Networked Body Sensing: Enabling real-time decisions in health and defence applications

Ramona Rednic, John Kemp, Elena Gaura, James Brusey
Cogent Computing Applied Research Centre,
Faculty of Engineering and Computing, Coventry University, UK
Email: aa6418@coventry.ac.uk

***Abstract*—This paper presents the application scenario, conceptual overview and implementation of a monitoring system targeted at monitoring EOD suit wearers during missions. The system's aim is to deliver prediction of heat stress risk in the operative and provide actuation of a cooling system integrated within the suit. Prior work established that such prediction requires real-time autonomous processing of skin temperature and body acceleration data, and thus a system implementation is presented based on two interacting subsystems that perform the required sensing and data processing. Posture classification is performed with an accuracy of 96.1%, and a heat stress prediction algorithm is demonstrated with an overall accuracy of 88.5% when predicting the occurrence of heat stress within the next 2 minutes.**

I. INTRODUCTION

A range of Body Sensor Network (BSN) systems have been proposed in the literature for monitoring the human body towards timely detection of health-related problems. The developers of these systems have targeted a variety of environments, but the focus of the sensing can be broadly split into two categories: physiological monitoring (skin temperature and heart rate), and posture/activity monitoring (using accelerometers and/or gyroscopes). Current systems are generally either designed to capture the evolution of particular parameters and ensure that alarms are generated when parameters stray outside a safe range, or to provide general monitoring solutions for patient status within a hospital or similar environment. The focus is thus on gathering and presentation/storage of data, rather than on autonomous real-time decision making. A survey of literature in the area shows that the field has, in this way, resolved many of the challenges related to data acquisition. The remaining challenges are largely related to data processing, summarisation, effective visualisation, and automated actuation of connected equipment in real-time, along with inferring decisions and making predictions on the basis of acquired data.

The contribution brought here is the concept and implementation of a end-to-end, real-time, on-body prediction system for reducing health risks due to Uncompensable Heat Stress (UHS). This involves gathering physiological data (multi-point skin temperature) and postural information (multi-point body acceleration) for the purpose of autonomous real-time modelling and prediction. The work is based on empirical data collected from Explosive Ordnance Disposal (EOD) operatives in mission-like protocols.

The paper is structured as follows: Section 2 presents examples of BSN-based systems from the literature targeted at physiological parameter monitoring in dangerous environments, and postural monitoring for general healthcare. Section 3 presents the application scenario that is considered in the work here. Section 4 gives a conceptual overview of the monitoring system developed by the authors, while Section 5 details the implementation of the system in terms of two sub-systems. Finally, Section 6 summarises and concludes on the work here.

II. RELATED WORK

A. BSNs in dangerous environments: physiological parameter monitoring

A range of BSN systems have been proposed in the literature for monitoring the human body towards assessment of health-related problems. The developers of these systems have targeted a variety of applications, often with a focus on monitoring patients in first response, hospital, or physiotherapy environments [6], [7], [10] or workers in dangerous environments.

A good example of a commercial product designed for the purpose of monitoring personnel carrying out missions in dangerous environments is the LifeShirt by VivoMetrics (evaluated by Heilman and Porges [8]). 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 full system is supplied in three parts: a lightweight, machine washable chest strap with embedded sensors; a data receiver; and VivoCommand software for monitoring and data analysis. The sensors embedded in the chest strap monitor the subject's breathing rate, heart rate, activity level, posture, and skin temperature at a single point, while the VivoCommand software displays the gathered data (along with 30 second average trends) in real-time on a remote PC.

A second notable system is the Smart Vest proposed by Pandian *et al.* [17]. The focus of their work was on traditional Wireless Sensor Network (WSN) issues such as power consumption, security, wireless network formation, and network communication protocols. In this system, a group of wireless sensors monitor a variety of physiological parameters: electrocardiogram (ECG) trace, heart rate, blood pressure, body temperature, galvanic skin response, arterial blood oxygen saturation (SaO2), respiratory rate, electromyogram (EMG) trace, electroencephalogram (EEG) trace, and movement via three-axis accelerometer. These sensors communicate with an on-body sink node which forwards the results wirelessly to a remote monitoring station.

