Leveraging knowledge from physiological data: on-body heat stress risk prediction with sensor networks

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Elena Gaura, John Kemp, James Brusey

***Abstract*—The paper demonstrates that wearable sensor systems, coupled with real-time on-body processing and actuation, can enhance safety for wearers of heavy protective equipment who are subjected to harsh thermal environments by reducing risk of Uncompensable Heat Stress (UHS). The work focuses on Explosive Ordnance Disposal operatives and shows that predictions of UHS risk can be performed in real-time with sufficient accuracy for real-world use. Furthermore, it is shown that the required sensory input for such algorithms can be obtained with wearable, non-intrusive sensors. Two algorithms, one based on Bayesian nets and another on decision trees, are presented for determining the heat stress risk, considering the mean skin temperature prediction as a proxy. The algorithms are trained on empirical data and have accuracies of 92.1±2.9% and 94.4±2.1%, respectively when tested using leave-one-subject-out cross-validation. In applications such as Explosive Ordnance Disposal operative monitoring, such prediction algorithms can enable autonomous actuation of cooling systems and haptic alerts to minimise casualties.**

I. Introduction

Uncompensable Heat Stress (UHS) is a dangerous and potentially fatal physiological state that occurs when the cooling required to maintain a steady thermal state is greater than the cooling capability of the environment [1]. A concept related to heat stress is that of heat storage. This is generally modelled using heat balance equations [2] based on the heat production within the body, heat loss via the skin, and heat loss via respiration. Heat storage occurs when the heat produced by the body is greater than the heat lost to the environment—the condition of UHS implies that stored heat is increasing.

UHS is a significant risk for human subjects exposed to hot environments while wearing protective equipment, as demonstrated for example by Jang *et al.* [3], who investigated heat stress in relation to soldiers in hot climates. Wearers of Explosive Ordnance Disposal (EOD) suits are particularly at risk during missions or training, as confirmed by a number of studies that investigated the onset of UHS in bomb disposal operatives [1], [4]. Gunga *et al.* [5] report on the frequency of heat stress incidents in bomb disposal operatives as well as documenting the rapid changes in the core body temperature and its potential to reach harmful levels. EOD suits (as shown for example in Figure 1) are heavy (for this example, 40 kg in total), enclosed, and thermally insulating, and are commonly used in hot climates. Moreover, during missions, operatives tend to exert themselves (walking, carrying equipment, or moving through and around obstacles). Solutions for reducing the risk of UHS in EOD missions are thus required.

Figure 1. Examples of a subject performing activities while wearing an EOD suit.

In response, several types of personal cooling systems (in the form of additional garments) have been proposed by protective equipment manufacturers. While such systems have been shown to be somewhat effective [6], [7], none presents a full solution for preventing the onset of UHS. One of the major UK EOD suit manufacturers (NP Aerospace Ltd, the industrial collaborator in the research here) proposed the use of a suit-integrated cooling system, based on a dry ice pack and battery-powered fans which circulate cool air into the suit. When the cooling was applied during mission like protocols, it effectively maintained the mean skin temperature levels within safe ranges, as further evidenced in Section V. However, this cooling system i) requires manual operation, which may be either forgotten or used sub-optimally by operatives and ii) has limited battery life. Thus, it would be desirable to have means of automating cooling to maximise its beneficial effect while also ensuring availability of cooling over lengthy missions. Considering the problem space, cooling optimisation and control can be realised by predicting UHS risk in real-time. This paper demonstrates that such predictions can be performed with sufficient accuracy for real-world use.

Empirical knowledge of the causal links between physiological phenomena, thermal discomfort, and heat stress is required in order to develop appropriate models and algorithms. In this work, such knowledge was drawn from experimental data from a number of subjects performing mission like protocols while their posture, heart rate, pulse, multi-point skin temperatures, core temperature and helmet CO2 were monitored. Based on the links found, Bayesian models appear to be capable of predicting risk. Alternatively, C4.5 decision trees can be used to predict danger without establishing an explicit model. Several non-intrusive sensing modalities have been identified by the authors as key to UHS prediction: mean skin temperature data calculated from four body locations, postural information (as can be inferred from two accelerometers), applied cooling, and ambient temperature. Leave-one-subject-out-cross validation was used to evaluate the predictor.

The central contribution of this paper is to demonstrate that real-time machine learnt prediction of UHS risk is viable with non-intrusive sensors. To our knowledge, this is the first work to produce a wearable system that can predict UHS risk on-body, in real-time.

The algorithms presented in this paper have been tuned for the specific physiological profile exhibited by EOD operatives during missions. However, the method is applicable to other scenarios. For those, tuning of the models will be required on the basis of appropriate empirical data.

The authors argue, thus, that wearable, non-intrusive sensor systems and subsequent real-time on-body UHS risk prediction could:

- further increase EOD operatives safety when integrated with personal fan operated cooling systems, by enabling optimal delivery of cooling;
- minimise mission casualties by enabling i) proactive changes to the mission, and ii) haptic alerts to the wearer based on the predicted risk.

The remainder of this paper is structured as follows: Section II presents related work in the areas of physiological strain estimation and wearable monitoring systems for military applications. Section III briefly describes the support system for the sensory data acquisition, UHS risk prediction and communications. Section IV details the data gathering protocols and resulting data sets used in developing the predictors. Section V establishes appropriate parameters for use in prediction. Section VI presents the Bayesian predictor as well as its evaluation and comparison with a decision tree predictor also developed by the authors. Finally, Section VII concludes the paper.

