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Postural activity monitoring for increasing safety in bomb disposal missions

James Brusey, Ramona Rednic, Elena I Gaura, John Kemp and Nigel Poole

Cogent Computing Applied Research Centre, Coventry University, Priory Lane, Coventry, CV1 5FB, UK

E-mail: e.gaura@coventry.ac.uk

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Abstract
In enclosed suits, such as those worn by explosive ordnance disposal (EOD) experts, evaporative cooling through perspiration is less effective and, particularly in hot environments, uncompensable heat stress (UHS) may occur. Although some suits have cooling systems, their effectiveness during missions is dependent on the operative's posture. In order to properly assess thermal state, temperature-based assessment systems need to take posture into account. This paper builds on previous work for instrumenting EOD suits with regard to temperature monitoring and proposes to also monitor operative posture with MEMS accelerometers. Posture is a key factor in predicting how body temperature will change and is therefore important in providing local or remote warning of the onset of UHS. In this work, the C4.5 decision tree algorithm is used to produce an on-line classifier that can differentiate between nine key postures from current acceleration readings. Additional features that summarize how acceleration is changing over time are used to improve average classification accuracy to around 97.2%. Without such temporal feature extraction, dynamic postures are difficult to classify accurately. Experimental results show that training over a variety of subjects, and in particular, mixing gender, improves results on unseen subjects. The main advantages of the on-line posture classification system described here are that it is accurate, does not require integration of acceleration over time, and is computationally lightweight, allowing it to be easily supported on wearable microprocessors.

Keywords: protective suit environments, posture monitoring, first responders

(Some figures in this article are in colour only in the electronic version)

1. Introduction

Bomb disposal missions provide armour designers, disposal technicians and mission controllers with a number of challenges, due to the extreme conditions at the bomb disposal site and the strain generated from wearing the armour and engaging in the bomb disposal activity. A typical bomb disposal mission will initially involve investigating the site using a remote controlled robot, and if possible, disarming the bomb remotely. Sometimes, however, it is necessary for a human bomb disposal expert to disarm the device. For this, the explosive ordnance disposal (EOD) expert will put on a protective suit and helmet (which weighs over 40 kg and is shown in figure 1), pick up a tool box of equipment, and walk the 100 or so metres to the site. To reach the bomb's location and fulfil the mission, it may be necessary to climb stairs, crawl through passageways, kneel, use specialist equipment or even lie down.

Within the enclosed suit microclimate, evaporative cooling through perspiration is less effective. Uncompensable heat stress (UHS) occurs when the body cannot cool itself as fast as heat is being generated due to muscular exercise (such as that required to walk in the heavy suit). Heat stress is debilitating, both physiologically and mentally, and can be

Figure 1. Explosive ordnance disposal (EOD) suit.

fatal if untreated. In hot environments, the risk of UHS is considerable. Hence, the suit manufacturer has incorporated a cooling system within the suit, which provides some thermal remedy but its effectiveness changes with posture.

Previous work [1, 2] has shown that, when wearing the suit, skin temperature changes significantly with posture and activity. This is illustrated in figure 2 (the associated experiment was performed without using the cooling system but similar or greater variations can be expected when the cooling system is used). During walking and crawling activities, the skin temperature for the chest, abdomen and calf drops significantly, whilst it increases for the arm, neck and thigh.

Local skin temperature variations are likely to be partly due to the exertion of nearby muscle groups but they may also be due to changes in thermal conductivity between the skin and the sensor, or changes in airflow. It is clear, nonetheless, that posture/activity is highly correlated with local skin temperature. Consequently, knowledge of the current posture should allow better estimates of the underlying thermal state[1] of the body than those produced using skin-temperature measurements alone. Such knowledge should also allow better prediction of how the thermal state will change in the near future.

