

Figure 1. Electronic architecture of the device.

C. System Architecture and Deployment

The paired EMG and single ECG and EDA sensors each require differential measurements, typically from wet adhesive electrode pads placed on the body. This resulted in 8 pairs of electrodes, to collect the signals, and a single electrode which serves as a common ground. The pair of EMG electrodes were placed overlying the left and right trapezius muscles at the level of the scapula and oriented along the muscle fiber; the pair of ECG electrodes were placed on the left and right pectoral muscles; and the pair of EDA electrodes, along with the ground electrode, were placed on the lower back. This positioning of these pads, in addition to the need for a comfortable, unobtrusive, and sterile design, served as criteria for developing the wearable device.

In order to attain feedback regarding the potential comfort and acceptability of candidate architectures, based on commercial wearable devices for purposes ranging from meditation to sleep to exercising [14-18], a survey was conducted to evaluate potential sensor placements. Proposed designs included a chest band, a "necklace," attached to underwear, an arm band and others. A total of 253 responses were obtained: 244 from the general population and 9 clinicians from the greater Boston area. Just under one-third of the participants indicated that they would find a soft chest-band design comfortable and unobtrusive.

Due to the need to place sensors on both the chest and back, the harness design, shown in Fig. 2, is suitable for wearing under scrubs and leaves the head and arms unencumbered. This is built off a commercially available posture brace, worn like a backpack and adjusted to fit snugly, but with no tension. A strap is added to the top to secure the EKG and IMU sensors.

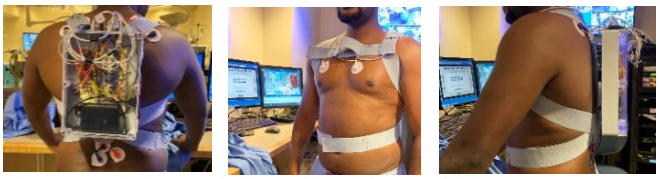

Figure 2. Back, front, and side profiles of the wearable harness on a surgeon volunteer at the STRATUS Center for Medical Simulation.

Electrode snap wires attach to the wet electrode pads placed on the body and are bundled and guided along the straps of the posture brace, and connected to 3.5 mm audio jacks. Two USB ports enable microcontroller access and recharging of the battery and a hole provides access to the on/off switch. The box is mounted to a rigid panel, between

the shoulder blades, on the back of the brace. In this iteration, the focus was on proof-of-concept to validate bio signal collection with the expectation that in future iterations the electronics can be greatly compressed.

The breathable material of the harness, the adjustable elastic straps and the placement of the electronics mid-back, with the weight transferred to the shoulders, ensured a comfortable design that is not expected to shift or chafe during hours of surgery. This backpack-like design allows most of the weight to be distributed on the back of the user. The device will not cause extra fatigue, which is crucial for real-world deployment. Hook-and-loop ends are attached to all straps to allow adjustability. This device can snugly fit on the user and be covered under scrubs, which allows surgical context deployment. The 5V architecture and effective double casing of the battery provides additional safety, and later the box will be sealed to prevent the ingress of sweat. Once the box is detached and the electrode wires removed, the harness can be laundered between uses and users.

III. RESULTS AND DISCUSSION

In order to verify that each sensor was recording as expected, a simple, controlled experiment was performed. In order to compare ECG data with the ground truth, a test subject executed a simple protocol while wearing both the prototype and an 8500 medical grade finger clip pulse oximeter. The entire task was recorded using a video camera and a timer to allow correlations to be drawn between the observed data and the actions performed. Data was recorded, offloaded, and post-processed in MATLAB.

The experiment was divided into 3 segments. First, the subject spent 100 seconds slowly pacing across; second, he performed a mini-workout of 5 push-ups; and third, he stood still for an additional sixty seconds. The first segment developed a baseline of physiological signals, the second segment provided a clear task that should be easily visible in the data, and the last segment was expected to show a change in physiological state resulting from physical activity. The physical activity was carefully recorded in a timeline in order to find artifacts in the experiment.

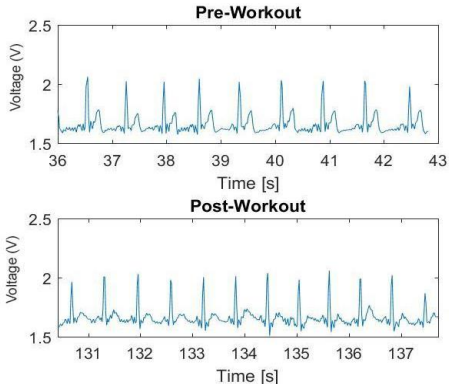

Figure 3. ECG signal before and after a workout.

Fig. 3 shows the ECG signal measured from the device before and after workout, where the horizontal axis is the time after the recording had started, and the vertical axis is the voltage output of the ECG sensor following the implementation of a low-pass filter in MATLAB. From the RR intervals displayed in both graphs, the heart rate was found to be 81 bpm and 98 bpm, before and after the workout respectively. The values measured with the pulse-oximeter were found to be 81 and 97 bpm – almost identical to the results obtained from this ECG.

