Objective Stress Monitoring for Live Training Exercises

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ABSTRACT

A primary goal of live and virtual training exercises for military forces, medical practitioners, and first responders is to develop readiness in a controlled, realistic environment. Once basic skills are learned, training transfer of complex skills from exercises to a high stakes, high stress environments increases when training exercises closely mimic the stress and tempo of operations. Objectively quantifying stress in real-time would provide key data to influence and evaluate immersive training exercises. The community has investigated a number of physiological-based indicators, many of which utilize lab-based equipment that limits the ability to use such approaches in military and first responder training exercises. A stress classifier was created to allow user physiological state to be monitored and classified in real-time in an ambulatory environment, and indicated high stress classification accuracy in healthy adults and those undergoing cognitive behavioral therapy for Post-Traumatic Stress Disorder (PTSD). While the stress classifier has been assessed using both healthy and clinical populations, the ability to extend its capabilities to military and first responders was required to determine classification accuracy and ruggedness in training and operational environments.

Field data collection events in collaboration with the Department of Homeland Security (DHS) First Responders Group and naval firefighter training with the Surface Warfare Officer School (SWOS) provided context relevant data to evaluate real-time stress measurement accuracy and reliability. Results from field studies in each of these two environments will be presented, along with a discussion of the findings, challenges and next steps for this technology. This paper will also summarize the unique ruggedization requirements for physiological-based algorithms and associated hardware, as well as related technologies for immersive training communities.

ABOUT THE AUTHORS

Zach Huber is a Sr. Research Associate on the Biosignature Analytics team at Design Interactive, Inc., focusing on research involving classification of human state. Zach has worked with data collection tools, augmented/mixed reality, and has led projects in developing and utilizing real-time stress classification. He has also worked on projects creating estimates of mental acuity from sleep inputs and developing training and assessment tools for children with Cerebral Palsy. Prior to joining Design Interactive, Inc., Zach was at the Spine Research Institute at the Ohio State University where his work focused on modeling the spine.

Dr. Brent Winslow Ph.D. is Chief Scientist at Design Interactive, Inc., and has over 15 years of experience in studying neuroscience at multiple scales from a bioengineering perspective. Brent's current work spans technologies for upper limb amputees to algorithms for evaluating human stress and resilience, as well as the acute and delayed neurophysiological effects of technology, including Virtual, Augmented, and Mixed Reality (VAMR) applications. Brent earned a PhD degree in Bioengineering from the University of Utah, where he studied the biocompatibility of neuroprosthesis and subsequent changes to neurogenesis and cognition. Prior to joining Design Interactive, Inc., Brent was at the Allen Institute for Brain Science in Seattle, WA, where his work focused on describing the mammalian connectome using genetic techniques and multiphoton imaging, as well as the development of millimeter scale wireless biosensing devices.

Ajmal Aziz is a Program Manager at the DHS Science and Technology Directorate (S&T) with broad experience in managing Advanced Technology programs for the homeland security enterprise. Ajmal currently manages a robust portfolio of research and development programs focused on emergency management and resilience, training and performance optimization and public safety research.

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INTRODUCTION

Human performance is affected by stress in a dose-dependent manner; while moderate stress can improve performance, severe stress can reduce performance due to biological and neural mechanisms (Lieberman et al., 2005). In addition to immediate effects, chronic exposure to high stress is associated with an increasing likelihood of mental illness development (Southwick, Vythilingam, & Charney, 2005). Available evidence suggests that members of the military and first responders are at high risk for such stress-related disorders. For instance, police officers' level of depression is double that of the general population, and officers are four times more likely to sleep less than 6 hours in a 24 hour period (Hartley, Burchfiel, Fekedulegn, Andrew, & Violanti, 2011). The rates of PTSD, suicide ideation and attempt are 10 times higher in Emergency Medical Services (EMS) professionals than the general population (Erich, 2014; Newland & EMT P, 2015). High rates of PTSD (Mitani, Fujita, Nakata, & Shirakawa, 2006), substance abuse (Murphy, Beaton, Pike, & Johnson, 1999), and depression (Fullerton, Ursano, & Wang, 2004) are experienced by firefighters. Given high stress occupations in military service and emergency response, there is a need to measure the impacts of stress on performance in order to effectively train individuals to perform successfully in the field (van Wingen et al., 2012), and to reduce the likelihood of long-range medical effects.