In the EOD suit monitoring application, the main aim is to make an early prediction of the onset of UHS and to (a) alert the operative, and (b) transmit an alert to a remote station. Note that remote transmission will not always be appropriate. It is usually the case that EOD operatives carry signal jamming devices to avoid having bombs remotely triggered and this means that radio communication is not possible. For this reason, the emphasis in this work is towards systems that can operate without external communication and perform processing locally within the suit, hence catering for point (a) above in all conditions. The usefulness of remote communication should not be discounted entirely, however, since there are many settings where radio communication is not jammed, such as during training exercises or in trials of different versions of the suit by the manufacturer.

In this work, the focus is on developing reliable posture or activity estimation. Development of predictive thermal models, based on a combination of multi-site skin temperature and posture, will be considered separately. The application delimits the set of postures and activities that need to be detected. For example, drinking coffee, typing at a keyboard or riding a bicycle need not be considered. Furthermore, the focus on postures that affect the relationship between thermal state and local skin temperatures implies that quite broad classifications can be used.

The approach used to classify postures is to use the C4.5 algorithm to learn a decision tree. Several other possible machine learning tools (Naive Bayes and Decision Tables) were evaluated and results are presented in section 5.2. Several other authors [3, 4] have explored a variety of algorithms such as IBL, Naive Bayes and Decision Tables in the context of determining activity from acceleration data and found that C4.5 worked best for their classification problems also. Ravi *et al* [5] have examined the use of metaclassifiers and found some further improvement over base classifiers. Such approaches have not been explored here but might be expected to yield similar levels of improvement.

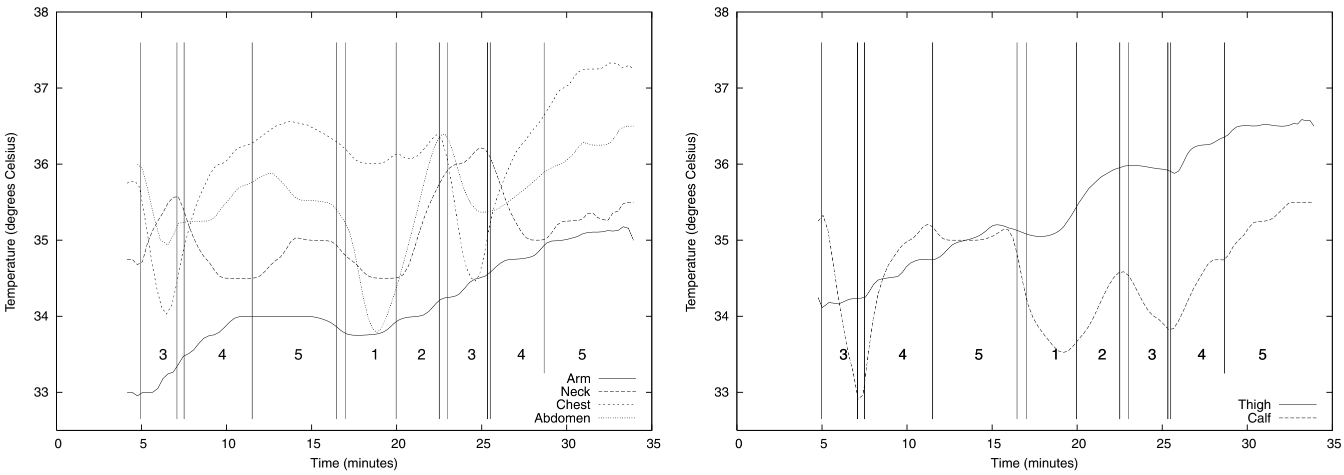
There are several other reasons to make use of decision trees. First, C4.5 pushes attributes that provide the most information to the top of the tree. This feature makes it easy to see whether some sensors are redundant or at least, less useful, in performing the classification. Second, the derived decision tree is readily converted into program code. The tree structure is simple enough to be coded in about three machine instructions per tree branch. Third, since the resulting code does not contain loops, a strict real-time limit can be set for its operation.

Furthermore, 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 (such as a piecewise linear transform), and therefore, a decision tree based on raw accelerometer measurements will perform just the same as a decision tree based on calibrated (according to, say, a piecewise linear transform) accelerometer measurements.

Philosophically, the approach to system design is application-led rather than technology-led. It is felt that this is important because there is clearly a danger within the wireless sensor network (WSN) domain to derive the technology first and search for a matching application afterwards.