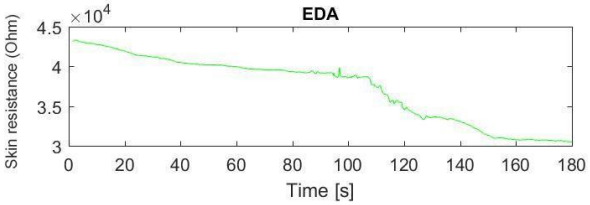

Figure 4. The EDA signal as a function of time during the entire task.

The resulting EDA signal, following a conversion to ohms [22] and the application of a median filter (the medfilt function in MATLAB) to remove spiked noise, is shown in Figure 4. The EDA signal can clearly be divided into 3 regions: from the beginning to 100s, from 100s to 120s, and from 120s until the end. In the first phase, resistance gradually decreased likely due to a slow accumulation of sweat from the electrode coverage. The second phase sees a sharp drop in skin resistance as a result of sweat from the pushups. In the third phase, the skin resistance dropped smoothly as the rate of sweat production reduced following the completion of the exercise.

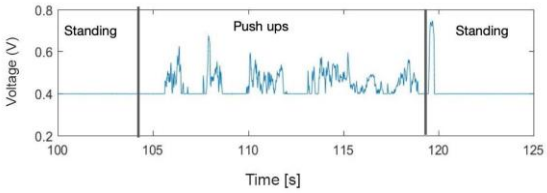

Figure 5. EMG data highlighting the push-ups section of the task.

For the EMG sensors, higher voltage outputs were expected to clearly manifest as activity of the trapezius muscles during the push-up segment of the test and remain minimal during the rest of the experiment. Fig. 5 shows the twenty-second window during which the subject performed five push-ups. Five bursts of activity of similar structure can be distinguished, aligning with the number of push-ups. The last sharp peak reflects the user standing up. Upper limbs are used in a short duration with intense contraction to assist positioning; thus, the peak is high in amplitude and short in time.

Fig. 6 shows the IMU data recorded during the push-ups. In both the gyroscope and the accelerometer data, 5 similar waveforms can be distinguished which indicate the upwards and downwards motions. It should be noted that, due to the orientation of the IMU on the chest and the fact that push-ups represent inclination, the motion was not constrained to a single sensor axis. However, the time in which the waveforms occurred can be cross-referenced easily with the rest of the data collected from other sensors. Hence, the orientation of the chest can be deduced from the above acceleration and angular velocity data. This in turn can be correlated to breathing. A testing method to verify respiration capture was not developed for this iteration.

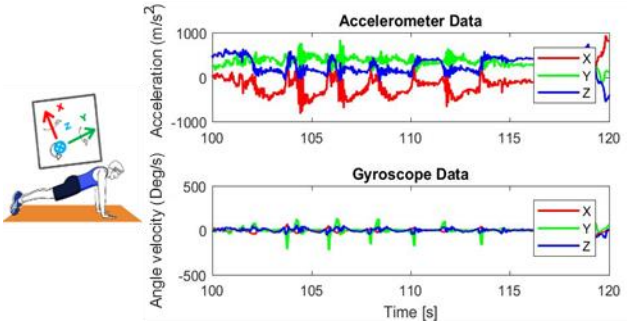

Figure 6. IMU data during push-ups section of the experiment..

IV. Conclusion

This preliminary proof-of-concept work demonstrates a device and architecture that can successfully collect multiple types of physiological data for stress measurement and reliably store data for future work. It is suitable to generate the data for the next phase of this project, a detailed review of the signals collected and their post processing.

The steps to improve the design are clear: The size and mass of the device can be greatly reduced by designing a custom circuit on a PCB, instead of using commercial sensors, and dedicated packaging. By purchasing a more precise ADC and a microcontroller with a high clock frequency, the signal quality could be drastically improved. Additionally, a LiPo battery could be used instead of a power bank, and a 3-D custom-formed casing, rather than an off-the-shelf box. Likewise, the harness can be made more comfortable and functional by custom sewing a harness with longer straps and "tubes" to hold the wires. The conversion to dry electrodes to improve longer-term comfort is also under discussion, but this will make adequate signal collection harder.

The next key step is data validation, in which data will be collected during a simulated surgery during which key periods and events are marked down. These can then be compared to the collected data to start building a metric for stress. Later, we will add the capability to stream the data to a dashboard so that it can be marked in real time. A variety of experiments in simulated ORs among different surgeon populations and surgical contexts will be needed to verify the robustness of the device.

The eventual goal is a running "stress display" that can be observed during surgery and, potentially, the development of an overall integrated "stress score" by which procedures can be compared quantitatively. Future work will be conducted at the STRATUS Center for Medical and real ORs to cover different surgical contexts and populations.

Acknowledgments

This work was conducted as part of the MIT Medical Device Design course and we thank the Mechanical and Electrical Engineering Departments and this year's corporate sponsors including Boston Scientific, SCG, Sumitomo Heavy Industries and Leo Pharma. We also thank the staff of the STRATUS Center for Medical Simulation for use of their facilities to test the prototype and the course instructors who are not listed as authors, including Alexander Slocum, Gim Hom, Dave Custer, Julian Chacon-Castano, Aaron Ramirez and Ellen Roche for their support.

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