A biosensor solution for real-time and prognostic health monitoring

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ABSTRACT

Research indicates commercial-off-the-shelf biosensor data can be used to identify warfighter physical performance and casualty or injury status. Currently, the algorithms and frameworks required to process and house this data are in the research stage of development. There is an urgent need for a platform to aggregate this wealth of information into a single stream of actionable information that can be interpreted at a glance during high-stress situations. The objective of this work was to develop an open, extensible software architecture for fusing diverse biosensor data into a comprehensive warfighter health status assessment that runs on a mobile device using the Android Tactical Assault Kit (ATAK) enabling easy adoption by military end-users. The purpose of this software framework was to augment the existing warfighter location and movement data provided by ATAK with actionable insights on physiological stress level and casualty risk. A secondary objective was for the software to be sensor agnostic with the prototype set to automatically scan for generic skin temperature, pulse oximeter, heart rate, and inertial measurement sensors. In order to provide the actionable insights on physiological stress and injury risk, established biomechanics algorithms were incorporated which have been shown to correlate with increased risk of musculoskeletal injury, acute musculoskeletal injury, and potential traumatic brain injury. Physiological predictive capability was integrated using the open-source BioGears engine. BioGears runs faster than real-time on mobile devices, enabling prediction of future physiological status that could require medical care from exertion, temperature stress or altitude. Simulation outcomes were verified with military relevant situational data from literature, as well as an experimental data collection during a challenging ruck march in a laboratory heat chamber. All objectives were met. Comparison with literature and experimental data demonstrated that physiological state during a ruck march could be simulated and highlighted areas for improvement.

ABOUT THE AUTHORS

Dr. Paulien Roos leads the biomechanics research group at the BEM division of CFD Research. She has worked in the field of biomechanics, injury prevention/ prediction, and rehabilitation her entire career. She has led multiple successful programs looking at rehabilitation, injury prevention, and human performance. She was the PI on the Phase II SBIR project that forms the base of the presented work. She has experience bringing products developed under SBIR funds to market, through the startup TheraVista Health that she co-founded (with Dr. Pickle). She holds a PhD in biomechanics from the University of Bath (UK, 2007). She held postdoctoral and academic positions at the University of Texas at Austin and Cardiff University.

Dr. Nathan Pickle is a Group Leader and Senior Research Scientist at CFD Research Corporation. He received his Ph.D. in Mechanical Engineering from Colorado School of Mines in 2016 and completed postdoctoral training at the University of Texas at Dallas. Dr. Pickle is an expert in musculoskeletal modeling and simulation, scientific software development, digital human avatars, human performance and rehabilitation. Dr. Pickle has served as PI or Co-I on a number of SBIR awards aimed at developing novel tools and technologies using the science of biomechanics. He is a Co-Founder of TheraVista Health, a healthtech startup that turns physical therapy exercises into engaging games for older adults with dizziness. He was a Co-Investigator on the award which supported the work presented in this manuscript.

Mr. Josh Hogue is a software engineer at CFD Research. He has designed numerous solutions within the health and medical domain, notably including a cloud-based application tailored for customizing and executing simulations pertaining to lung function and pulmonary drug delivery. His expertise extends to user interface implementation for the automated scenario generation from images and videos for simulations of blast overpressure exposure on service members. Additionally, he architected a cloud-based health triaging platform and mobile apps aimed at facilitating seamless synchronization, dissemination, and visualization of health metrics among soldiers, squad leaders, and platoon sergeants.

Dr. JoEllen Sefton is the director of Auburn University's Warrior Research Center and the Neuromechanics Research Laboratory in the School of Kinesiology. She has an extensive research portfolio focused on improving human performance through research and applied knowledge across a wide range of populations. Sefton holds a bachelor's degree from Ohio University, a master's degree from Central Connecticut State University, and a PhD from the University of North Carolina at Charlotte.

Dr. Phillip Whitley is an experienced researcher with over 30 years of experience studying the human performance effects of extreme environments and developing methods of augmentation and mitigation. Dr. Whitley received his Ph.D. in Bioengineering from Clemson University in 1983. He has worked for the US Navy, in academia, as a government contractor and as a commercial consultant in the areas of physiological response measurement, simulation, warning and protection in adverse military environments and spinal injury causation and mitigation during head-supported mass combat operations, helicopter crash and pilot ejection. Dr. Whitley has been the PI for multiple SBIR Phase I, II and II.5 projects that address the protection needs of the warfighter. Dr. Whitley is a Fellow of the Aerospace Medical Association where he has received the Professional Excellence Award in 2008, the A. Howard Hasbrook Award for safety, survivability or crashworthiness in 2014 and the Stapp Award for aerospace injury biomechanics in 2018.