The paper is structured as follows: section 2 examines related work, focusing, in particular, on research relating to

[1] The term 'thermal state' is used here to refer to stored heat energy within the body and is sometimes estimated by a weighted average of various skin temperatures and the core temperature. Thermal state is a useful metric since core temperature tends not to vary under normal conditions and so makes it hard to predict the onset of abnormal conditions. Also, while skin temperature varies, individual local skin temperatures are not necessarily indicative of a problem with thermoregulation.



(a) Upper body (b) Lower body

Figure 2. Skin temperature over time whilst wearing the suit (without using the cooling system) during different activities. The vertical lines in each graph show the start and end of activities. Each activity is represented by a number: (1) walking, (2) kneeling while putting weights into and out of a rucksack, (3) crawling, (4) arm exercise, (5) sitting and (6) standing.

wearable posture tracking and identification systems. The system design for the postural activity monitoring prototype is outlined in section 3, which includes a description of the in-suit modelling (referred to in this paper as in-network modelling) and information extraction aspects of the prototype. The implementation of the prototype is reported on in section 4. Experimental results and the prototype evaluation are presented in section 5. Finally, the paper concludes with observations drawn from the work so far and outlines future work.

2. Related work

Several attempts have been reported in the literature towards tracking the movement or position of human subjects [3, 6–10]. Generically, based on the sensor types and their location on the monitored body, tracking systems can be classified as non-vision based, vision based with markers, vision based without markers and robot assisted systems. The first category includes approaches similar to that adopted in the system presented here. Vision-based tracking with markers uses remote optical sensors (cameras) and identifiers on the body. This method is suitable for deployment in controlled environments and has been pervasively used in cinematography, medical science, sports science and engineering [11, 12]. Vision-based tracking without markers entirely exploits cameras/machine vision to track the movement [13]. High-speed cameras are required, as it is commonly accepted that at least 60 frames per second are needed for accurate tracking [14]. Robot-assisted tracking (or robot-guided systems), mainly used in rehabilitation, incorporate sensor technologies to apply ‘move–measure–feedback’ training strategies. In this type of system, human movement is corrected by a robotic device using electromechanical and electromagnetic sensors attached to the body in order to make the user apply more force in their movements or to support the user while they perform the exercises [14].

Non-vision-based posture tracking systems have been implemented for use in both rehabilitation programs [15] and movie graphics production. The system developed by Biswas and Quwaider [6] is the closest to the system proposed here, but differs in implementation and design perspective. Biswas and Quwaider’s system uses, as hardware basis, the Mica2Dot wireless node with an integrated two-axis piezoelectric accelerometer. To determine position, a novel radio-frequency-based proximity sensing method is used for monitoring the relative movements of body segments. These data are then processed off-line, using a hidden Markov model, in order to identify the subject’s posture. The system is capable of identifying a limited set of postures: sitting, standing, walking and running.

Several other examples of systems for posture classification exist, developed for the patient care application area, mostly involving patient rehabilitation. An interesting system of this type was developed by Pansiot *et al* [16]. 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. In terms of each sensed silhouette, the derived information includes the aspect ratio and mean velocity. Sensor fusion is performed, based on a Gaussian Bayes EM classifier, using the e-AR and silhouette information. Bayes Net Toolkit (BNT) is used for the implementation of the classifier. Some activities are classified perfectly, whilst others (e.g. sitting) have a recall as low as 0.47. Pansiot’s approach is inappropriate here as it entails an instrumented environment.

Farella *et al* [17, 18] designed and implemented the WiMoCa, a wireless sensor node based on triaxial integrated accelerometers and used it to detect human gestures and postures. The platform (containing an RF component, an LIS3L02DQ accelerometer, an ATmega8 microcontroller and a power supply) is used to detect three different postures:

sitting, standing and lying. The full system has three WiMoCa nodes placed on the trunk, thigh and shin of the subject being monitored. The system does not track dynamic postures such as walking and crawling; it is used for static postures classification only.