II. Related work

The goal of the work presented in this paper is to predict heat stress risk on-body and in real-time, to alert the user or to allow a cooling system to act pre-emptively rather than reactively. Furthermore, in order to be practical in the EOD suit, this prediction should only require input parameters that can be monitored (in real-time) using non-invasive wearable sensors.

To the authors' knowledge, no similar systems have been reported to date. However, research efforts have been individually directed at i) gaining an understanding of physiological strain and the production of off-line models and ii) developing and deploying wearable physiological monitoring systems in military applications. The two strands of work, reviewed below, have been supported by distinct research specialisms: physiologists and computer scientists/engineers, respectively.

The identified research gap is thus with the integration of the findings in the two domains and the shift i) from sense-and-send, data driven monitoring systems to wearable real-time knowledge generators, and ii) from off-line modelling and estimation of heat strain to prediction of future strain and associated risk.

A. Non-invasive estimation of physiological strain

A number of research works assess the heat stress phenomena related to operatives working in hot, harsh environments and/or wearing protective suits [3], [8]. Fewer works however attempted the modelling of thermal physiological strain. Two models have inspired the work in this paper and are discussed below.

Buller *et al.* [9] present a method of calculating physiological strain using skin temperature and heart rate. This method was evaluated in conjunction with the Physiological Strain Index (PSI). PSI uses core temperature and heart rate, and was developed previously by Moran *et al.* [10]. Buller's aim was to provide a method of determining the risk of heat strain in civilian and military first responders via non-invasive sensors. PSI is calculated as,

$$5\frac{T_{core(t)} - T_{core(0)}}{39.5 - T_{core(0)}} + 5\frac{\mathrm{HR}_{(t)} - \mathrm{HR}_{(0)}}{180 - \mathrm{HR}_{(0)}},$$

with the risk threshold (for the purpose of determining accuracy of the new method) being a rating of 7.5. Resting core temperature and heart rate were assumed to be 37.12 ℃ and 71 beats/min based on prior work [10]. Using the skin temperature based model, classification was performed with up to 87.8% accuracy when using PSI as the baseline. This preference for non-invasive sensors (even if it causes a loss in accuracy) is an important element in designing a system that can be developed into a successful product—invasive sensors, such as for core temperature, tend to make users uncomfortable and increase the time required for deployment, both of which factors are counterproductive in emergency situations. The work here, similarly, focuses on the use of parameters that can be monitored using non-invasive sensors.

Furthermore, Buller *et al.* [11] present a method of estimating core temperature based on heart rate. Their method employs a Kalman filter, treating the heart rate data as noisy observations of the core temperature state. The aim was to produce a model that was simpler than the existing heat transfer models and would thus be more suitable for field deployment. The model was tested using data from three other studies encompassing both laboratory and field experimentation, with temperatures of between 20 °C and 40 °C, low to moderate work rates, and durations of between 2 and 8 hours. The overall root mean square error of the developed model was 0.30±0.13 °C, with over 85% of all estimated core temperature values being within 0.5 °C of the observed value.

B. *Wearable monitoring systems*

A wide variety of wearable physiological monitoring systems have been reported in the literature, targeted at first responders, military personnel and other workers exposed to harsh environments. The Smart Vest presented by Pandian *et al.* [12], [13], for example, includes wireless sensors for monitoring a variety of physiological parameters: ECG, heart rate, blood pressure, body temperature, galvanic skin response, blood oxygenation, respiratory rate, EMG, and movement. Another example is the LifeGuard system, presented by Mundt *et al.* [14], intended as a general solution for monitoring of astronauts, soldiers, firefighters and first responders. It includes sensing of: acceleration; ambient, skin, and core temperature; ECG and respiration; blood oxygenation; and systolic and diastolic blood pressure. Heart rate is derived from the ECG output. Finally, the LifeShirt by VivoMetrics is a commercial product designed for the purpose of monitoring personnel carrying out missions in dangerous environments. The LifeShirt is aimed at personnel engaged in firefighting, hazardous materials training, emergency response, industrial cleaning using protective gear, and bio-hazard-related occupational work. The sensors, embedded in a chest strap, monitor the subject's breathing rate, heart rate, activity level, posture, and single point skin temperature.

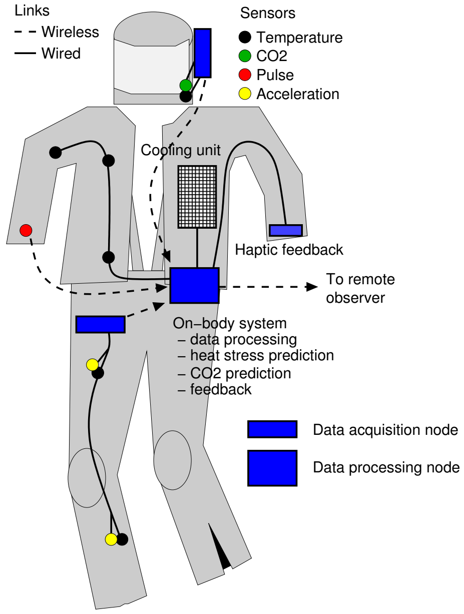

Figure 2. Overview of on-body system supporting the heat stress prediction algorithm.

More generically, within the health care application domain, intensive efforts are expended to produce reliable physiological data acquisition and wireless transmission systems aiming at low cost and increased reliability [15], [16] as well as increased wearability for long-term monitoring [17].