The human stress response can be measured via psychological and physiological measures. Subjective stress can be measured using self-report surveys such as the State-Trait Anxiety Inventory (STAI; (Spielberger, Gorsuch, Lushene, & Vagg, 1983)), but such approaches suffer from problems with exaggeration or under-reporting (Kruegar, 1998). The stress response can also be inferred from behavioral changes, such as task performance; however, these measures also have limited temporal resolution as complex tasks typically do not have continuously measurable performance variables. A promising means of capturing individual stress responses in real-time is via physiological measurement. Physiological changes following stress exposure include increased sympathetic autonomic nervous system (ANS) activity, resulting in neurotransmitter release and subsequent physiological effects on multiple organ systems, including heart rate changes via the vagus nerve, pupil dilation, vascular constriction, and an increase in sudomotor activity (G.S. Everly & Lating, 2013). In concert with autonomic activity, severe stress also increases hypothalamic-pituitary-adrenal (HPA) axis activity, resulting in increased plasma/saliva concentration of stress related hormones including glucocorticoids (GCs) such as cortisol (Restituto et al., 2008). Stress-related biomarkers are measurable by collecting serum or saliva and measuring protein expression, or via wearable physiological monitoring systems.

Previous approaches to physiological stress detection have employed a number of different physiological variables, including: cardiovascular state via pulse photoplethysmography (PPG) or electrocardiography (ECG); skin conductance/electrodermal activity (EDA); electromyography (EMG) of specific muscle sites such as the trapezius; and measurement of respiration, all of which are responsive to physiological stress (George S Everly & Lating, 2002). Following stress induction and data collection, supervised learning methods have been used to develop stress classifiers. However, a number of limitations have been observed in previous work, including individual subject variability in physiological responses to stress (De Santos, Sánchez-Avila, Bailador-Del Pozo, & Guerra-Casanova, 2011), low classification accuracy due to the physical activity of subjects which triggers similar cardiovascular and electrodermal physiological signals as stress (Sun et al., 2010), and hardware that is not usable outside of controlled laboratory conditions (Alamudun, Choi, Gutierrez-Osuna, Khan, & Ahmed, 2012; Plarre et al., 2011).

In order to address concerns with previous approaches to stress detection, and leveraging both the emergence of new wearable devices with clinical grade sensors and rapidly advancing mobile computing capabilities, a stress classifier was developed (Winslow et al., 2016) within a clinical therapy setting. Use of the stress classifier and associated mobile application was associated with a significant reduction in veteran stress, anger, and anxiety in a randomized controlled trial (Winslow, et al., 2016). While the stress classifier has shown to provide high accuracy, real-time stress detection during typical everyday activities, active duty military and first responders operate in more demanding environments. These professionals routinely operate substantially higher kinetic activity tasks within extreme environments while wearing personal protective equipment (PPE) – all of which have the potential to degrade stress detection accuracy or damage sensing technology. The purpose of this paper is to describe optimization and ruggedization steps taken to improve stress classification in military and first responder environments, and discuss the findings, challenges and next steps for this technology.

Stress Classifier Development

A stress classifier was originally developed for use in daily living (Dechmerowski, Winslow, Chadderdon, Schmidt-Daly, & Jones, 2014; Winslow, et al., 2016), supporting analysis of an individual while they are mobile throughout their environment. However, the hardware sensor and algorithm was not robust enough to adequately account for conditions that occur during military training, where environmental and task stressors are more extreme, causing higher noise in the raw sensor output. To better align the stress classifier with conditions that may be experienced by first responders or military personnel, a number of changes were made to optimize and ruggedize the stress algorithm to support these extreme environments.

Accepting new data modalities

As originally implemented, the stress classifier utilized cardiovascular information from an optical sensor from a wrist worn sensor which provided a solution that would be worn during daily living via PPG. PPG waveforms represent temporal changes in arterial blood volume in a region of tissue (Figure 1). PPG sensors pair light sources, typically red (approximately 650 nm) and infrared (IR, approximately 950 nm) and appropriately tuned photodetectors using either reflected or transmitted PPG. Identification of consecutive peaks or valleys in the PPG signal can be used to determine heart rate, heart rate variability, or other features including peripheral oxygen saturation.

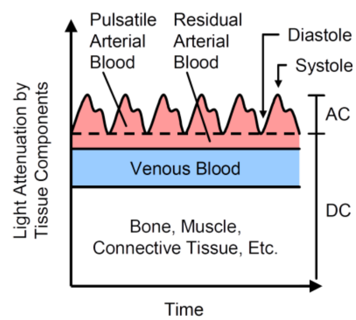


Figure 1. PPG signal components (Johnston, 2006).