Identifying human posture with inertial (accelerometer and rate gyroscope) and magnetic (magnetometer) sensors was also attempted by Fontaine *et al* [19]. Data are acquired from 10 to 15 sensor cubes (each containing 6 sensors to allow full three-axis sensing over the two modalities: acceleration and magnetic field) and used to animate a skeleton in real time. The skeleton is represented by a simplified collection of 'bones' that approximate the human skeleton, and is animated using the Kaydara Filmbox. The need for magnetic sensors calibration each time the system is used in a different environment makes this system less portable, as well as time consuming to set up.

The variety of systems and applications in the literature, similar to those described above, show that posture tracking is a relatively well-covered research subject with a number of branches and applications: from activity detection [20, 21] to position recognition [6, 8, 9], to real-time movement recognition tasks for martial arts [22] and manufacturing environments [23], added to gait measurement [24]. The systems reported, although by and large application specific, often share a common sensor placement on the body in order to accurately detect the subject's movement and limb positions [25–27] but require different degrees of movement sensing accuracy to fulfil the specific application.

Full body motion tracking systems, such as Arvind *et al*'s Orient [28] or the commercial Xsens moven system [29], use a combination of triaxial accelerometers, rate gyroscopes and magnetometers. Such systems integrate the signal produced over time, which tends to amplify any bias and causes the position estimate to drift over time. If being used to establish position, it is usual to incorporate another location sensor (such as GPS) to correct for drift periodically.

Sun *et al* [10] have integrated activity classification and dead reckoning techniques in step-based pedestrian navigation. They implemented a system using a tri-axial accelerometer (AK897A) and an electronic magnetic compass, sampling at 64 Hz. In terms of posture classification, main focus was to examine the difference between walking, standing still and other irregular motion. Using a probabilistic neural network (PNN), classification results were 98.5% for walking, 100% for standing still and 83.1% for irregular motion. Features used included acceleration standard deviation, energy and frequency-domain entropy.

Other systems exist which detect posture-related events, such as steps while walking. An example of this is the system implemented by Ying *et al* [30] for automatic step detection for patients with Parkinson's disease. Several methods of detection have been evaluated by Ying, such as the Pan–Tompkins method, the template-matching method and the peak-detection method, based on combined acceleration signals. The system implemented consists of a dual axis accelerometer (ADL322) and passive low-pass filtering. The Pan–Tompkins method is reported to be easy to implement, but fluctuations in the signal can result in false peak-searching intervals. The template-matching method has the advantage that the algorithm is capable of detecting the steps self-adaptively. This, however, depends on the first template, which may be incorrect. 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* [31] as part of a wider personal health monitoring system.

One of the most challenging activity recognition problems is everyday activity. Bao and Intille [3] have developed a classifier for such activity based on acceleration sensors. For their system, they acquired acceleration data from 20 subjects using five biaxial ADXL210E accelerometers with a ± 10 g range mounted on a *hoarder* (data collection) board. Sensors were placed on the right hip, right shin, left thing, upper left arm and right wrist. Twenty different activities were studied, including not only walking and sitting but also folding laundry, bicycling and vacuuming. The training was done in a semi-naturalistic environment without researcher supervision. Activity recognition was performed using decision tables, IBL, C4.5 and Naive Bayes, with best results obtained using C4.5. With training performed for a specific user, 77% of activities were correctly classified, whilst with unseen subjects, performance dropped to 73%.

Laerhoven *et al* [32] have also looked at everyday activities. They augmented their activity recognition system with a rhythm model that captures the user's normal daily pattern of behaviour. Their wrist-worn sensor consists of a combination of accelerometers and tilt switches. The combination is used mainly to reduce power requirements; information from the tilt sensors are used to wake up the more detailed accelerometer measurement system when it is needed. Activities included such things as having breakfast, relaxing in the sauna and watching TV. The *k*-nearest neighbour (KNN) classifier was used to differentiate between 13 activities with 82–84% accuracy.