The systems above share a common design feature: they are generally implemented as data gathering and reporting systems—that is, they gather data from the sensors and report the values to a base station. The fundamental difference in the work presented here is that the UHS risk prediction algorithm is intended to be integrated with an on-body system, moving beyond a "sense and send" style of system to provide in-network information extraction and thus to enable autonomous actuation of safety systems, such as suit-integrated cooling. Furthermore, the system aimed at in this work reports high-level information, to a remote observer and/or the wearer, to aid their decision making.

III. Target system

The body sensor network system concept for supporting the heat stress risk prediction algorithm presented in this paper is shown in Figure 2 (based on previous work [18]). Note that i) the concept system is integrative of additional functions such as real-time CO2 levels control in the helmet; ii) subsystems delivering various functions of the integrative concept have been previously published by the authors and are referred to below. In the main, the concept relies on: i) sensors acquiring data; ii) nodes processing and transmitting data/information/actuation commands within the system, and iii) models/algorithms (such as the hear stress risk prediction which is the subject of this paper) held on specific nodes extracting information and knowledge from the data and issuing feedback (within and without the system) and actuation to integrated fans.

Sensors integrated into the protective clothing have a wired connection to the three wireless system nodes, with one node serving each "segment" of the protective suit—helmet, jacket, and trousers. Two of the three nodes (Data acquisition nodes situated in the helmet and trousers) are responsible only for gathering data, performing data checks and filtering, and then wirelessly transmitting the data to the third node (Data processing node situated in the jacket). The Data processing node, in addition to gathering data from the attached sensors, is responsible for: i) inferring postural information from acceleration data; ii) inferring knowledge from the sensory data and postural information and relaying this knowledge to the operator and the remote observer, and iii) issuing actuation commands to the cooling unit. The knowledge envisaged to be delivered by the system in the EOD scenario is as follows: i) predicted heat stress risk, ii) helmet CO_2 level alerts. Differential (helmet and jacket respectively) fan actuation is envisaged for i) regulating the CO2 levels in the helmet, and ii) alleviating the risk of heat stress. Feedback is provided to the operative via haptic mechanisms and additionally, to a remote observer via remote visualisation software. In both cases, the feedback provides a warning that heat stress will begin to occur in the near future or that CO_2 levels in the helmet are exceeding safety thresholds. Gaura *et al.* [18] provides further details (including pictures of sensors) on the prototype implementation of a system such as the above, considering a number of practical requirements imposed by the EOD application. Details of design, implementation and performance for the posture classification system are given in [19], and the CO2 levels modelling and regulation are described in [20]. The modular system concept allows for functional subsets to be implemented as required by various applications; for example if only heat stress risk prediction is of interest, the helmet node and associated sensing and precessing/actuation do not need to be included.

When supported by an on-body system such as the one described, the UHS risk prediction algorithm proposed here is real-time in the sense that it can reliably produce a prediction and haptic warning within less than a second thus enabling timely response by the wearer, remote observer, and / or cooling system. This time guarantee is partly based on the $O(1)$ complexity of both Bayes Net and Decision Tree predictors in terms of the input parameters and partly on performance trials on a Gumstix embedded processor, which executed them in 8 ms and 0.8 ms, respectively. (Note that the set prediction period considered here is two minutes, whilst the data acquisition rate is 1 Hz.)

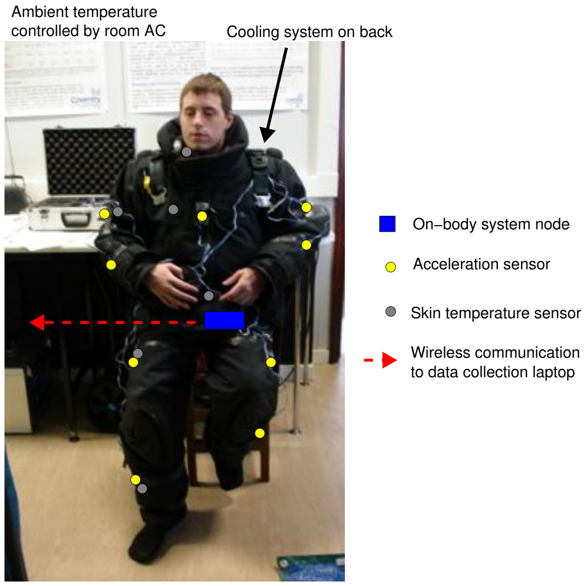

Figure 3. Prototype system being used to gather experimental data.

Table I
Experimental conditions.

Ambient temperature	Cooling type	Total trials
20	NC	8
20	HC	9
20	CC	9
40	NC	10
40	HC	8
40	CC	8

Figure 3 shows a prototype implementation based on the above concept. The prototype was widely used to support the authors' research on the physiological and microclimate phenomena within an EOD suit. The data gathered using the specific prototype shown has been used in other work (Gaura *et al.* [18] and Brusey *et al.* [19]).

IV. Data gathering protocol

The training and testing of the algorithm implemented here was based on experimentally gathered physiological data. The experimental protocol imitated aspects of an EOD mission in order to maximise validity for the case study application.