PPG signals are highly artifact prone. Sources of artifact include: motion between the PPG signal and source due to user movement, vibration, etc. (Subhagya, Aruna, Janardhan, & Ramakrishna, 2017); ambient light interferences, which saturates the PPG photodetectors (Hanowell, Eisele, & Downs, 1987); skin pigmentation (Sinex, 1999); and user medical state, including presence of anemia or hypothermia (Chan, Chan, & Chan, 2013).

As compared to PPG, ECG is associated with less artifact (Limaye & Deshmukh, 2016), and the presence of a distinct R wave, due to ventricular depolarization, provides very high accuracy assessment of heart beat. Unlike the optical signal underlying the PPG, ECG represents the electrical activation of various components of the cardiac cycle, including: the P wave, associated with atrial depolarization; the R wave, a component of the QRS complex, associated with ventricular depolarization; and the T wave, associated with ventricular repolarization. Successive R waves can thus be used to quantify heart rate and heart rate variability (HRV), with less contamination due to movement or other artifact.

In order to ruggedize the stress classifier, an ECG filtering and QRS feature extraction algorithm was implemented based on work by Zong et al. (Zong, Moody, & Jiang, 2003). The high motion environment often encountered by first responders requires filtering of the data in order to reduce the noise levels. As part of this algorithm, bandpass filtering was incorporated to remove baseline wander, low frequency noise artifacts, powerline harmonics, and high frequency noise.

To further address these challenges, an additional sensor channel was introduced to control ECG noise. Two ECG channels were integrated, which allowed flexibility in data available for analysis; when one channel was disrupted by noise, the system could suppress that channel and switch to record from the clean channel.

It is expected that with these changes, the stress classifier will be better suited for capturing and analyzing stress within a first responder or military environment (Figure 2).

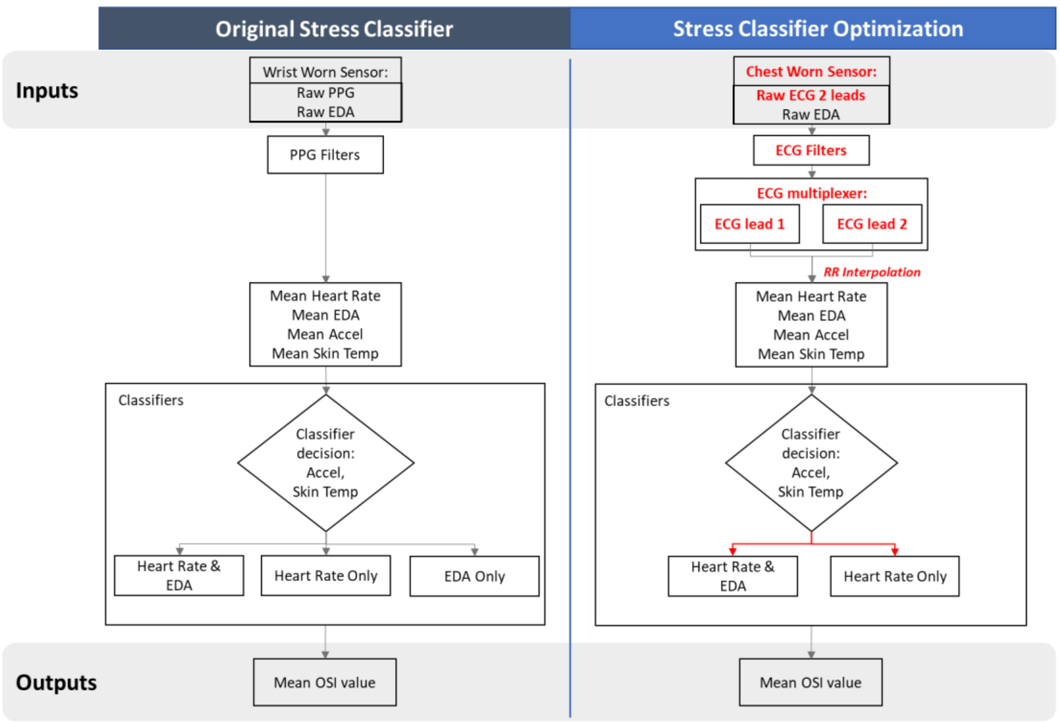


Figure 2. Stress classification changes depending on significant movement

METHODS

Participants

Participants were taken from different populations, including the Surface Warfare Officer School (SWOS) Learning Site, Mayport Florida within the Navy (n=10; 7 male, 4 Basic Course, 6 Advanced Course) and trainees at the Federal Law Enforcement Training Centers (FLETC) in Glynco, GA (7 males) between December 2017 and June 2018. All studies were approved by an independent Institutional Review Board and each participant provided informed consent prior to beginning the study.