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BACKGROUND

There is an extensive suite of physiological sensors available to warfighters that can monitor their physiological status (Friedl, 2018; Sawka & Friedl, 2018). These sensors provide a wealth of information on their health status, including heart rate, breathing rate and skin temperature. Other measures such as core temperature, estimated energy expenditure, and risk of musculoskeletal injury (MSKI) cannot be directly measured and require analyses of sensor-data to be estimated. The recent proliferation of wearable sensors presents challenges in integration of different sensor technologies, combining various biometric measurements into a holistic view of overall health status, and presentation of data in a meaningful way that facilitates informed decision making (Friedl, 2018).

Extrapolating data from wearable sensors to provide insight into current health status or to predict future health status is challenging. A number of regression-based approaches have been developed to estimate metrics such as risk of hypo- or hyperthermia (Moran et al., 1998a, 1999a) or metabolic energy expenditure (Looney et al., 2019, 2022) using easily measurable signals such as heart rate and skin temperature. However, these equations are only valid for the input parameters (e.g., load carried, biological sex) and conditions (e.g., ambient temperature, terrain grade) under which the equations were developed and may not generalize to other conditions or individuals. An alternative to regression-based approaches is to leverage artificial intelligence (AI) techniques, such as machine learning (ML) to train an artificial neural network using vast amounts of data (James Jin Kang, 2021; Nikolaos Papadakis et al., 2023). Like regression-based approaches, AI methods are computationally fast once the neural network has been trained. In addition, AI approaches can incorporate diverse data streams for which empirical or first principles relationships are unknown. However, this strength is also a weakness, as the neural network is often a “black box”. The vast amount of training data required is also a limitation.

Physics-based computational simulation is a promising approach for integrating various streams of sensor data and addressing the limitations of regression- or AI-based approaches. Physiological simulation engines, such as the open-source softwares BioGears (Applied Research Associates, Inc.) and Pulse (Kitware, Inc.), represent the body as an interconnected system of modules (Bray et al., 2019). Sensor data can be used to validate and correct simulated values when available, and when sensor data are not available those metrics can be estimated using the simulation. Each individual physiological module (e.g., cardiovascular, respiratory) utilizes a physics-based lumped parameter model that is not tied to specific scenarios, such as amount of load carried. BioGears has been thoroughly validated with data from literature and experimental data for several different medical and exercise applications. Thus, a simulation-based approach has the potential to effectively generalize to novel real-world scenarios.

The objective of this project was to develop an open, extensible software architecture capable of fusing diverse biosensor data to generate a comprehensive biomechanical and physiological assessment of user health status (e.g., temperature stress, risk of musculoskeletal injury and mild traumatic brain injury). The goal of the open design of the software was to facilitate integration with various visualization tools as well as integration as a subsystem of other health monitoring platforms. Another goal was to use data visualization techniques to display health status so users can glance at a mobile device and quickly understand the location and movement of each member of a team, the level of physiological stress they are experiencing, and indicators of musculoskeletal injury risk. This study also aimed to develop a software platform for health status assessment that was sensor agnostic and extensible and also to perform initial verification of the physiological assessments using experimental data as well as data from literature. The goal was for the physiological simulations to predict increases in heart rate, breathing rate and core temperature that occur during exercise to be within 20% of experimental and published data. The comparison to experimental data was to evaluate the capability of the simulations of the physiological response to estimate personalized physiological responses. The experimental data were collected in a laboratory setting specifically for this study. The comparison to published data was to evaluate the capability of the simulations to estimate more generic physiological responses in real-world military relevant scenarios.

METHODS

Design of the system software platform

The software platform was developed as a plugin for the Android Tactical Assault Kit (ATAK). A custom ATAK widget was developed for displaying health status data to users. Separate standalone Android applications control sensor communications and BioGears. These applications run in separate processes from ATAK, and pass data to the ATAK widget for display. To the extent possible, the software was designed to be sensor and algorithm agnostic. A publisher/subscriber software architecture was implemented such that sensors were registered to supply certain data streams (e.g., heart rate or skin temperature) and algorithms can subscribe to the data streams they require as input. The prototype system was tested with a CoreTemp skin temperature sensor (CORE, Zürich, Switzerland), a Nonin pulse oximeter (Nonin 3230, Plymouth, MN), a Polar heart rate monitor (Polar Verity Sense; Polar, Kempele, Finland), and five inertial measurement units (IMU; Xsens DOT; Xsens, Enschede, The Netherlands). In order to make the software capable of operating on the edge (without network access), sensors were selected that provide connections directly via Bluetooth protocols and did not require access to sensor-specific user accounts or server-based applications.

Besides real-time monitoring, the system was capable of providing prognostics, because the simulations of physiological responses to exercise and environment could run faster than real-time on the software platform (McDaniel et al., 2019). Such insights enable advanced warnings that can give users the opportunity to take preventative measures. These preventative measures were left to the user's discretion but could include cooling or rest breaks for imminent heat stress, additional rest breaks or redistribution of load with increased risk or acute MSKI, or direct medical assessment with a potential mTBI. Physiological simulation engine requirements included the ability to be compiled for Android, run faster than real-time, and provide realistic physiological responses to exercise in military relevant scenarios. Two open-source engines exist; BioGears (by ARA) and Pulse (by Kitware) (Bray et al., 2019). These were compared to define which one performed best for simulating physiological responses in military relevant scenarios. Both originate from the same software; however differences exist. We initially performed a small comparison study simulating military relevant scenarios from literature with both software packages and compared their results. BioGears produced results more consistent with literature data.