Data from a total of 52 trials was used [21], [22]. In these trials, twelve male subjects (heights 169–176 cm, weights 67–91 kg, ages 18–40) underwent a mission-like protocol while wearing the EOD suit at ambient temperatures of 20 °C and 40 °C. Three different in-suit cooling variations were used—no cooling (NC), chest cooling (CC), and head cooling (HC). Each subject performed one trial with

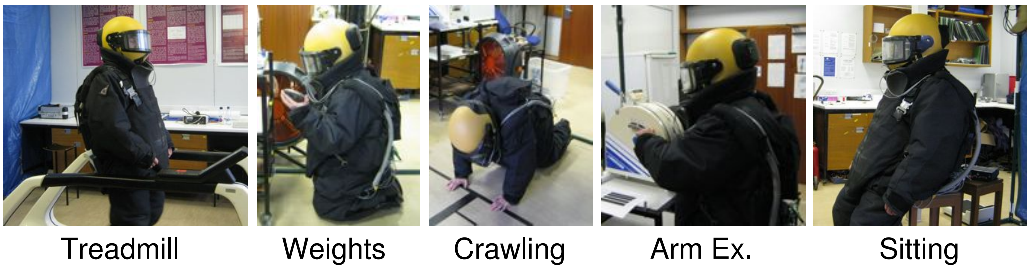

Figure 4. Activities performed during data gathering experimentation.

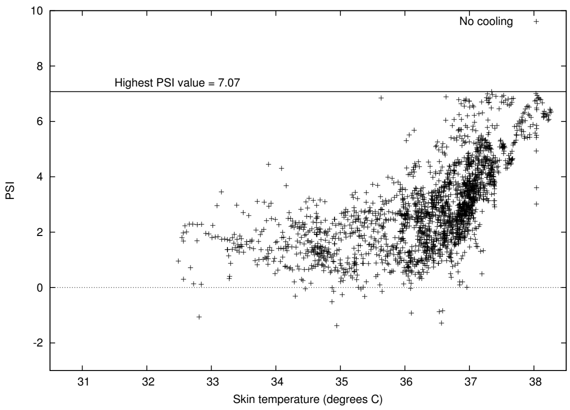

Figure 5. PSI versus skin temperature over the course of the experimental trials performed here.

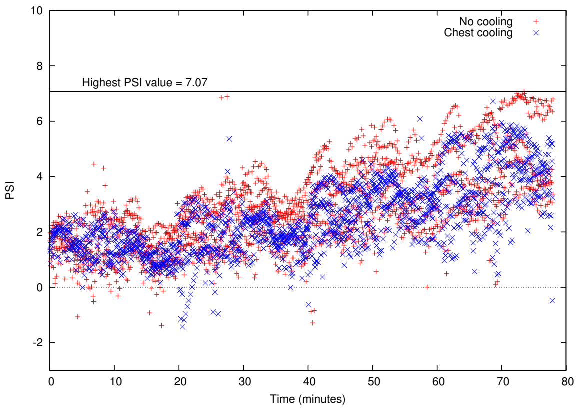

Figure 6. Calculated PSI values over the course of the experimental trials performed here.

each combination of ambient temperature and cooling type. Table I summarises the trials considered here. Each trial consisted of four identical back-to-back cycles of: walking on a treadmill (3 mins), kneeling while moving weights (2 mins), crawling (2 mins), postural testing (2.5 mins), arm exercise while standing (3 mins), and cognitive tests while sitting (6 mins). These activities are shown in Figure 4.

PSI values (as described in Section II-A) were calculated over the course of the experimental trials performed. They were found to approach the 7.5 threshold set by Buller *et al.* [9], reaching a maximum of 7.07. By this metric, the trials can be seen to stay within the safe range of physiological stress, though the safety limit may be exceeded it in longer trials. For the trials considered in this work, PSI begins to noticeably increase when skin temperatures are above around 36 °C. PSI values were extrapolated to exceed the threshold of 7.5 at around 38.5 °C, dependent on the subject's heart rate. This is consistent with literature findings and confirms the elevated UHS risk in EOD operatives. Figures 5 and 6 show the PSI values for the trials considered in this work and the PSI trends over the course of trials, respectively.

V. Heat stress prediction parameter selection

A variety of factors contribute to the onset and evolution of heat stress. Building an accurate heat stress risk prediction model that meets the requirements of a given application relies on the selection of an appropriate set of parameters. The specific parameters selected may vary from one application to the next. In the EOD scenario, four parameters were selected based on 1) their observable effects on, or representation of, the subject's physiological state and 2) their ability to be monitored via non-invasive sensors. These parameters were: skin temperature, activity type, ambient temperature, and cooling type. Furthermore, two other parameters were considered but not included: core temperature and stored heat. This section demonstrates the relevance of these parameters for the chosen application, along with a discussion of additional parameters that may be necessary in other applications.

A. *Skin temperature*

Due to the difficulties in measuring core temperature (see the discussion below), skin temperature is often selected as the basis of core temperature estimation or as a direct measurement proxy [23], [24]. There are some constraints in the use of skin temperature as it depends on the ambient temperature, local air circulation, and blood circulation. These factors cause skin temperature to vary over a much wider range than core temperature and,

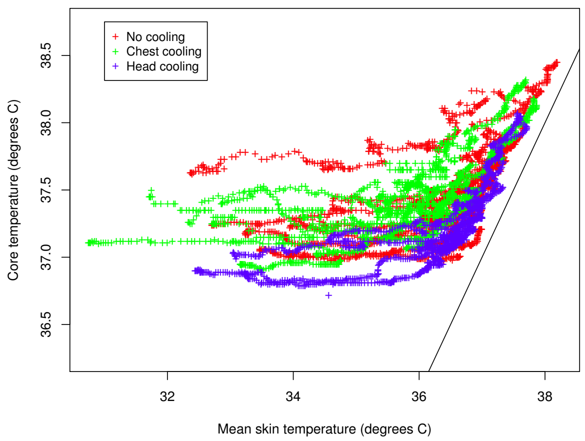

Figure 7. Subject mean skin temperature and rectal temperature. The line indicates equal mean skin and rectal temperatures.