Equipment

All participants were fitted with the Equivital EQ02 Life Monitor (Cambridge, GBR). The Equivital system has two components - a sensor electronics module (SEM), and a body worn sensor vest. ECG electrodes, skin temperature sensors, and a strain gauge for evaluating respiration are integrated into the sensor vest. The SEM included onboard power, processing electronics, and a wireless transmitter. An additional EDA sensor was connected to the SEM to provide inputs for the stress classifier.

Procedure

Naval Firefighting Training

Data was collected at two SWOS training courses, the Beginner (416) and Advanced (419) Firefighting and Damage Control Courses. Experimenters did not have control of trainee tasks, yet were provided access to capture physiological data and observe training to contextualize indicators of training events to relate back to physiological data captured. During the beginner course, the participants observed instructors using different types of fire extinguishers and hoses. The participants then practiced using the hose in an open field. Following the practice, participants donned PPE, which included fire resistant coveralls, a flash hood, a self-contained breathing apparatus (SCBA) tank and mask, and entered a training area where they fought two simulated fires. The first fire was a large engine room fire (Class B fire). The participants rotated through the line so that everyone had a chance to be at the front of the line, closest to the fire. They then put out a smaller electrical fire (Class C) with a fire extinguisher. The advanced course was designed to be more open-ended than the beginner's course. In the Advanced course, the participants were assigned to teams, and different types of fires (Class B and C) were started throughout the course of the three day event. After a fire was identified, the participants had to travel to the fire location, assess the type and extent of the fire, and then extinguish it. As the training progressed, each scenario became increasingly more difficult by increasing the number of fires and the amount of instructor input that was provided. The last day simulated an attack on a ship that caused multiple fires randomly occurring throughout the ship that the trainees were expected to deal with without instructor input.

DHS

Law Enforcement Officers

Use of force training was conducted within a DHS S&T Facility that included multiple rooms and floors, and live actors were used to enhance scenarios. The trainees went through eight different scenarios, each requiring a different response. They were given minimal information to begin, and had to determine the best course of action. Example scenarios included arresting a compliant individual with a weapon, arresting a non-compliant individual after a chase, and deciding to use the Taser or handgun when a threat was presented. The unknown information in the scenarios that the officers were exposed was expected to create anticipatory stress. Following each scenario, the officers underwent a debrief with trainers, where an after action review session (if conducted) assessed each decision the law enforcement officer made during the scenario.

RESULTS

Stress Classifier Ruggedization

The stress classifier ruggedization described above allowed for data to be collected in environments with extreme motion and other potential interference. Figure 3 illustrates an example of how ECG signal was optimized - transforming noisy ECG signals captured during high motion activity to a clear QRS complex.

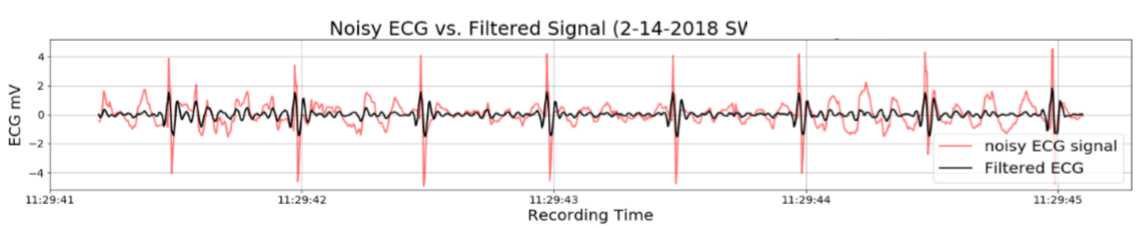


Figure 3. Application of filtering to raw ECG signals (red) for clean data (top), data with baseline drift (middle) and noisy ECG data (bottom).