Finally, the LifeGuard system was proposed by Mundt *et al.* [16]. This device is intended as a general solution for monitoring of astronauts, soldiers, firefighters and first responders. The LifeGuard system consists of an on-body Crew Physiologic Observation Device (CPOD) and a portable base station. The CPOD is capable of logging gathered data as well as wirelessly transmitting data to the base station via Bluetooth. The sensors available include: accelerometers; ambient, skin, and core temperature via thermistor probes; ECG and respiration via chest electrodes; peripheral blood oxygen saturation (SpO2); and systolic and diastolic blood pressure via a cuff-based device. Heart rate is derived from the ECG output. The device was tested in several environments including underwater (as a space station analog) and at high altitude.

Works such as those above focus on capturing large amounts of physiological data which can then be transmitted to a remote receiver for visualisation, storage, or later processing. In-network processing and autonomous operation in these applications are not common topics of research.

B. BSNs in general healthcare: posture monitoring

Posture and activity tracking are relatively well covered research subjects, with a number of branches and applications, including activity detection [13], [17], position recognition [14], [3], real time movement recognition for martial arts [9], and gait measurement [2].

Several examples of systems for posture classification exist that were developed for patient care applications, often involving patient rehabilitation. One such system was developed by Pansiot *et al.* [18]. This system integrates an ear-worn activity recognition (e-AR) sensor with wall mounted video camera based systems that extract silhouettes from the video image and also extracts optical flow to detect motion. Two types of information are derived from the e-AR sensor: tilt, and a movement frequency spectrum. Sensor fusion is performed, based on a Gaussian Bayes EM classifier, using the e-AR and silhouette information. Some activities are classified perfectly, whilst others (e.g. sitting) have a recall as low as 0.47.

Other systems detect posture-related events, such as steps while walking. An example of this is the system implemented by Ying *et al*. [20] for automatic step detection for patients with Parkinson's disease. Several methods of detection have been evaluated by Ying. The system implemented consists of a dual axis accelerometer (ADL322), and passive low-pass filtering. The Peak-detection method was concluded to be most suitable for deployment on microprocessors with limited computing power, as it can be written as a fixed-point algorithm. Step recognition has also been researched by Milenkovic *et al*. [15] as part of a wider personal health monitoring system.

It has been observed, as described above, that posture recognition in itself is a widely researched topic, with developed systems delivering a high level of accuracy in each specific targeted application. However, the generation of postural or activity information is often a goal in itself and is often performed offline. In contrast, the work here requires postural information to be generated in real-time in order to support further predictive modelling operations performed by the monitoring system.

III. Application scenario

This paper treats one scenario that reflects the need for real-time actuation of wearable devices, prediction of behaviour from the data and ability to mine in real-time across a mix of parameters (physiological and postural). The scenario is that of monitoring EOD operatives during missions—a specific application example taken from the wider range of applications that may be targeted in the defence field and applications in the wider realm of workers in dangerous environments (such as described in Section II-A). The physiological strain undergone by EOD operatives during missions is well documented, as well as the possible remedial actions: 1) heat stress, particularly the dangerous condition of UHS, is a concern for wearers of EOD suits [5], [19], 2) effective prevention of heat stress in an EOD operative requires the use and predictive actuation of adequate in-suit cooling systems [11], and 3) such prediction relies on knowledge of posture. In addition to heat-related health problems, the concentration of Carbon Dioxide (CO_2) within the helmet may potentially reach dangerous levels due to the lack of natural ventilation [12], and thus predictive actuation of the cooling system can also bring benefits in this regard. In order to sense physiological data and provide effective actuation in real-time, a natural solution was that of a BSN-based design.

The system described here was thus developed as a monitoring system to enable increased safety of EOD operatives through: i) monitoring of physiological parameters and body acceleration, ii) inference of health state and postural information from data, iii) autonomous actuation of the in-suit cooling system, and iv) provision of appropriate data, information and alerts to both the remote observer and the operative as appropriate.

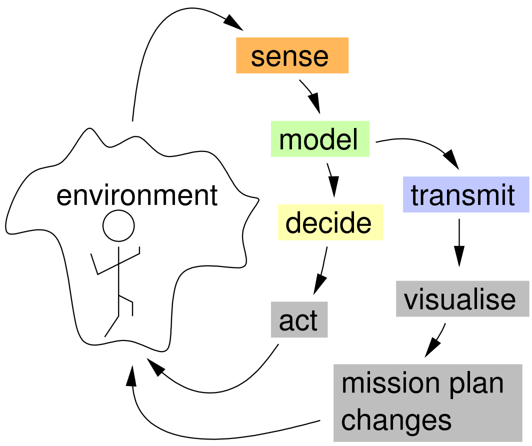

Figure 1. Conceptual design of prototype system.