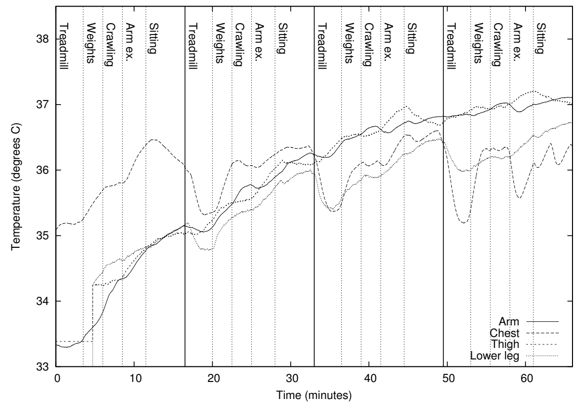

Figure 8. Skin temperature data for a sample subject gathered during a mission-like protocol while wearing an EOD suit.

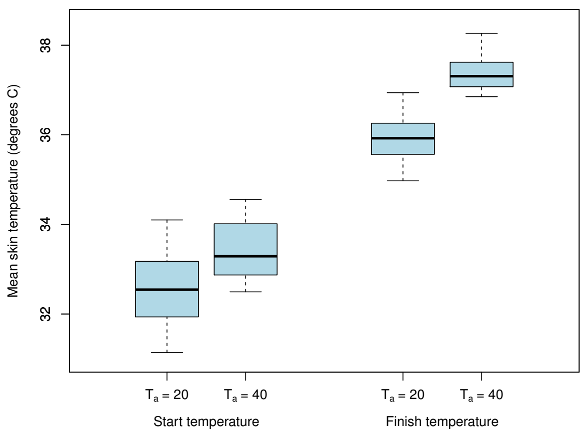

Figure 9. Comparison of starting and finishing mean skin temperatures at 20 °C and 40 °C ambient temperature with no cooling.

combined with the body's regulation of core temperature, reduce the correlation between the two.

Figure 7 shows mean skin temperature (calculated using $0.3T_{\text{chest}} + 0.3T_{\text{arm}} + 0.2T_{\text{thigh}} + 0.2T_{\text{calf}}$) against core (rectal) temperature for 12 subjects undergoing the mission-like protocol in a total of 26 trials. It can be seen that for skin temperatures below around 36 °C, core temperature is regulated consistently and shows no correlation with skin temperature. However, above 36 °C core temperature correlates with skin temperature with an offset of around 0.25 °C to 0.75 °C. This contributes to the similar rise in PSI described in Section IV.

As skin temperature is correlated with core temperature above 36 °C, it follows that skin temperature can be used as a proxy for core temperature at temperatures near to the range that is considered dangerous. Furthermore, it is clear that the variation in skin temperature below this point is a reflection of real physiological variation that cannot be identified by examining core temperature alone. This change in the relationship between skin and core temperature above around 36 °C means that skin temperature can be used to predict that core temperature will increase.

B. Activity type

It can be seen from Figure 8 that the evolution of skin temperature is dependent on activity. During the walking and crawling activities, for example, the skin temperature of the chest and calf dropped significantly, while the temperature of the arm and thigh increased. Such skin temperature patterns are likely to be the result of a combination of physiological factors (more heat produced by the muscles during strenuous activities for examples) and the airflow paths within the suit. If kneeling, for example, then cool air supplied by a fan to the upper body will have very little effect on cooling the legs. The clear dependence of skin temperature on activity type means that activity/posture represents an important factor in predicting heat stress.

C. Ambient temperature

Figure 9 shows skin temperature at the start and end of the trials in different ambient temperatures for subjects performing the mission-like protocol with no cooling. It can be seen that ambient temperature has a large impact on skin temperature—the difference between skin temperatures at 20 °C compared to 40 °C increases significantly by the end of the trials compared to the start. Furthermore, though not the topic of this section, it can be seen that for each ambient temperature tested, the interquartile range of the skin temperatures at the ends of the trials is much smaller than at the start. The reduced range implies that skin temperature may become more predictable when the EOD suit has been worn for some time. This is likely to be related to the heavy insulation provided by the

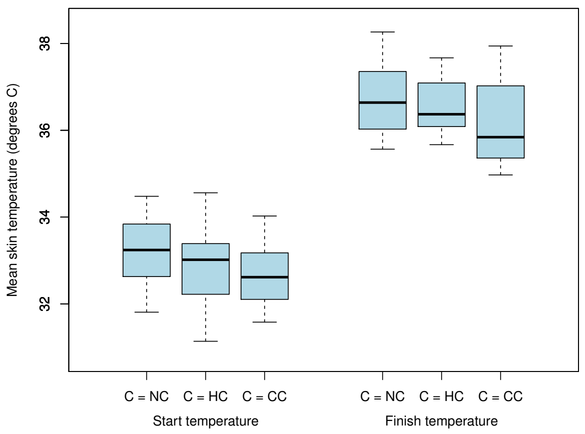

Figure 10. Comparison of starting and finishing mean skin temperatures at 40 °C with the three cooling types (NC=no cooling, HC=head cooling, CC=chest cooling).