SWOS

Figure 4 displays the HR, EDA and stress data of one trainee from the SWOS Advanced Course. This data is representative of the remaining participants. All participants went through the same overall scenario, but had different roles within that scenario. The scenario is broken down into a Preparation Phase (putting gear on) and the Fire Task Phase (actively fighting fire). The stress level is reported on a scale from 0-10.

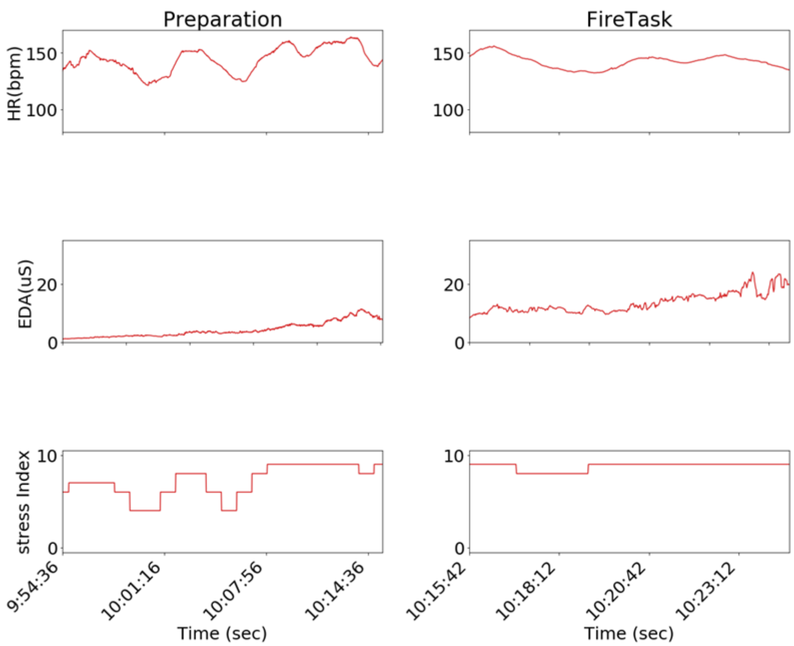
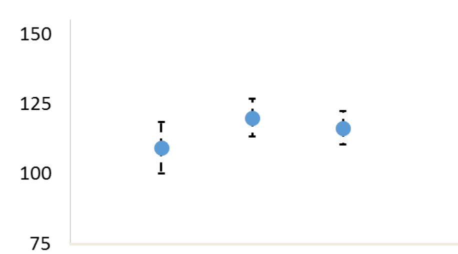


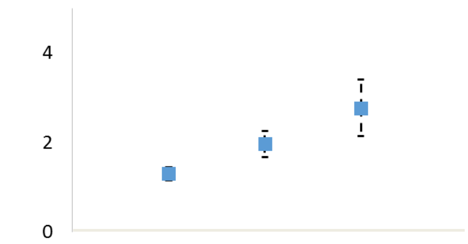
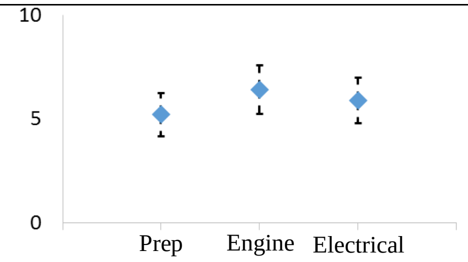
Figure 4. Representative data from a single trainee through SWOS Advanced Course.

Table 1 presents the mean and standard deviation of heart rate, EDA, and stress level from all 4 participants during preparation, engine fire, and electrical fire tasks within the Basic Course. Participants 1 and 2 had experienced firefighting training previously in addition to being more experienced as shown in Table 1, and as such their data is discussed separately from participants 3 and 4.

Participants 1 and 2 had an average increase in heart rate of 25.7 beats per minute (bpm) between the preparation and firefighting task, an average increase of 0.6 microsiemens (μS) EDA, and an average increase of 3.3 points on the stress scale. Participants 3 and 4, on the other hand, showed an average decrease in heart rate of 8.1 bpm, an average decrease of 2 μs EDA (Participant 3 only), and an average decrease of 1.4 points of stress level. The EDA for participant 4 was lost due to the sensors disconnecting as the SCBA tank straps slid on the participant's shoulders.