The BioGears computational physiology engine was compiled for the Android operating system. The BioGears software is able to simulate a human model's (a soldier in this case) physiological response to exercise as well as environmental conditions (temperature, humidity, altitude, and clothing). Soldier characteristics (sex, height, weight, age, and type of clothing worn (clo value)), environmental conditions (temperature, humidity, and oxygen content (representative to altitude)), and exercise intensity were provided as inputs to the simulation. Subject characteristics were chosen as necessary for each of the sub-studies; they were either matched to data from literature, to experimental subjects, or to the user of the system. Exercise intensity was estimated using the Load Carriage Decision Aid (Grenier et al., 2012) and estimated VO2 max:

$$Estimated\ EI\ = \frac{0.4 * LCDA\ in\ Watts/kg}{15(220-\text{Age})/60)\ \text{x}\ 0.35} \qquad (1)$$

The Load Carriage Decision Aid used as input walking speed and incline that were calculated from position data tracked through ATAK, as well as the load carried, and sex provided as input data. Real-time weather and altitude data were obtained from ATAK. BioGears generated a detailed physiological state of the soldier, including heart rate, breathing rate, core temperature, and sweat rate. These were fed into algorithms to predict risk of heat and cold injury (Moran et al., 1998a, 1999a).

Biomechanics algorithms were integrated to identify increased risk of MSKI (Roos et al., 2014; Sheerin et al., 2019) and to identify acute musculoskeletal injury (Roos et al., 2014) or potential gait-indicated traumatic brain injury (Balasubramanian et al., 2015). These algorithms used lower limb angular velocities and body torso velocities calculated using the IMU data.

The system was designed to make decisions in the field, and health status determination logic and visual indicators were added to the system. Decision tree algorithms were developed to assess whether a sudden change in for example gait asymmetry was likely caused by the environment (e.g. terrain) or was indicative of potential injury. ATAK positional data and data from surrounding system users were used to inform these decision trees. The actionable insights used green (no critical alerts), amber (imminent (in the next 5 minutes) mission critical level), red indicators (current mission critical level). Alerts for heat stress and medical triage were based on existing methods used by the military. These were the physiological stress index (PSI) (Moran et al., 1998b), cold stress index (CSI) (Moran et al., 1999b), and the Simple Triage And Rapid Treatment (START) (Wendelken et al., 2003). The musculoskeletal and TBI injury risks were currently treated as not being critical alerts and exceeding the thresholds defined in the decision tree algorithms would result in a notification, not a green, amber, or red alert.

Hierarchical roles were used to determine the amount of data available to a user. The “Soldier” role viewed their own data, the ”Squad Leader” role viewed the status of all squad members, and data were aggregated at the squad level for the “Platoon Sergeant” role. For each of these views, the main view was a dashboard that shows the green, amber, and red status together with a map view and details on the type of critical alerts. For the squad and platoon view these are aggregated. The user can click through and view live sensor data and outcome parameters if desired. Communication between devices was performed using existing protocols so that the software is compatible with standard TAKServer instances. The ATAK cross-soldier communication was tested via visual positioning updates (seeing all soldiers in the same group on each other’s ATAK client). The synching of health status information between devices was demonstrated via emulating soldier yellow/red conditions and verifying that squad leaders and platoon sergeants would see those squad and platoon health changes within the customized system panel displayed on the right within the ATAK interface.

Experimental Evaluation of BioGears Simulations for Military Relevant Scenario

An experimental study was performed with one of its goals to evaluate the performance of the BioGears software to estimate heart rate, breathing rate, core temperature, and skin temperature during a military relevant task. Since our initial comparison of simulation data using the Pulse and BioGears engines already showed that BioGears performed better for military relevant scenarios, only BioGears was used here for comparison. The experimental study was a randomized cross-over trial and part of a larger study that was part of the overall funded project that this study falls under. A goal of this study was to verify whether the physiological response in military relevant exercise scenarios could be predicted with BioGears simulations. All participants provided informed consent and visited the laboratory at three separate occasions. The data included below is part of a larger study (in review).