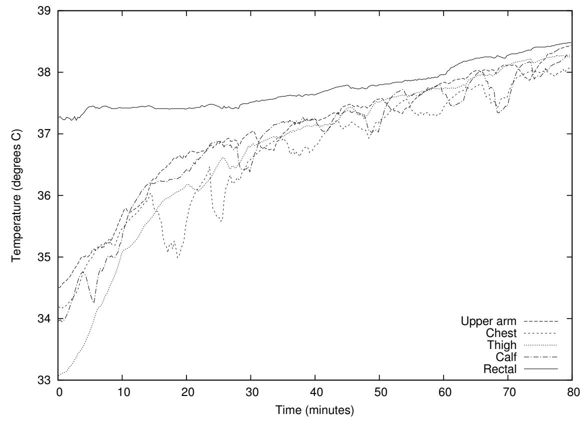

Figure 11. Skin and core temperature data gathered during a mission-like protocol while wearing an EOD suit.

suit causing the thermal environment within to become slowly more uniform (with applied cooling or ambient airflow into the suit being the primary cause of non-uniformity at this stage).

D. Cooling type

Air flow around the body is an important factor in heat stress risk, in terms of both the speed of the flow and which body segments are experiencing it. EOD operatives are exposed to airflow provided by the integrated cooling system when this is operating. During the trials described previously, the following cooling variations were used: no cooling (NC), head cooling (HC), and chest cooling (CC). In each case, cool air was blown onto the subject's back at a rate of around 200 ℓ/min.

Figure 10 shows the mean skin temperature at the start and end of each trial. It can be seen that there are minimal differences between the NC and HC conditions at the end point of the trials, but the CC condition results in lower overall skin temperatures. This is expected as cooling applied to the trunk will have a direct impact on the arm and chest temperatures measured, as well as allowing the body to dissipate more heat from the core.

E. Core temperature

Figure 11 shows the measured core (rectal) temperature of a sample subject undergoing a mission-like protocol at 40 °C ambient temperature with no cooling. It can be seen that the core temperature was initially stable and began to rise with the skin temperature as the experiment progressed. This demonstrates the process described for UHS in Section I, wherein the subject's thermoregulatory system is unable to maintain a stable core body temperature. As shown previously in Figure 7, core temperature appears to generally begin to rise at skin temperatures above 36 °C. Based on this, for EOD suit wearers, core temperature increases (and thus early signs of heat stress) begin to occur at a skin temperature of 36 °C.

Data gathered from eight subjects performing the mission-like protocol at 40 °C with no cooling was analysed and it was found that all subjects displayed an increase in core temperature over the course of the protocol. The trends exhibited were similar to those seen in Figure 11. In each case, the difference between starting and ending core temperature was between 0.2 °C and 0.7 °C, with an average of 0.5 °C. The maximum rate of change observed was 0.28 $°\text{C}\cdot\text{min}^{-1}$.

In many real-life applications (such as EOD missions) it is not practical to measure core temperature using rectal probes—Gunga *et al.* [5] list several reasons for this including difficulty in sanitising sensors and problems related to making the subject uncomfortable. Furthermore, although aural sensors were tried, they were uncomfortable when wearing the helmet, frequently dislodged and the resulting temperature data was not reliable. For this reason, core temperature was not selected as a parameter in the risk prediction model implemented here.

F. Stored heat

The progression of heat stress will be different in the two following situations, despite all previously mentioned parameters being identical:

1) Average skin temperature of 36 °C, currently walking in 40 °C ambient air temperature with chest cooling applied for the last five seconds.
2) As above but with chest cooling applied for the entire mission duration.

These cases differ as in the first subject has reached an average skin temperature of 36 °C with no cooling and thus applying cooling at this stage is likely to provide some benefit. In the second case, the subject has reached 36 ℃ despite cooling *already being applied*. This fundamental difference despite the same state being observed at the moment described (based on the previously stated parameters) means that there is at least one additional parameter inherent to the system. This parameter is likely to be related to heat storage within the body—where heat dissipated is less than heat generated, resulting in a cumulative effect.

The experimental data used for demonstration of the algorithm here was obtained with no cooling or ambient temperature changes applied during the trials (in order to control the number of factors influencing the results). This means that the effect of changing conditions cannot be analysed rigorously. This limitation is discussed further in Section VI-A with regard to its implications for the algorithm implementation demonstrated here.

VI. Heat stress prediction algorithm

The goal of the algorithm presented here is to predict the onset of heat stress and more generically heat stress risk such that action can be taken to avoid it. The algorithm is thus based on the probability that skin temperature will exceed a given "danger" threshold within a particular prediction time period. As described previously, skin temperature is used as a proxy for core temperature as 1) it is more readily accessible with non-intrusive sensors and 2) above temperatures of around 36 ℃ the two parameters are well correlated. The correlation above 36 ℃ means that increases in skin temperature beyond this point are reflected in a corresponding increase in core temperature, therefore this is the range in which we can consider the subject to be entering a "danger" state and it makes sense for the algorithm to be targeted at these temperatures. Below this, core temperature appears largely unaffected by skin temperature.

The following sections describe two proposed approaches (Bayes Net and Decision Tree) for heat stress risk prediction, provide testing results based on experimental data, describe an implementation within a wearable sensing system developed previously by the authors, and present some additional results that could form the basis of further work.