Table 1. Mean values of participants' heart rate, EDA, and Stress Level from the Basic Course

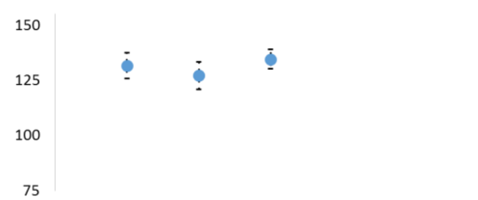
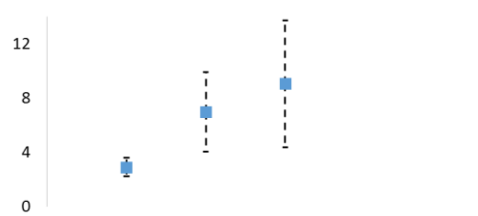
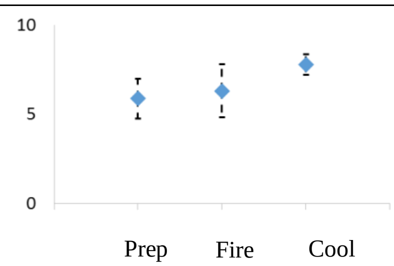
Metric	Participant (Baseline)	Preparation	Engine Fire	Electrical Fire	Plot – Group mean and standard deviation
Heart Rate (bpm)	1 (84.1)	106.4	123.4	122.3	
	2 (73.1)	87.4	122.9	122.1	
	3 (81.1)	131.6	132.7	122.6	
	4 (99.4)	111.8	100.9	98.4	

EDA (µS)	1 (0.9)	1.0	1.3	1.8	
	2 (1.0)	1.6	2.2	2.3	
	3 (0.9)	1.3	2.4	4.2	
	4 (--)	--	--	--	
Stress Level (0-10)	1	4.6	7.4	7.2	
	2	3.4	7.4	7.2	
	3	8.2	7.9	6.5	
	4	4.6	2.9	2.6	

*Because of low n, individual trainee data is shown on left side of table; graphs display mean and standard deviation values across observed task conditions. EDA displays electrodermal activity, which increases as stress increases, and stress level is displayed on a 0-10 scale, which has been set to a baseline of each individual.

Table 2 presents the means and standard deviations of heart rate, EDA, and stress level for 4 of the participants that completed the Advanced Course. The remaining 2 participants' data is not displayed here, as they were in charge of communication, and were not actively fighting any fires. The events of interest are segmented by Preparation, Firefighting tasks, and Cooldown. Note that physical activities were being performed (e.g., going upstairs in full PPE and dressing down) during Cooldown.

Table 2. Mean values of participants' heart rate, EDA, and Stress Level from the Advanced Course

Metric	Participant (Baseline)	Preparation	Fire- Task	Cooldown	Plot – Group mean and standard deviation
Heart Rate (bpm)	1 (108.4)	137.2	127.2	129.0	
	2 (108.3)	116.8	112.6	128.8	
	3 (109.4)	143.8	142.9	132.6	
	4 (90.3)	128.2	126.0	147.9	
EDA (µS)	1 (2.9)	3.0	4.9	5.7	
	2 (--)	--	--	3.1	
	3 (1.38)	4.2	13.6	23.0	
	4 (0.9)	1.5	2.4	4.4	
Stress Level (0-10)	1	8.0	9.0	8.5	
	2	5.2	4.0	7.2	
	3	7.2	8.8	9.0	
	4	3.0	3.5	6.5	

DHS

Figure 5 displays the HR, EDA and stress data of one trainee from a DHS stakeholder through a training event. This data is representative of the remaining participants. All participants went through the same scenarios in a different order. Four different scenarios are identified in the dataset (highlighted in yellow/orange). The stress level is reported on a scale from 0-10, with 0-2 Green (no stress) 3-6 Yellow (moderate stress) and 7-10 Orange (high stress). Participants exhibited an anticipatory stress response, showing an increase in stress level (lower graph) before the scenario begins, and then decreasing once the scenario begins.