IV. The Enabling Concept

One of the central concepts driving system development in this scenario is that data processing must be performed by system devices mounted on the body. Autonomous operation is essential because a long-range radio link to a central location will not necessarily be available due to the use of radio jamming devices by the operative (in order to prevent remote detonation of the explosive device). A relatively powerful hardware platform is thus required to support real-time on-body data processing, particularly during system development when a variety of algorithms are tested for suitability.

Due to the need for autonomous operation, the system described here is based around the use of two control loops as presented in Figure 1: one autonomous loop contained within the EOD suit, and one loop partially external to the suit involving the mission observer. As an outcome of sensing and data processing, the internal autonomous loop performs actuation of the cooling system and provides feedback to the operative, while the external loop enables the remote observer to plan strategically. The following stages within the loops are:

Sense: Physiological data such as multi-site skin temperature, heart rate, and helmet CO_2 concentration is gathered, along with acceleration data from multiple body segments. Calibration and outlier rejection are applied to the data.

Model: The Model stage converts sensor values into an estimate of the state of the suit wearer and their immediate environment. Alerts are also generated for individual physiological parameters should abnormal or dangerous conditions be identified. A variety of sensor fusion based information extraction and modelling strategies are also part of this stage, primarily: determination of posture, prediction of future heat stress conditions, and prediction of helmet CO_2 levels.

Decide: The state information extracted in the Model stage (specifically thermal and CO_2 information) is supplied to a decision-making engine, which produces the pattern for actuation of the cooling system.

Act: At the Act stage, the result of the Decide stage is transformed into hardware commands and executed to provide the required cooling level. Additional outputs can also be provided in the form of haptic feedback to the suit wearer based on alerts generated by the Model stage or outputs of the Decide stage.

Transmit: Information and, optionally, data is transmitted to the remote mission observer, for storage and visualisation.

Visualise: The information and, optionally, data reported by the instrumentation system is displayed to remote observers on a computer. Though the system is capable of operating autonomously to achieve the goal of providing the EOD operative with increased comfort and safety, this component of the system brings a mission observer (who can judge the information within the larger context of the mission) into the loop. The observer is provided with the ability to monitor the state of the subject and check that the system is functioning correctly. They can also remotely place requests for detailed data to be delivered by the instrumentation system.

Mission plan changes: The remote observer may choose to implement changes to the mission plan in response to the information provided by the instrumentation system. For instance, if the system indicates a consistently high chance of heat stress occurring in the operative, then they may be required to return to the base station more frequently to take in fluids and install new cooling system batteries.

V. End-to-End Implementation of a Health State Prediction System

Following from the scenarios presented in Section III, and as shown in Figure 2, a prototype health state prediction system was implemented, based on two interacting sub-systems, with the goal of gathering health and posture related data, providing prediction-based actuation of safety equipment, and allowing remote visualisation of relevant information. The two sub-systems were named Medusa2 (responsible for gathering physiological and environmental data and running the predictive algorithms) and Class-act (responsible for gathering body segment acceleration data and providing postural information to the Medusa2 system). The Medusa2 system also demonstrates several additional robustness related features with regard to sensor and communications errors (particularly for the long-range communications link to the remote monitoring station).

Figure 3 illustrates the division of system nodes between suit segments and the placement of sensors for a fully integrated monitoring system of the type proposed. A Data Acquisition Node (DAN) is allocated to each suit segment. Data is collected by the sensors and passed to their associated DAN via a wired connection. A Data Processing Node (DPN) is located in