A. Bayes Net

At the core of the first predictor is a probabilistic model based on a Dynamic Bayesian Network (DBN), as shown in Figure 12. As described in Section V, activity A_t, cooling level C_t, ambient temperature $T_{a,t}$, and mean skin temperature $T_{sk,t}$ are assumed to be sufficient to allow prediction of future mean skin temperature within the application case study (in the general case, C would be replaced with a more detailed set of airflow parameters). Furthermore, for the purpose of this implementation it is assumed that the tuple $\langle A, C, T_a, T_{sk}\rangle$ has the Markov property (that is, knowing the past history would not improve the prediction). This is clearly a simplified model of the thermal interactions internally and externally to the human body, but it is proposed that such simplifications do not significantly impact the predictive ability of the model in this case. In more complex datasets with varying ambient temperature and applied cooling it is likely that this simplifying assumption will result in reduced model accuracy unless additional parameters or relationships between parameters are considered.

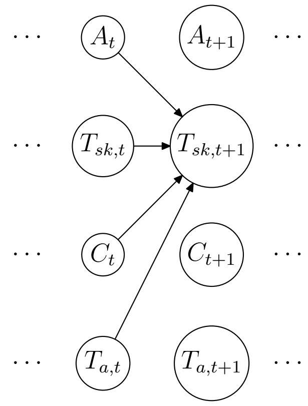

Figure 12. A simple DBN model of the effect of cooling C_t, activity A_t, ambient temperature $T_{a,t}$, and mean skin temperature $T_{sk,t}$ on future mean skin temperature $T_{sk,t+1}$.

In addition to the model state parameters, there are two further parameters that must be determined prior to training and using the predictor:

1) A unit of time defining how far into the future the prediction is needed. In this work, *two minute* prediction is used and so $t+1$ is taken to mean "the current time plus two minutes." The maximum rate of change of core temperature observed during experimentation was 0.28 ℃·min^{-1}, giving a maximum change of around 0.6 ℃ over the prediction period. This is lower than the maximum allowable change of 2 ℃, providing a safety margin of at least 5 minutes (assuming the same high rate of change is maintained) within which any corrective action can take effect.
2) The mean skin temperature to be used as a "danger" threshold. Here, a threshold value of $T_d = 36.5$ ℃ is used for two reasons: 1) due to the safety limits of the trials used to form the model, data at very high temperatures is unavailable, and 2) as described previously, the temperature range at which core temperature is affected by skin temperature starts

at around 36 °C. Choosing a threshold of 36.5 °C means that the algorithm will warn of possible changes in core temperature prior to them occurring.

The combination of prediction time period and danger threshold are dependent on the requirements of the application and any appropriate safety regulations. It is likely that the danger threshold will generally be set to between 36.5 °C and 37.5 °C for the reasons given previously. Nonetheless, very low thresholds are inappropriate since skin temperature and core are uncorrelated at lower skin temperatures. Significantly higher thresholds may be precluded by the difficulty in safely obtaining experimental training data. High thresholds will also mean that risk alerts are only issued for extreme heat-related health conditions.

The model allows us to predict the probability of heat stress by finding the probability of the threshold temperature being reached or exceeded within the prediction period. For brevity, d (for "danger") is defined to be the event $T_{sk,t+1} > T_d$ ($\bar{d}$ is its negation) and S is shorthand for the state elements exclusive of skin temperature (A_t, C_t, and $T_{a,t}$). Therefore, the goal is to determine $P(d|T_{sk,t}, S)$. Training data gathered from experimental trials using the suit is used to find Probability Density Functions (PDFs) $P(T_{sk,t}|d, S)$ and $P\left(T_{sk,t}|\bar{d}, S\right)$ and then Bayes' rule is applied to find $P(d|T_{sk,t}, S)$ via

$$P(d|T_{sk,t}, S) = \alpha P(T_{sk,t}|d, S)\, P(d, S)$$

where α is a normalising constant such that the conditional probability of d and $\bar{d}$ sum to 1. Specifically,

$$\alpha = 1/\left(P(d|T_{sk,t}, S) + P\left(\bar{d}|T_{sk,t}, S\right)\right)$$

To form a good fit for the available data, each PDF is approximated using a Gaussian Kernel Density Estimator. In the implementation here, the Gaussian KDE estimator from Python's SciPy library was used with bandwidth estimation via Scott's Rule [25].

In the case study application, autonomous actuation of the in-suit cooling system would be based on the danger probability $P(d|T_{sk,t}, S)$. In the case that it is greater than a defined threshold p_d then the cooling system would be actuated to prevent the operative's skin temperature from reaching the threshold temperature T_d. A reasonable probability threshold p_d is 0.5 meaning that, when exceeded, danger is more likely than not.

B. Decision Tree

As an alternative approach, C4.5 Decision Trees were trained to predict danger or no danger (rather than estimating danger probability) based on the same physiological parameters. The same input parameters were used—mean skin temperature, activity type, cooling actuation, and ambient temperature, while a class label of "danger" or "no danger" was derived from whether the core temperature exceeded the danger threshold at any time in the following 2 minutes.

C. Results

The data sets used for selecting key predictor parameters were described in Section IV. For the purpose of training and testing the predictor however, only data from trials performed at 40 °C ambient temperature was used since skin temperature in the trials at 20 °C rarely exceeded the safety threshold chosen.