Participants were nine healthy college aged, physically active individuals (5 males and 4 females), aged 19-35. The subject demographics were as follows, the mean age was 22.4 ± 4.5 years, the mean height 173.7 ± 7.5 cm, the mean weight 80.9 ± 13.9 kg, and the mean VO2 max 43.8 ± 10.6 mL/kg/min. The inclusion criteria were to be: 1) free of musculoskeletal injury; 2) comfortable carrying out exercise tasks at elevated temperatures; 3) agree to adhere to study requirements; and 4) able to pass a health screening. The exclusion criteria were: 1) to have a known medical physical or psychological condition preventing participation in exercise; 2) being in rehabilitation from recent musculoskeletal injury; 3) having been diagnosed with asthma, a history of heart condition, or high blood pressure; 4) experiencing pain in the chest at rest, during activities of daily living, or when performing physical activity or exercise; 5) having been prescribed medically supervised physical activity only by a primary care physician, or 6) being pregnant. Study protocols were approved by the local Institutional Review Board.

Baseline Testing

The height and weight of each participant was measured using a SECA scale and stadiometer (SECA, Hamburg, Germany). Age and sex were recorded. Resting physiology was measured using the Equivital EQ02+ LifeMonitor with the BlackGhost package (Equivital, Cambridge, United Kingdom) for heart rate, respiratory rate, skin temperature, and core temperature.

A standard Bruce protocol (Bruce, 1971) for treadmill graded exercise testing was performed to define maximal oxygen consumption (VO2 max). This was used to understand baseline aerobic fitness and to quantify relative intensity during the exercise protocols. The Bruce protocol involved incremental increases in speed and incline every three minutes after one warm-up stage. The warm-up stage began at 2.74 mph and 0% incline. For the first stage after the warm-up speed remained the same and incline was increased to 10%. Each subsequent stage involved a sequential increase in both speed and incline. Participants were asked to give their best effort and continue until they could not continue any longer. The test was terminated once participants reached volitional fatigue. VO2 max was determined as the maximal oxygen consumption achieved during the test.

Load Carriage Protocol

The load carriage protocol provided the data that were used to verify the BioGears simulations. Participants walked on a treadmill (ESPEC North America, Inc., Hudsonville, MI, USA) until exhaustion or for 40 minutes maximum. Speed of the treadmill was set at three miles per hour and incline of the treadmill was varied according to a set schedule and elevations in an environmental chamber set to 26.7°C (80°F) at 50% relative humidity. The testing protocol began with a warm-up at 2.5% incline for three minutes. Stage 1 involved walking for three minutes at a 2.5% incline, followed by seven minutes at a 7% incline. Stage 2 included three minutes at a 2.5% incline, followed by seven minutes at a 10 % incline. Stage 3 involved three minutes at a 2.5% incline, followed by seven minutes at a 12 % incline. Finally Stage 4 included three minutes at a 2.5% incline, followed by seven minutes at a 14 % incline. The protocol was terminated when participants reached a core temperature of 38.9°C, reached exhaustion, or indicated that they wanted to stop. Participants wore an Army Combat Uniform (blouse and pants), military boots adapted, and a rucksack weighted with a load equal to 30 percent of the participants body weight.

During both the VO2 max testing and the load carriage protocol ventilation and expired gases were measured using the ParvoMedics True One 2400 metabolic cart (ParvoMedics Inc. Salt Lake City, UT, USA). The metabolic cart measurements include oxygen consumption (VO2), kilocalories (kcals), and Metabolic Equivalents (METs). The gas analyzer was calibrated for volume (Hans Rudolph Series 5530 3L syringe; Shawnee, KS, USA) and gas composition (16% O2 and 4% CO2) prior to each participant testing session. Participants were fitted with a head gear, mouthpiece, and nose clip (Hans Rudolph, Inc.; Shawnee, KS, USA) for oxygen measurements. During performance heart rate and skin temperature were monitored continuously via the Equivital EQ02+ LifeMonitor and Black Ghost Software (Hidalgo, Cambridge, UK). The Equivital software provides regression equation-based estimates of core temperature.

Simulations

The protocol exercise stage parameters were used to calculate a BioGears exercise intensity (EI) with the Load Carriage Decision Aid methodology developed for BioGears (Equation (1)). The EI was used to simulate the level of exertion over the prescribed duration. Physiological simulations were run using BioGears (version 7.5.0) using the command line interface with individual parameters specified in an XML file as required by BioGears. The predicted data for heart rate (HR), respiratory rate (RR), skin temperature, and core temperature were extracted and compared to the Equivital subject data collected during the load carriage protocol.

Demonstration of software – long duration march simulation

After verification of the BioGears simulations with the experimental data for a military relevant protocol, a test case was conducted to examine response during a long duration march. This was purely a virtual exercise, since no experimental data were available for verification. The Pikes Peak Highway was chosen for demonstration purposes. It is a well-documented route, is easily identifiable on maps, and provides challenging environmental changes (temperature and altitude) for testing the physiology simulations. Male and female soldier ruck marching responses while wearing 0, 30, and 40% of body weight loads were modeled in BioGears.

The elevation and distance of the Pikes Peak Highway was derived from the Strava website data (https://www.strava.com) for the cycling route. The distance-elevation plot from this dataset was digitized using DigtizeIt (Version 1.5.7) to obtain discrete points. Since BioGears can run exercise simulations using duration, these discreet points were used, as digitized, to calculate the duration and exercise intensity for the soldier using the previously described method for determined EI using VO2 max from LCDA MEE calculations. The grade for the LCDA calculation was determined from the distance and elevation data.