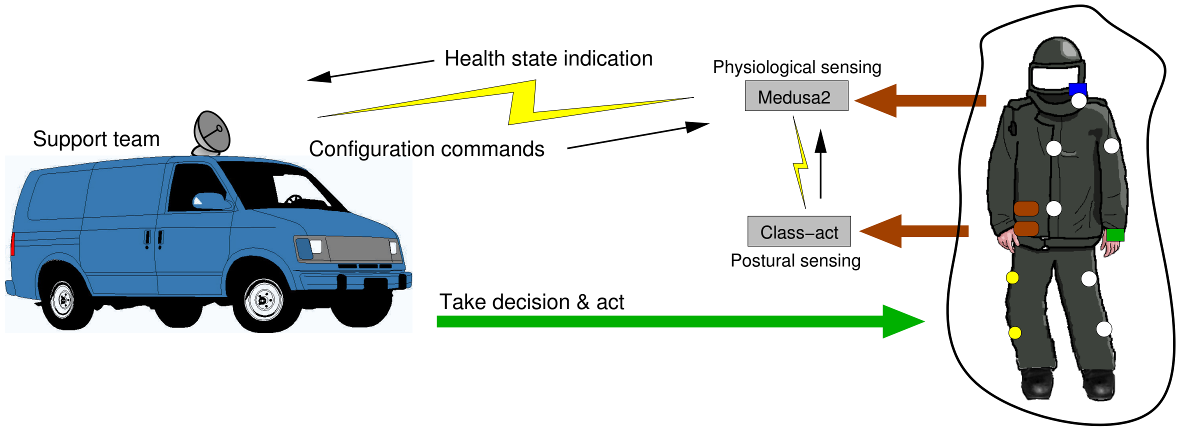

Figure 2. EOD operative monitoring system overview. Sensor types shown on the operative: white—skin temperature; yellow—accelerometer; blue—helmet CO_2 ; green—pulse oximeter (pulse rate and blood oxygenation).

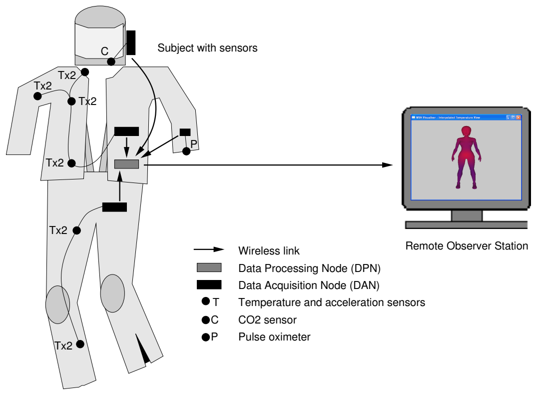

Figure 3. Medusa2/Class-act system node and sensor configuration.

the jacket segment of the suit to enable easy access to the cooling fan electronics, which are fully contained within this segment for both a fan blowing air into the jacket and one providing air into the helmet. While the figure demonstrates the configuration for the integrated case, the prototype Medusa2 and Class-act systems are described separately below to emphasise the unique tasks carried out by each.

A. *Medusa2: gathering physiological data*

The focus of the Medusa2 sub-system was on two central elements: 1) predictive actuation of the in-suit cooling system to prevent heat stress occurring in the EOD operative, and 2) robust autonomous operation given the potential for sensor and communication failures in the harsh conditions of the real-world deployment scenario considered here. The heat stress prediction algorithm used is described in Section VI. To help ensure that the system could operate autonomously, several features were implemented that reduce the impact of sensor and communication errors that may occur:

- The skin temperature sensors are mounted in pairs at each location, and the data from each pair is processed jointly via a Kalman filter. This means that if one sensor in a pair fails then the system can continue to function using the data from the remaining sensor.
- A linear extrapolation feature is implemented on the DPN so that if communication fails temporarily with a DAN, the data processing algorithms can continue to function using estimates of the current data values.
- Data is buffered on the DPN prior to transmission to the base station, and a system of receipt confirmations is implemented. This allows retransmission of data in the event that the long-range link is temporarily interrupted.
- Prioritisation of data is implemented on the DPN so that important information and alerts are transmitted before less important data. This works with the buffering feature such that new data is prioritised over historical data once connectivity is restored after a communications loss.

A functional evaluation of the system was performed to ensure that it met the requirements of the application. The battery life was found to be around 4 hours, which is sufficient for the EOD application. The Bluetooth communication links used in the prototype were found to be able to support a maximum of 85 “data units” per second (a data unit being a distinct piece of data or information, for example a skin temperature measurement), which is in excess of the expected requirements of the system, including the additional postural data generated by the Class-act system. The link latency was found to be 0.04 seconds, which is significantly shorter than the 1 second sampling period used for most of the Medusa2 sensors. Finally, the maximum link range when using the Bluetooth radio was found to be between 5.5 metres and 63.5 metres depending on the local environmental obstructions. While this does not satisfy the requirements of the application (in which the operative may be over 100 metres away from the remote station), it was sufficient for the prototype testing and evaluation. In all cases, the link range would be sufficient for node-to-node communications.