To summarize, the majority of the systems presented above perform motion capture or movement event detection type tasks, rather than real-time posture classification as required by the application discussed here. Those systems that do perform posture classification are limited to specific subsets of postures as dictated by the specific application. The system brought forth in this paper aims to provide real-time, on-line classification and visualization of a wider set of postures which cover those that may be encountered during typical bomb disposal missions. The system design produced towards this aim is described below.

3. System design

The system design for the posture assessment instrument has been driven by a mixture of constraints largely falling into the following categories:

- Suit related constraints, such as its modular structure and the need to avoid running wires between the various garment components, and the overall wearability of the instrument.

- Application related constraints, such as the intermittent use of signal jamming devices during a mission, communication distances and physical obstructions in the environment.
- Safety critical concerns, such as the need for in-suit decision making and alerting the operative and mission control of unsafe conditions.
- Scope of the instrument, such as its dual use as a field deployable system as well its use in laboratory trials for both physiological research and suit design analysis.

In response to the suit-related constraints, the overall design of the system is structured around a mix of wired and wireless communication. Multiple sensing packages are wired to each processing node. The wiring will be incorporated into the fabric of the suit or an undergarment in future. Although wireless communication from each sensor package might seem feasible, this would both increase the size and weight of the sensor packages and require additional batteries or power-harvesting devices, hence decreasing the wearability of the system. Since there is a need to sense body segment acceleration at a number of points, such an approach would be unwieldy.

Wireless communication will allow communication within the components of the instrument given that the instrumentation for the jacket and trousers needs to be physically separate to ease robing and disrobing. This mix of wired/wireless communication is similar to that of the Xsens moven inertial tracking system [29]. Hence the system here is designed as a three-node body sensor network with three tiers of communication: sensor package to processing nodes (wired), node to node within the suit (wireless) and node to base station/remote monitoring unit (wireless).

With regard to application-related constraints, there are a number of reasons to expect and allow for intermittent communication, such as the use of signal jamming devices during bomb disposal missions, and temporary obstruction of the radio signal as the user moves about. Since the instrument has to serve a safety critical application, it must sustain operation during loss of communication with the remote monitoring unit. Consequently, the system must support two modes of wireless communication: one, short-range communication, between body worn nodes that is insensitive to signal jamming devices, and the other, long-range communication to the remote monitoring unit (base station). Wireless short-range communication that is immune to signal jamming devices is an open problem, however possible options to be explored include near-field communication [33]. Due to the nature of the long-range communication, a single node maintains this link.

A unifying aspect of the safety requirements, including the need for in-suit actuation of cooling, alerting the operative of unsafe conditions and catering for wireless link loss without information loss, is that all require delivery of information rather than data.

Responding to the above requirement, the prototype developed here processes the acquired data locally, in-network, at one of the nodes that are worn within the suit (the jacket node is used for processing but the trouser node could also be used; see figure 5), rather than at a remote base station, thus enabling local-information-based decisions.

At mission control, a visualizer should provide an easily interpretable display of the posture of the wearer. A simple ‘stick figure’ type illustration was adopted as described further in this paper. All constraints discussed in this section have been considered and implemented in the prototype reported here, with the exception of near-field communications.

Classification of posture is performed using decision trees as discussed in the introduction. Weka [34] is used to perform all machine learning, and the resultant trees are converted to Python to run on the nodes.

3.1. Features used

The first feature used for training was the 12-bit uncalibrated acceleration values for each of three axes, over a total of nine sensors.

It is common to examine both frequency-domain and time-domain features; however, as Bharatula [4] points out, frequency-domain features alone yield relatively poor classification results for this type of accelerometer-based activity classification. Since the aim here is to perform all processing on a low-power microcontroller or microcomputer, and since frequency-domain feature extraction is computationally complex, there seems little advantage in including such features. Furthermore, frequency features are overly sophisticated for this application—it is not desirable, for example, to know how quickly someone is walking or to distinguish between slow and fast walking rates.