Two different subjects were simulated. A 19-year-old male subject of 77.1 kg body mass, 1.80 m height, and a 19-year-old female with a body mass of 59.0 kg and height of 1.63 m. Both models had a baseline heart rate of 72 beats per minute and a baseline respiratory rate of 16 breathes per minute.

Marching speed was specified by consulting the US Army Infantry Small-Unit Mountain Operations Tactics, Techniques and Procedures (ATTP 3-21.50, Table 5-3 Dismounted Movement Rates, 28 February 2011), which indicates the marching speed for elevated terrain is between 0.55 and 0.8 m/s. The upper bound of 0.8 m/s was selected for use in the simulations. After every 50 minutes of marching a 10-minute rest period was inserted into the simulation, where rest was defined as an EI of zero.

The march started at an altitude of 2,143 m and ascended to 4,300 m for this march, thus the atmospheric pressure was changed with elevation using the atmospheric pressure-elevation relationship (https://www.engineeringtoolbox.com/air-altitude-pressure-d_462.html):

$$p = 7.5 \times 10^{-3}[1.01 \times 10^{5}(1.0 - 2.26 \times 10^{-5}h)^{5.25}] \qquad (2)$$

where h is the elevation in meters and p is the atmospheric pressure in mmHg.

Environmental temperature also changes during ascent. A temperature drop of 22.9°C is the average change from the base to the peak altitude. An initial temperature of 22°C at the starting point was arbitrarily used and was decreased in an arbitrary linear fashion with elevation to 5.4°C at the peak. A delimited file was created containing EI, atmospheric pressure, duration, and environmental temperature which varied based on the distance-elevation data. The clothing value for the event was set to 1 CLO.

RESULTS

The system software platform

Figure 1. The different views in the system's ATAK app.

A proof-of-concept system was developed with information displays shown in Figure 1. The figure shows an individual user view with their sensor data and their squad members in a map view, a squad leader specific view to see data on all squad members with warnings when squad members had amber or red alert messages, and a platoon leader view, to see an overview of the different squads in the platoons. Which were color coded for alerts where a number indicated the number of squad members displaying an amber or red alert. Leaders could drill down to the individual users and could also see positional data on a map view. Since critical alerts could not be tested in real-world scenarios, the algorithms that were used to generate the critical alerts were tested with emulated scenarios. In these emulated scenarios, sensor data were generated that should result in critical or imminent critical conditions. All alerts were displayed as would be expected from the sensor data.

Experimental Evaluation of BioGears Simulations for Military Relevant Scenario

A comparison of the predicted versus subject data of the experimental study in the heat chamber are shown in Figure 2 for one subject (P003) as indicative of the typical response.

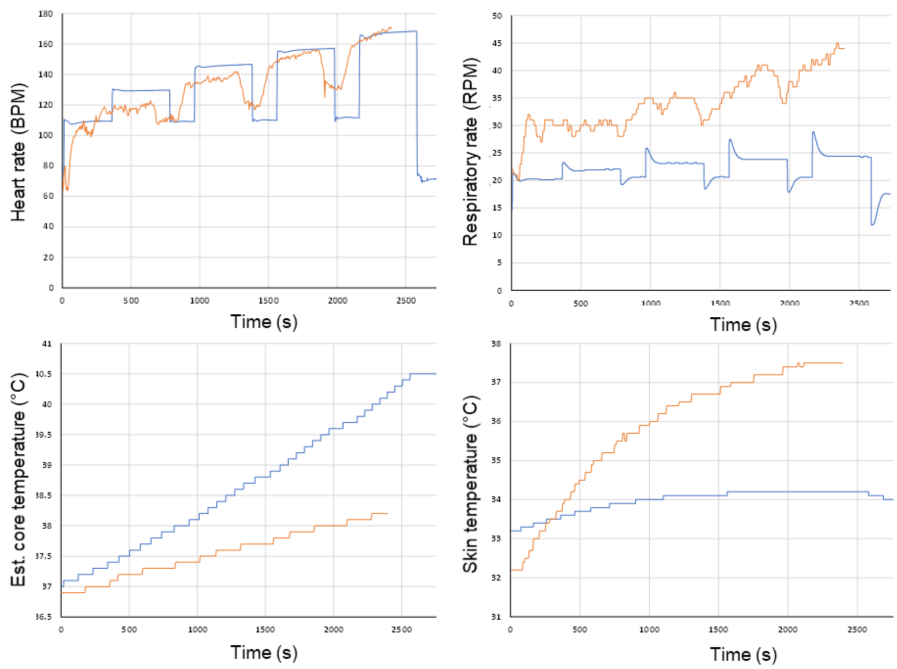

Figure 2. Example Comparison of BioGears simulation (in blue) results to Subject P003 response (in orange).