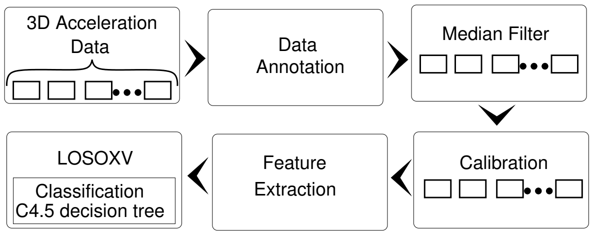

Figure 4. Data processing flow for posture classifier training.

B. Class-act: deriving postural information

The focus of the Class-act system is to gather acceleration data from various points on a subject's body and determine their current posture in real-time. In order to achieve this, the C4.5 algorithm is used to learn a decision tree capable of performing the classification. Decision trees as a classifier type provide several advantages. First, the C4.5 algorithm pushes attributes that provide the most information to the top of the tree. This feature makes it easy to see whether some sensors are redundant or at least, less useful, in performing the classification. Second, the derived decision tree is readily converted into program code. Third, since the resulting code does not contain loops, a strict real-time limit can be set for its operation. Finally, due to the nature of C4.5 decision trees, a monotonic transform on any feature has no effect on the resultant tree in terms of classification performance. In principle, basic calibration of accelerometers is performed using a monotonic transform and therefore, a decision tree based on raw accelerometer measurements will perform just the same as a decision tree based on calibrated accelerometer measurements. This was shown in the context of classifying acceleration data by Brusey *et al.* [4].

The data processing flow for training the posture classifier using experimental data is shown in Figure 4. Note that a median filter with a window size of three samples is applied to help eliminate single-sample transient errors. A sliding window of 30 samples is used for the feature extraction process. Both the raw data and the selected data feature are used for classification. The feature computation is required in order to differentiate static from dynamic postures. In previous work by Brusey *et al.* [4] the need for features is investigated in depth.

The training and testing set for the system consisted of data gathered from 40 experimental trials across 17 subjects (a total of 6 hours and 20 minutes of data). The subjects were required to perform particular postures along with tasked activities (for example kneeling while moving items from one container to another). Data was gathered for eight postures determined (via communication with application experts) to be the most commonly encountered during EOD missions: sitting, standing, walking, kneeling, crawling, and laying down (on one side, front, and back).

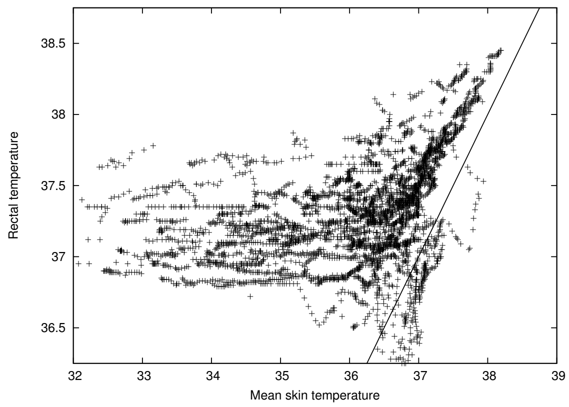

Figure 5. Subject mean skin temperature and rectal temperature. The solid line indicates equal mean skin and rectal temperatures.

Leave-One-Subject-Out Cross-Validation (LOSOXV) was adopted as a validation method for the system. The best results were obtained when using windowed variance as a data feature, with the sensors placed on the upper arms, forearms, chest, thighs, and calves. In this configuration, the accuracy overall across all eight postures and 17 subjects was 96.1%. The Class-act sub-system thus met well the requirements for the predictive algorithm to be successfully implemented.

VI. Heat stress prediction

Due to the danger of heat stress in the EOD operative, importance was placed on developing an algorithm capable of providing autonomous actuation of the in-suit cooling system *prior* to heat stress occurring.

The heat stress prediction algorithm developed is a probabilistic model based on a Dynamic Bayesian Network (DBN) incorporating the subject's current posture/activity, the cooling applied to the subject, and the subject's mean skin temperature as a proxy for core temperature. In this model, it is assumed that activity A_t, cooling level C_t, and mean skin temperature $T_{sk,t}$ are sufficient to allow prediction of future mean skin temperature and that the tuple $\langle A, C, T_{sk} \rangle$ has the Markov property. While core body temperature is the critical parameter in determining heat stress, Figure 5 demonstrates that, for EOD suit wearers, core temperature correlates with skin temperature once the latter exceeds approximately 36 °C, making it possible to use skin temperature as a proxy for core temperature when considering effects such as heat stress. Two additional parameters 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."
2) The mean skin temperature to be used as a "danger" threshold. Here, a relatively low threshold value of $T_d = 36.5$ °C is used due to the safety limits of the trials used to form the model.