Of the temporal domain features, the following were considered:

windowed mean (WM). The mean acceleration for a particular axis over a fixed period of time (or window) can be used to minimize the effect of any sudden movement by weighting more heavily longer duration acceleration such as that due to gravity. Unfortunately, the mean will tend to confuse movement that is periodic with a stationary posture. A 5 s window (50 samples at 10 Hz) was used to form the window for this and other windowed features.

windowed mean square (WMS). The mean square of the acceleration over a time window can be used to help distinguish periodic movement from stationary postures.

moving average square (MAS). The exponential moving average of the square is similar to the windowed mean square but requires less memory to compute. The MAS estimate is given by

$$S_t \leftarrow \alpha Y_t^2 + (1-\alpha)S_{t-1},$$

where Y_t is the accelerometer measurement.

windowed variance (WVar). The variance of the acceleration over a time window. This feature was tried in comparison with WMS since it provides an indication about how the acceleration is oscillating but is independent of the mean value.

Kinetic energy was also considered as a possible feature, since the kinetic energy of the limbs during dynamic movement

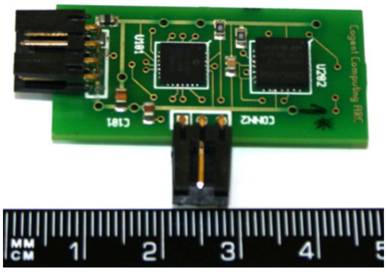


Figure 3. Sensor board, which includes a PIC microcontroller, I2C buffer, triaxial accelerometer and digital temperature sensor.

will be higher. The main difficulty with estimating the kinetic energy is that it is based on velocity rather than acceleration and thus requires integration of acceleration over time. The velocity estimate would be expected to drift from the true value if there are even small errors in the acceleration measurement and so this feature was not included.

4. Implementation

The BSN reported here consists of two suit-integrated nodes (one for the jacket and one for the trousers) and a base station. The Gumstix Verdex XM4-bt devices are used as the main processing and communications platform. The Gumstix devices are fully functional single board computers with a footprint of $80 \times 20 \times 6.3$ mm^3 and a weight of 8 g. The Gumstix devices contain a 400 MHz Marvell PXA270 XScale CPU and have integrated Bluetooth communications on-board. This processor board is considerably in excess of the computational requirements for evaluating (not building) a decision tree but the added computational power simplifies the prototyping process, allowing, for example, Python to be used for most of the software development. At the same time, the Gumstix devices are small and light enough to be easily carried in a pouch or pocket.

Several bespoke acceleration sensor boards (figure 3) are connected to each Gumstix device via an expansion board which provides I2C bus connections and connects to the Gumstix via the Hirose connector. Each sensor board consists of a microcontroller, a temperature sensor, a triaxial accelerometer and a I2C bus extender. The board was designed as a low-cost, small-size, low-power wearable solution based on commodity components. The microcontroller is a Microchip PIC24FJ64GA002, while the accelerometer used is a STMicroelectronics LIS3LV02DQ. The Gumstix devices communicate via Bluetooth, node-to-node and node-to-base station. The base station (mission control PC) receives and displays posture information (in 'mission' mode) or posture information and acceleration data (in 'analysis' mode). When in mission mode, it is only necessary to transmit an update when the posture changes.

The sensors were positioned on the subject's body (chest, biceps, forearms, calves and thighs) as shown in figure 4. A single acceleration sensor was used per body segment. Extensive experimentation was conducted to ensure that this body sensors configuration provided sufficient data towards classification of the set of positions needed for the application at hand. It should be noted here that, for differentiating accurately the standing and walking posture, ankle sensors coupled with hip sensors are suggested to produce best classification performance [35]. This approach could not be adopted here as one of the implementation aims is to not only minimize the number of body worn sensors (to conform with user requirements and increase wearability) but also to have the inertial sensors mounted in the same locations as the temperature sensors in the over-arching instrument (hence, the dual role of the board in figure 3, which hosts temperature sensors as well). With regard to temperature sensing, the sensors positioning (as per in figure 4) is well documented in the literature and hence a fixed implementation requirement here to allow seamless integration of the postural instrument.