Table 1. The level of agreement between the BioGears simulation results and the experimental data, with in the left column different ranges for the percentage differences. The table shows the percentage of simulations for which the difference was within each range, for heart rate, respiratory rate, skin temperature, and estimated core temperature.

	Heart Rate (BPM)	Respiration Rate (RPM)	Skin Temperature (°C)	Est Core Temperature (°C)
<10%	47%	19%	96%	100%
10-20%	11%	23%	4%	0%
20-30%	23%	11%	0%	0%
>30%	19%	47%	0%	0%

To assess the level of agreement between the BioGears and experimental results, a process was developed to compare the average value for each physiological measure to the predicted physiological measurement during the specific exercise stage (excluding any resting and warm up phases). The level of agreement was determined by modifying the method used by BioGears. BioGears uses a color-coding system to describe the level of agreement of their simulation results with the published experimental results. The color-coding system is made up of green indicating a less than

10% error, yellow indicating a less than 30% error, and red indicating a greater than 30% error. For this work these levels were expanded to be in increment of 10% such that 0-10%, >10 and <= 20%, >20 and <=30%, and > 30% comprised the ranges of percent difference with the experimental data. Table 1 shows the level of agreement between the BioGears simulation results and the experimental data. Approximately half of the average exercise stage heart rate predictions were within 10%. The converse was observed for the respiratory rate predictions of which about half were over 30% different.

Demonstration of software – long duration march simulation

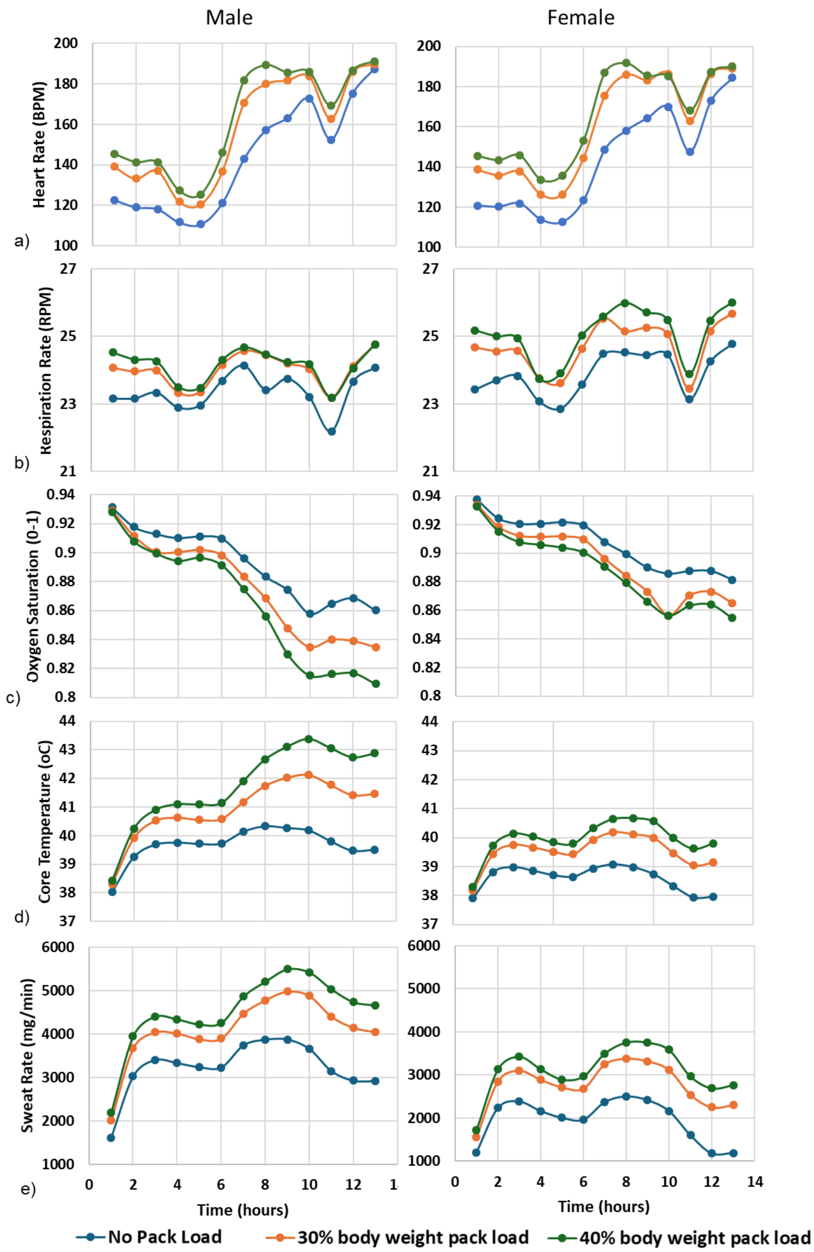

Figure 3. Male (left) and female (right) heart rate (a), respiratory rate (b), oxygen saturation (c), core temperature (d), and sweat rate (e) predicted response for the different loading conditions (blue: zero pack load, orange: 30% body weight pack load, and green: 40% body weight pack load). Data points show the average of the work (ruck marching) period of each hour to improve clarity of the plots.