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

$$P\left(d|T_{sk,t}, A_t, C_t\right) = \alpha P\left(T_{sk,t}|d, A_t, C_t\right) P\left(d, A_t, C_t\right)$$

where α is a normalising constant such that the conditional probability of d and $\bar{d}$ sum to 1. To form a good fit for the available data, each PDF is approximated using a Gaussian Kernel Density Estimator.

To evaluate the predictor, data from a total of 26 trials was used [1]. Twelve subjects underwent a mission-like protocol while wearing the EOD suit at 40 °C ambient temperature and three different in-suit cooling variations—no cooling (NC), chest cooling (CC), and head cooling (HC). The trials 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). The first cycle performed in each trial was excluded from the data used in the analysis here due to non-representative rapid changes in skin temperature during this cycle.

Figure 6 shows mean skin temperature against $P(d)$ for each of the three cooling variations.

Applying the trained model to a test data set yields the graph in Figure 7. For evaluation purposes, the output from the predictor is classed as correct if the generated probability is over 0.5 when the future mean skin temperature is over 36.5 °C, and vice versa (the regions shown shaded grey in Figure 7). Given this criteria, the overall accuracy of the predictor was 88.5% for the test data used. This demonstrates that the model is a usable predictor of whether the danger threshold will be exceeded.

VII. Conclusions

This paper presented the application scenario and conceptual overview of a monitoring system targeted at monitoring EOD suit wearers during missions. The aim was to provide predictive actuation of the in-suit cooling system to prevent heat stress in the operative, and such prediction required the real-time autonomous processing of skin temperature and body acceleration data. Based on the scenario and system concept, a system was described that is composed of two independently developed, but co-dependent, sub-systems responsible for different elements of data gathering and modelling. The first sub-system, Medusa2, gathers physiological data such as skin temperature and performs predictive modelling to determine the