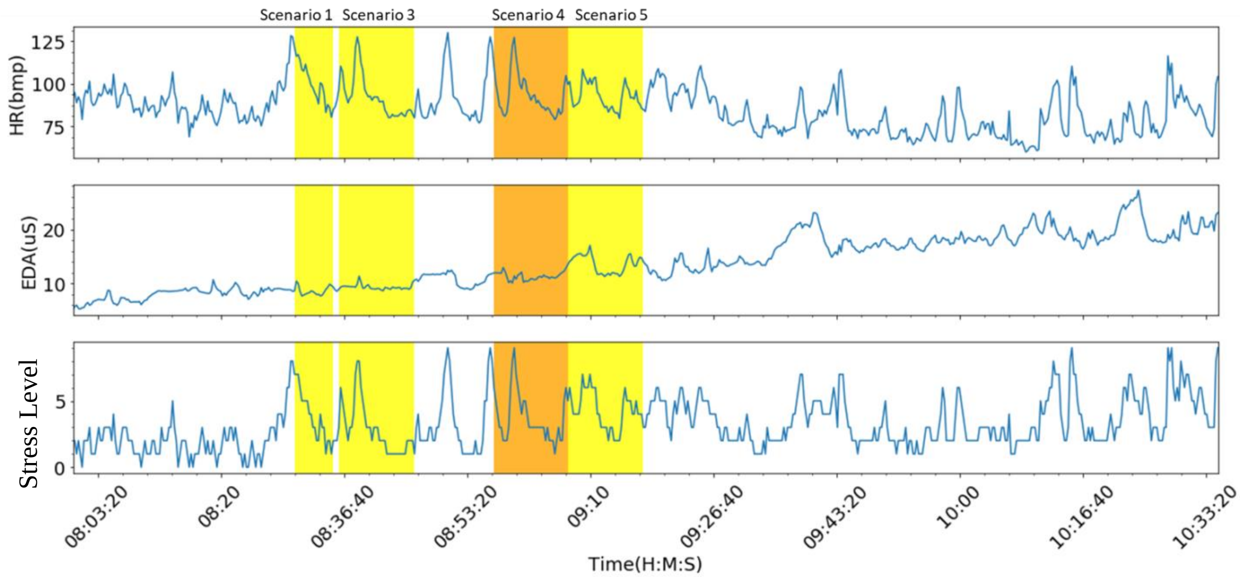


Figure 5. Data from DHS stakeholder throughout a training event.

DISCUSSION

Stress has the potential to degrade military performance and lead to long-term adverse medical outcomes. Real-time, physiological stress analysis should accompany training, to allow for insight into administering training that is realistic, and selecting trainees most prepared for the field.

The ruggedization procedures implemented demonstrated success in capturing physiological data within multiple extreme environments, all including high heat, humidity, and motion. The combination of new sensor modalities, new filtering techniques, and sensor redundancy allowed for the extraction of meaningful data from environments where PPG or unfiltered ECG would have had too much noise to effectively use the data to classify stress.

Across many of the participants, increased stress responses were observed during the time leading up to the actual scenario, which may indicate a stress response caused by anticipation of the activity that is about to be undertaken (see Figure 3). While all participants had at least some experience in their domain, none of the students were aware of what to expect during the training event. The stress level typically reduces once the scenario begins and the training knowledge takes over. Anticipatory stress is a common observation in EMS (Backé et al., 2009), firefighting (Robinson, Leach, Owen-Lynch, & Sünram-Lea, 2013), and military service (Friedman, 2006). Variable levels of stress were observed across trainees, likely due to a combination of expertise, time since last training or operational experience, and role in the training scenario. To account for individual differences, the data is baseline normalized to each individual difference in HR and EDA data across participants.

One of the goals of the initial investigations was to determine the technical feasibility of assessing individual stress during training from both a sensor and data science perspective. The extreme temperatures, humidity and excessive movement associated with field training exercises for the courses introduced challenges with respect to the sensor hardware, including hardware protection and hardware placement to maintain sensor integrity and to provide clean and complete data sets.

Results from this study demonstrate the capability to capture physiological data that can provide a validated indicator of stress within extreme environments used during military and DHS personnel training. Modifications were made and evaluated that included sensor modalities less prone to movement artifact, ruggedized hardware, and refined feature extraction for extreme environments, in able to support field data collection during existing training scenarios.

Further testing should include a thorough review of available sensors that are compatible with the domain (e.g., tasks such as full water immersion), as the marketplace is continuously expanding with mobile, wearable physiological sensors. Further, studies should be also conducted with increased sample size and more controlled scenarios to better understand the impact of specific training stressors that occur in the training environment, and the impact of training mitigations to address high stress. Finally, solutions to support real-time transmission of data in representative training environments that include cement buildings with multiple rooms and water submersion (limiting Bluetooth data transmission), and task conditions such as PPE, which could potentially interfere with the real-time transmission of data need to be explored. In the future, real-time data could facilitate adaptive training.

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