To determine the ability of both approaches to generalise to unseen subjects, leave-one-subject-out cross-validation (LOSOXV) was used, with the trials for one subject removed in each iteration for testing purposes and the remainder of the trials used for training. This test approach, combined with the use of multiple subjects with varied anthropometric features (such as differing heights, weights, etc), gives realistic performance estimates in the face of subject to subject variability since all tests involve *unseen* subjects. The accuracy of the Bayes Net classifier was determined based on the criteria that the probability output should be at least 0.5 when the future mean skin temperature is 36.5 °C or higher. Given this criteria, the overall accuracy of the predictor was 92.1±2.9% (at the 95% confidence interval) averaged across the 12 cross-validation iterations (minimum 83.2%, maximum 97.0%). The variation in performance shows that the approach is somewhat subject dependent, while the narrow band for the 95% confidence interval indicates that it is not overly so. While the model is not perfect, it is a usable predictor of whether the danger threshold will be exceeded.

The overall accuracy obtained with the decision tree-based predictor was 94.4±2.1% (at the 95% confidence interval). Based on the data available, it cannot be decided that the decision tree approach is necessarily better since the confidence intervals overlap. This shows that the assumption that the Markov property holds was reasonable for the data used, as the decision tree considers each data sample in isolation with no additional knowledge of the modelled system.

D. Further evaluation

Although the model is not intended to predict thermal sensation, it is interesting to compare the danger probability obtained from the Bayes Net predictor with the subjective sensation reported by participants during trials (sensation was recorded

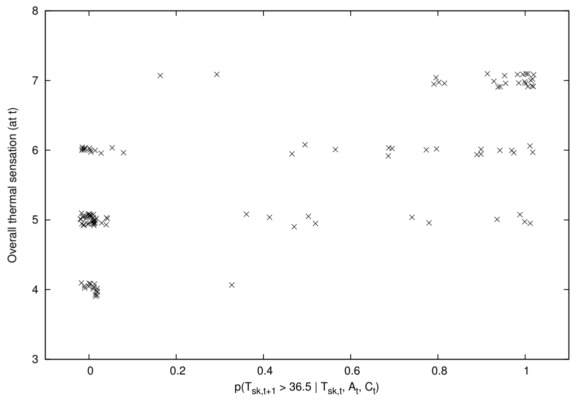

Figure 13. Comparison of predicted danger probability with thermal sensation (with horizontal and vertical jitter applied to more clearly show clusters of results).

on a scale from 0 to 8 with 0 being "unbearably cold", 4 being "neutral", and 8 being "unbearably hot"). This is shown in Figure 13. It is interesting to note the strong correlation—no situations where neutral sensation (4) was reported were considered dangerous by the Bayesian model while only two reports of being very hot (7) were considered "safe". The relationship is less clear for reported sensations of 5 and 6 (warm and hot respectively), with both reported values being associated with probabilities over the full output range. However, for a sensation of 5, the majority of the results still lay near to a probability of zero (34 points for $p < 0.05$ and 11 points for $p \geq 0.05$). The Spearman rank correlation coefficient for the results in Figure 13 is 0.71.

Given the complexity of the system concept to support the risk prediction algorithm, one area that required additional investigation was that of the effect of measurement uncertainty within the input data on the result. For example, the postural activity of the subject was manually annotated in the trials but in deployment, this would be provided by a machine-learning based classification algorithm (as described in Section III) that has known measurement uncertainty and which is described elsewhere [19]. The sensitivity of the DBN model presented here to this uncertainty was estimated by (a) randomly selecting activity and cooling type; (b) randomly sampling skin temperature based on experimental trial distributions according to activity and cooling type; (c) randomly sampling the postural classifier output based on its confusion matrix. The resulting performance of the DBN prediction algorithm, over 600,000 samples, was reduced by 0.05% (compared with manual posture annotation). This demonstrates that the method is likely to perform well in deployment using posture as classified by a machine-learning based algorithm such as the one described in [19].

VII. Conclusions

A DBN-based model and C4.5 decision tree have been developed to allow heat stress risk prediction, using only parameters that may be monitored via non-invasive sensors. The potential for UHS to occur in wearers of protective clothing creates a need for a predictive on-body monitoring and actuation system to increase wearer safety. Specifically, the case study of EOD operatives during missions was considered here and the key parameters for a predictive model of heat stress were described. Refinement of the model parameters may allow the same prediction mechanism to be employed in a variety of other applications.

For the EOD application, based on experimentally gathered data, the DBN predictor was shown through cross-validation to be 92.1±2.9% accurate in predicting the rise of skin temperature beyond a defined safety threshold. The decision tree-based predictor (implemented for comparison) produced a similar accuracy of 94.4±2.1%. The Bayes Net approach may be preferred in some cases as it provides probability of risk rather than a danger or no danger binary output. It should be noted that these prediction accuracies can be expected across a range of environmental conditions in temperate and hot climates. Furthermore, the system is designed for 2 minute prediction and a danger threshold of 36.5 °C. Should a different prediction period or threshold be required, either predictor would need to be retrained.

While not the original intention behind the predictors, it was also shown that the DBN output correlated well with reported thermal sensation. This relationship could be explored in further work aimed at establishing the nature of the link between thermal sensation/comfort and the risk of UHS calculated by the predictors proposed in this paper. Furthermore, inclusion of historical data, for example through a "stored heat" parameter to the model, is an avenue for investigation towards more accurate risk assessment, backed up by experimental data gathered in more varied conditions (with varying cooling and ambient temperature during individual trials for example). Field validation of the proposed work will also need to be carried out for a large variety of ambient temperatures to allow for further tuning of the methods.

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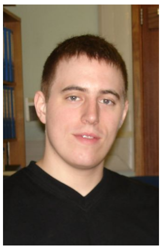

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