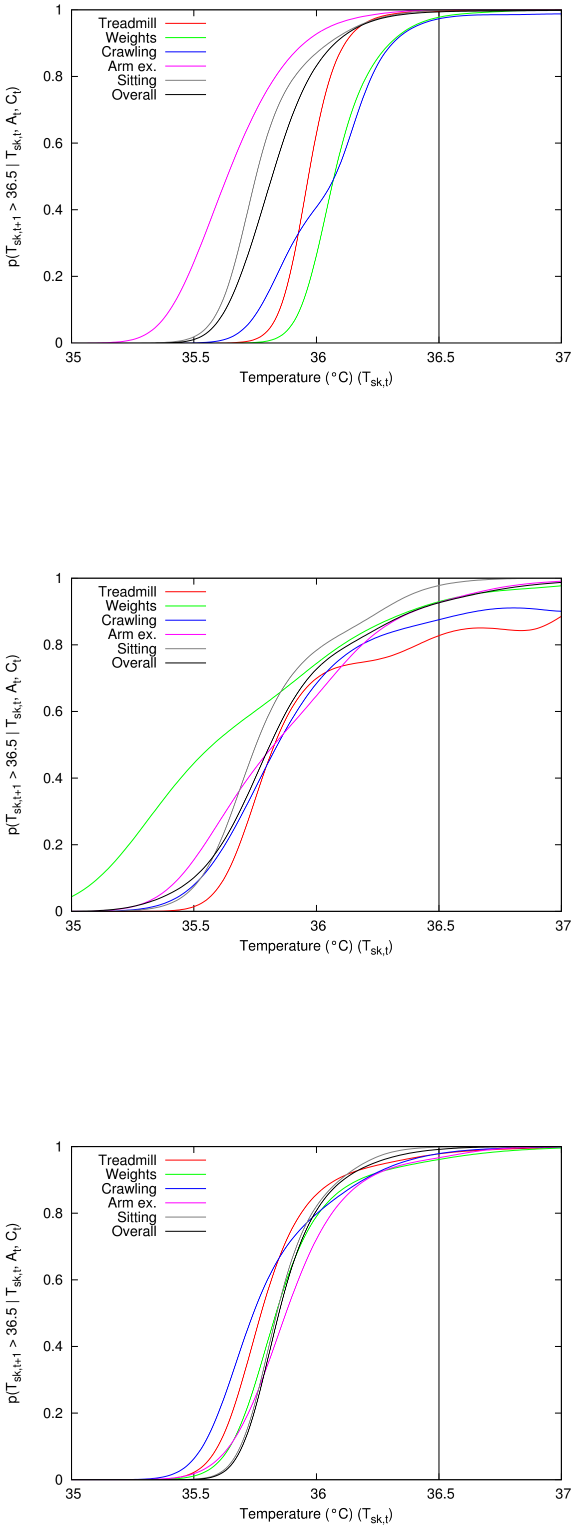

Figure 6. Mean skin temperature against $P(T_{sk,u} \geq T_d|T_{sk,t})$ for three cooling variations with $T_d = 36.5$ °C. Top: no cooling. Centre: chest cooling. Bottom: head cooling. Curves are shown for individual activities and for an aggregate (as would be used if activity information is not known).

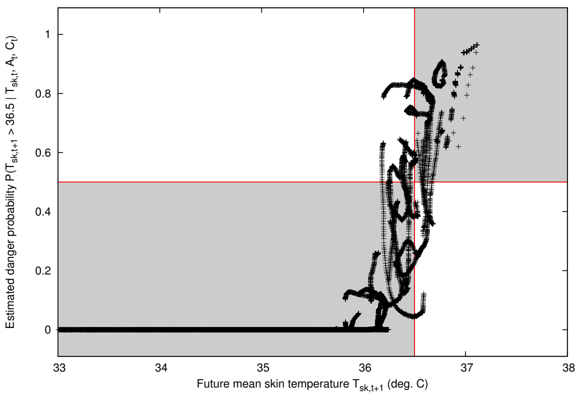

Figure 7. Performance of the Bayesian model on test data with the "future" mean skin temperature horizontally (i.e. the temperature after 2 minutes). The shaded regions are counted as accurate—probability below 0.5 for future temperatures below 36.5 °C and above 0.5 for temperatures above.

future probability of heat stress (with an accuracy of 88.5% for a two minute prediction). However, for this to occur, postural information is required as an input. The second sub-system fulfils this requirement by sensing body acceleration data and determined the current posture (with a 96.1% accuracy over the full set of eight postures selected and 17 training/testing subjects). Both sub-systems have been extensively evaluated in laboratory settings during mission-like protocols.

The combination of small lightweight sensing devices (in this case temperature sensors and accelerometers), machine learning techniques, and Dynamic Bayesian Networks together provide a powerful solution to automatic posture recognition, predictive physiological modelling, and pre-emptive actuation of safety equipment. The shift away from sensing as an end in itself and towards autonomous real-time data processing provides a range of benefits and brings sensor network systems a step closer to becoming self-contained knowledge-driven solutions for a variety of applications.

REFERENCES

[1] Unpublished data supplied by C. Douglas Thake and Fiona Brown (HLS Faculty, Coventry University).

[2] Stacy J. Morris Bamberg, Ari Y. Benbasat, Donna M. Scarborough, David E. Krebs, and Joseph A. Paradiso. Gait analysis using a shoe-integrated wireless sensor system. *IEEE Transactions on Information Technology in Biomedicine*, 12(4):413–423, 2008.

[3] Subir Biswas and Muhannad Quwaider. Body posture identification using hidden markov model with wearable sensor networks. In *3rd International Conference on Body Area Networks (BodyNets '08)*, pages 1–8, Tempe, Arizona, 13-15 March 2008. ICST, Brussels, Belgium.

[4] James Brusey, Ramona Rednic, Elena I. Gaura, John Kemp, and Nigel Poole. Postural activity monitoring for increasing safety in bomb disposal missions. *Measurement Science and Technology*, 20(7):075204 (11pp), July 2009.

[5] S. S. Cheung, T. M. McLellan, and S. Tenaglia. The thermophysiology of uncompensable heat stress: Physiological manipulations and individual characteristics. *Sports Med.*, 29(5):329–359, May 2000.

[6] Dorothy Curtis, Eugene Shih, Jason Waterman, John Guttag, Jacob Bailey, Thomas Stair, Robert A. Greenes, and Lucila Ohno-Machado. Physiological signal monitoring in the waiting areas of an emergency room. In *BodyNets '08: Proceedings of the ICST 3rd international conference on Body area networks*, pages 1–8, Brussels, Belgium, 2008. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering).