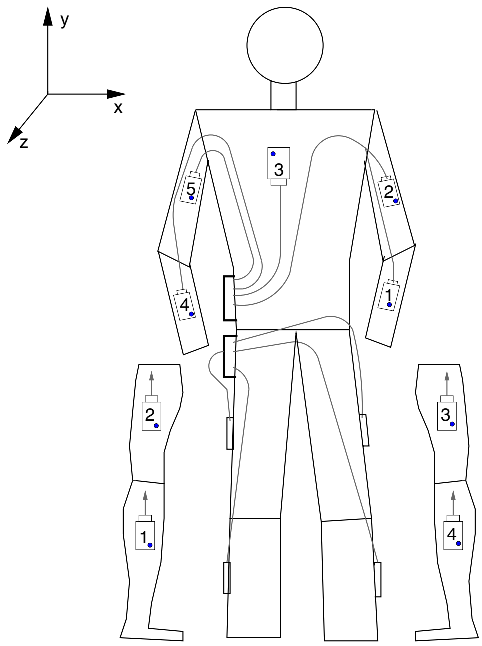


Figure 4. Positioning of sensors and nodes on the body.

The five sensors used for the upper body are connected to one node, whilst the four sensors fitted on the lower body are connected to a second node (see figure 5). Bluetooth communications are used for both the short-range communication (that is, passing data from the lower body node to the upper body node for processing) and for long-range communication (between the network and the base station). The Bluetooth radio provides a convenient means of establishing a small network such as that implemented here. Although Bluetooth transfer rates are limited, they are more than adequate for this application. At the remote monitoring point, postural information is delivered for real-time visualization using stick figures.

5. Prototype evaluation

5.1. Experimental setup

Eleven volunteers of different builds were used for acquiring training and testing data. The volunteers group was mixed

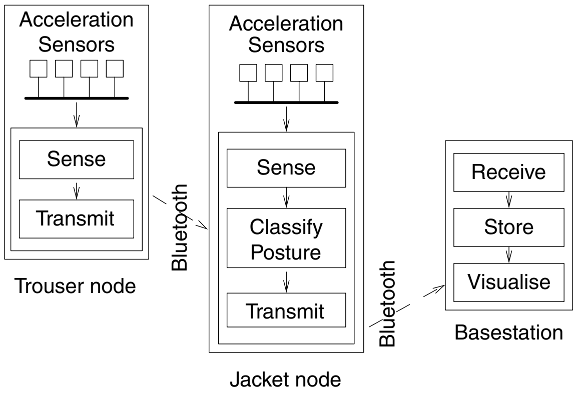


Figure 5. System schematic showing communication between the two Gumstix nodes within the suit (one each for trouser and jacket) and also to the external base station.

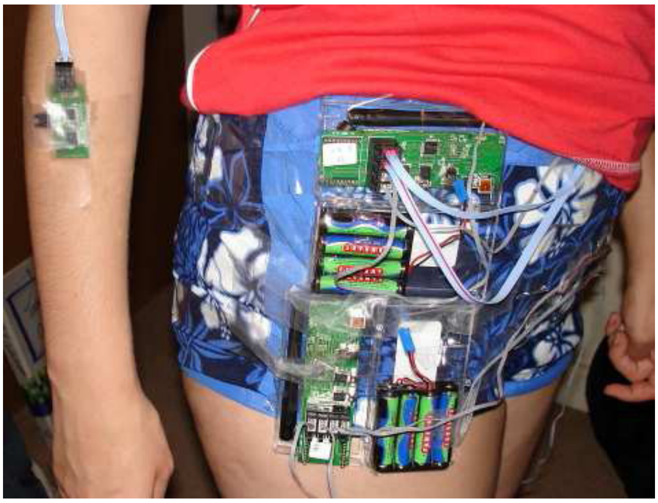


Figure 6. Subject with processing nodes on hip.

Figure 7. Snapshots of subject and visualizer during system evaluation.

males (7) and females (4) with heights between 1.6 m and 1.83 m and weights between 60 kg and 89 kg. The sensors and nodes were placed as shown in figure 4 and were taped firmly using medical tape (see figure 6 for nodes and fitting). Experiments were conducted with both skin-taped sensors and sensors fitted over light clothing. Acceleration readings were taken at a rate of 10 Hz, and postural activity was also assessed and displayed at this rate.