The simulation results are shown for the male and female simulation subjects over the Pikes Peak Road course and the changing altitude and temperature conditions with ascent. Since there are no measured data for comparison, the relative effects of increase loading and terrain with environmental conditions are observed for anticipated physiological response.

For the male results, as expected, heart rate and respiratory rate increase with increased pack load and terrain-altitude difficulty with the relative difference between 30% and 40% body weight pack loads being appropriately different but small (Figure 3 a and b). The HR reaches a maximum for the loaded cases at 8.3-9.7 hours with a decrease around 11 hours and return to maximum to the end. The large transient transitions in both predicted measures comes from the rest periods and the physiological model control system.

Blood oxygen saturation decreased with increasing pack load and terrain-altitude difficulty (Figure 3 c). For altitude alone exposures the reported oxygen saturation is 0.83 at 4,300m with the loaded Pikes Peak march between 0.85-0.88 at that altitude.

With increased loading and march difficulty the core temperature increases in response to the work produced and sweat rate increases to help control body temperature (Figure 3 d and e). At the higher altitudes core temperature declines again.

For the female results, heart rate and respiratory rate increase with increased pack load and terrain-altitude difficulty with the relative difference between 30% and 40% body weight pack loads being appropriately different but small (Figure 3 a and b). Heart rate reaches a maximum for the loaded cases by 8.3 hrs. through to the end.

Blood oxygen saturation decreases with increasing pack load and terrain-altitude difficulty (Figure 3 c). The relative differences in pack load conditions appear appropriately expected.

For the female results, increased loading and march difficulty results in increased core temperature and sweat rate (Figure 3 d and e).

Figure 4 shows an arbitrary notional 3-state scheme using a Go-Warning-Attention, green-yellow-red, paradigm. A “Go” state was determine for heart rate < 190 BPM and SpO2 > 85%. A “Warning” state was determined for heart rate ≥ 190 BPM and SpO2 > 85%. An “Attention” state was determined for SpO2 ≤ 85%. The state level was incremented one level, not exceeding level 3, for Core Temperature > 39^{o}C. Areas of apparent overlap are indications of dithering about two states. While the male simulation subject starts in the “green”, the core temperature crosses the threshold in one hour increasing the state to “yellow” whereupon HR and/or SpO2 thresholds are exceeded to the “Attention” state. While the female simulation subject’s cardio-respiratory responses were similar to the male responses, the female core temperature in the no-load simulation transiently rose above the threshold and then retreated to just below that threshold until 6.8 hours where, exceeding the threshold, the state shifted to “Warning”. In the loaded female simulations, the same interplays of heart rate, SpO2 and core temperature caused state changes.

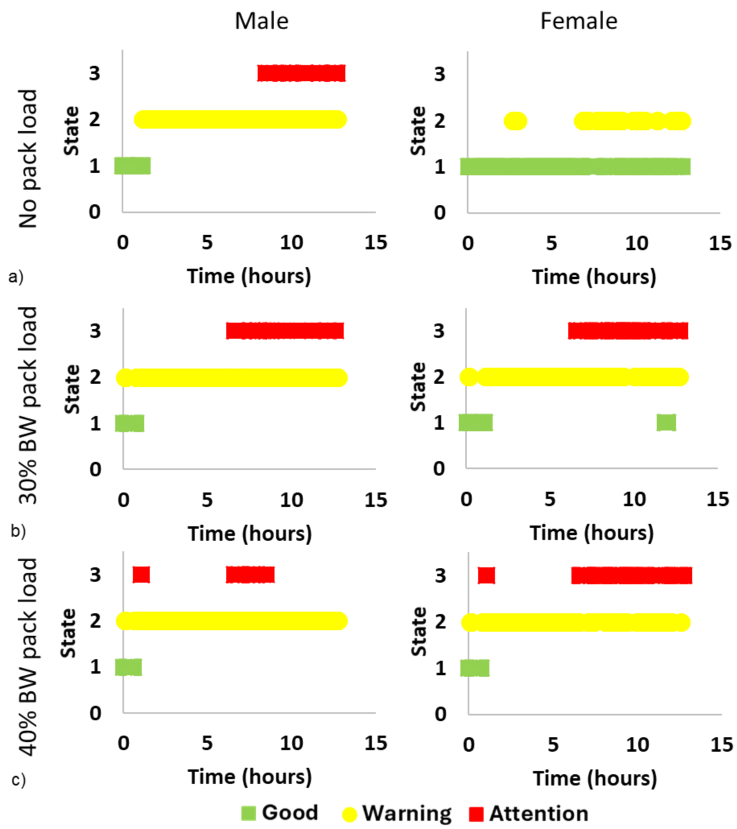

Figure 4. Male (left) and female (right) state (green: good, yellow: warning, and red: attention) for a simulated Pikes Peak march with no, 30% body weight, and 40% body weight pack load.