[7] Tia Gao, Tammara Massey, Leo Selavo, David Crawford, Borrong Chen, Konrad Lorincz, Victor Shnayder, Logan Hauenstein, Foad Dabiri, James Jeng, Arjun Chanmugam, David White, Majid Sarrafzadeh, and Matt Welsh. The advanced health and disaster aid network: A light-weight wireless medical system for triage. *IEEE Transactions on Biomedical Circuits and Systems*, 1(3):203–216, September 2007.

[8] Keri J. Heilman and Stephen W. Porges. Accuracy of the lifeshirt (vivometrics) in the detection of cardiac rhythms. *Biological Psychology*, 75(3):300–305, July 2007.

[9] Ernst A. Heinz, Kai Kunze, Matthias Gruber, David Bannach, and Paul Lukowicz. Using wearable sensors for real-time recognition tasks in games of martial arts - an initial experiment. In *Proceedings of the 2nd IEEE Symposium on Computational Intelligence and Games (CIG*, pages 98–102, Reno/Lake Taho, Nevada, USA, May 2006.

[10] Emil Jovanov, Aleksandar Milenkovic, Chris Otto, and Piet C de Groen. A wireless body area network of intelligent motion sensors for computer assisted physical rehabilitation. *Journal of NeuroEngineering and Rehabilitation*, 2(1):6, March 2005.

[11] John Kemp. *Body Sensor Networks for Health Monitoring: A Safety Critical Mission Application*. PhD thesis, Faculty of Engineering and Computing, Coventry University, UK, 2010.

[12] John Kemp, Elena Gaura, James Brusey, and Doug Thake. Embedded sensing and actuation for helmets co_2 levels control. *International Journal on Smart Sensing and Intelligent Systems*, 4(1):160–185, March 2011.

[13] Nicky Kern and Bernt Schiele. Multi-sensor activity context detection for wearable computing. In *European Symposium on Ambient Intelligence*, Eindhoven, The Netherlands, November 2003.

[14] Kai Kunze, Paul Lukowicz, Holger Junker, and Gerhard Troster. Where am I: Recognizing On-Body Positions of Wearable Sensors. In *In: LOCA'04: International Workshop on Locationand Context-Awareness*, pages 264–275. Springer-Verlag, 2005.

[15] Aleksandar Milenkovic, Chris Otto, and Emil Jovanov. Wireless sensor networks for personal health monitoring : Issues and an implementation. *Computer communications*, 29(13–14):2521–2533, 2006.

[16] Carsten W. Mundt, Kevin N. Montgomery, Usen E. Udoh, Valerie N. Barker, Guillaume C. Thonier, Arnaud M. Tellier, Robert D. Ricks, and Robert B. Darling. A multiparameter wearable physiologic monitoring system for space and terrestrial applications. *IEEE Transactions on Information Technology in Biomedicine*, 9(3):382–391, September 2005.

[17] P. S. Pandian, K. P. Safeer, Pragati Gupta, D. T. Shakunthala, B. S. Sundersheshu, and V. C. Padaki. Wireless sensor network for wearable physiological monitoring. *Journal of Networks*, 3(5):21–29, May 2008.

[18] Julien Pansiot, Danail Stoyanov, Douglas McIlwraith, Benny P.L. Lo, and G. Z. Yang. Ambient and wearable sensor fusion for activity recognition in healthcare monitoring systems. *4th International Workshop on Wearable and Implantable Body Sensor Networks (BSN 2007)*, 13:208–212, 26-28 March 2007. ISSN 1680-0737.

[19] C. D. Thake, M. J. Zurawlew, M. J. Price, and M. Oldroyd. The effect of heat acclimation on thermal strain during explosives ordnance disposal (EOD) related activity in moderate and hot conditions. In *Proceedings of the 13th International Environmental Ergonomics Conference (ICEE 2009)*, pages 113–117, Boston, USA, August 2009. University of Wollongong:Australia. ISBN: 978-1-74128-179-8 (online).

[20] Hong Ying, C. Silex, A. Schnitzer, S. Leonhardt, and M. Schiek. Automatic step detection in the accelerometer signal. *4th International Workshop on Wearable and Implantable Body Sensor Networks (BSN 2007)*, 13:10–85, 26-28 March 2007. ISSN 1680-0737.