DISCUSSION

A software platform has been developed that uses prognostic simulation and algorithms to provide clear actionable insights and advanced warnings on mission critical conditions. The software platform was capable of triaging actionable insights with customizable triage levels which allows warfighters to clearly communicate mission critical information to those that need to take preventative action providing them with a comprehensive biomechanical and physiological assessment of user health status of the warfighter in need of medical care. This software has an open, extensible software architecture and is sensor agnostic.

Verification of the BioGears simulations for a military relevant marching scenario indicated heart rate was predicted within 10% for approximately half of the exercise stage. Heart rate tended to visually agree well with experimental data, with some minor synchronization issues. The predicted heart rate responses were more abrupt than the observed physiological response. The respiratory rate comparison revealed a definite lack of agreement between the predicted and measured data with errors that were mostly over 30% (see Table 1). While the predicted respiratory rate did increase in response exercise, the high levels of experimental respiratory rate were not exhibited. The BioGears respiratory rate's initial response was similar to experimental data but deviated after. Further research is needed to better understand the control mechanisms behind this.

The skin temperature response differed between experimental and simulation data (Figure 2). This difference could be due to the difference in measurement site for the experimental data and the BioGears computational summation of temperature nodes. Therefore, these results may not be directly comparable. The experimental core temperature was estimated by regression equations in the Equivital software and compared to the predicted core temperature. The predicted core temperature rose faster and higher than the experimental data. An interesting effect was seen observing the skin and core temperature responses. The experimental response showed a rising skin temperature with a core temperature within limits exhibiting a degree of temperature control. The BioGears skin temperature did not rise to a comparable level to experimental skin temperature while the core temperature did rise to a high level perhaps indicating a lack of temperature control to dissipate heat to the environment. However, at 26.7°C and 80% relative humidity, heat transfer may be limited.

The overall percent differences were however mostly small (<10%; Table 1). Interestingly, the skin temperatures were generally less than 10% different than the experimental data and the core temperatures less than 5% different. This meant that our hypothesis that the simulations could predict physiological responses during exercise within 20% of experimental data was accepted. However, small differences in core temperature have great consequences. For example, the percentage difference between a normal core temperature of 37°C and a danger core temperature of 39°C is 5.4%.

After verification of the BioGears simulations for military relevant scenarios with experimental data, simulations were performed of a long duration march (Pikes Peak) with male and female models. For both the male and female models heart rate and respiratory rate increased with peak load and terrain-altitude difficulty. Respiration may not be as responsive as human response data would indicate. As expected, blood oxygen saturation decreases with altitude. Present in the female predictions were spikes corresponding to some rest periods during the early part of the march for the 40% BW load and in the later part of the march for the 30% BW loads. A definitive explanation for these responses is not apparent since this response does not appear in the male results.

As expected with increased loading and march difficulty the core temperature increased in response to the work produced and sweat rate increases to help control body temperature. Interestingly these increases were seen in the presence of decreasing environmental temperatures. For the male model, the core temperature exceeded the 39°C danger threshold by the first hour for all simulation cases but the female model lagged crossing for several hours in the unloaded case but crossed similarly to the male for the loaded cases. Sex differences in core temperature response during repeated exercise in the heat have been reported (Anderson et al., 2022).

A notional 3-state system applied to the Pikes Peak results highlighted the potential of turning complex physiological data into actionable insights in the field. While the state approach used simple thresholding, more work is needed to optimize the state approach using more advanced means of classification in addition to machine learning based on individual and population data.

Verification focused on physiological simulations and software platform performance. Future work is needed to demonstrate the efficacy of the algorithms for injury in military settings. The algorithms that were used have been shown to indicate injury in lab settings only to date.

In conclusion, this study developed a modular, extensible software tool to aggregate sensor data. A computational physiology engine (BioGears) was compiled to run on Android. It ran faster than real-time (over 3 times faster) allowing prognostic insights. Analysis and decision-making algorithms were implemented and developed to convert measured sensor data into meaningful health status diagnostic assessments that could directly inform decision making. Algorithms that had been demonstrated in a laboratory environment were leveraged. A visual display was developed that displays the health status to a user. This was designed so that health status could be understood at-a-glance. In future, additional tuning of the models with military relevant data is required to better predict respiratory rate and core temperature responses. Because of the open and modular software architecture and its sensor agnostic nature, the system can be expanded with novel sensors and algorithms as they become available and stay up to date with the state-of-the-art. Ultimately, the system will provide commanders with the ability to monitor the status of their team using a mobile device to track the location and movement of each team member, as well as physiological stress, and risk of musculoskeletal injury, and TBI. The ability to make real-time decisions with this level of information will increase effectiveness, reduce injury, and save lives.

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