Three different activity regimes were used (R1, R2 and R3). The R1 regime was composed of sitting, standing, walking, kneeling, crawling, lying on one side, lying down on their front and lying down on their back. Each posture was maintained for 1 min, with the subject performing light arm movement tasks combined with variations from the set positions (such as, for example, leaning back, forth, sideways, whilst walking and standing). Figure 7 shows one of the subjects in each of the eight postures studied, along with the remote visualizer running on-line and real time. The R2 regime focused on mission-like activities regime, which included (1) walking (3 min), (2) kneeling while putting weights into and out of a rucksack (2 min), (3) crawling (2 min), (4) arm exercise while standing (4 min), (5) sitting (3 min) and (6) standing (1 min). The R3 regime expanded on the above further by including more natural movements (such as lifting weights whilst standing or unpacking a box whilst kneeling). Each volunteer performed each regime once. Time-constraining each activity simplified annotation of the resulting data. About 40 min of accelerometer measurements over nine tri-axial accelerometers were gathered per subject.

Bao and Intille [3] argue for all testing to be performed in a natural environment since volunteers will tend to constrict their movement in some way when performing in the laboratory environment. Although some efforts have been made, particularly with R2, to duplicate the environment of EOD missions, it has not been yet possible to acquire data from the suit's main end user.

5.2. Classification results

5.2.1. Static postures. A clear result was that static postures are correctly classified just using raw accelerometer measurements and no other features. To demonstrate this, a tree was trained using seven subjects (including both males and females) to classify six static postures (sitting, standing, kneeling, lying on one side, lying face down and lying face

Table 1. Performance for decision tree classification of static postures. The overall result is based on stratified cross validation from the training data. Subjects S1 to S4 were not used for training. Classification performances are given as percentages.

	Tree size	S1	S2	S3	S4	Mean
Raw accel. (static postures)	27	99.86	100	99.90	99.95	99.93
WM only	23	93.31	99.87	92.58	99.91	96.42
Raw accel. (dynamic postures)	883	82.00	98.10	88.68	80.85	87.41

Table 2. The effect of gender on classification performance. The F-tree was trained with only female subject data and tested on males, whilst vice versa for the M-tree. Both trees were trained with static postures only.

Subject	% correct
F-tree	
S5	91.36
S6	82.33
S7	100
Mean	91.23
M-tree	
S9	88.60
S10	95.98
S11	68.89
Mean	84.49

up). Four other (unseen) subjects were used to test the tree, which gave weighted average precision and recall greater than 0.999 for all subjects and overall, 99.93% correctly classified. A summary of the results is given in table 1. These results show the percentage of postures correctly classified for four subjects who were not used in training (S1–S4). The mean result shown is the average performance over the four subjects.

The worst performance per posture was a precision of 0.984 for classifying one of the test subjects when lying face up. The tree had only 27 nodes and mainly uses data from sensors on the leg and chest. The tree uses data from one arm sensor to help distinguish a small number of lying face down/kneeling cases from lying on one side but otherwise the arm sensors are ignored.

Other work (such as that of Bao and Intille [3]) has considered using a windowed mean (WM) instead of the raw measurement value, on the basis that it reduces noise. For the set of static postures used here, however, performance dropped when using WM features only (see table 1). When dynamic postures, such as walking and crawling, are included, performance degrades considerably.

5.2.2. Effect of gender. It was noticed early in evaluation that if females were not included in the training, the classifier tested poorly when used with females. To examine this effect further, a tree (denoted M-tree) was trained with males (three subjects) and then tested on females (three subjects) and vice versa (denoted F-tree). Results for the two trees are shown in table 2. Mean performance for all female test subjects for the M-tree was 84.5%. The worst performance was for one subject where all 'lying on one side' instances were classified as lying face down. For the F-tree, 91.2% of postures were correctly classified over all male test subjects. Worst case performance occurred with the precision for lying face up, which, for one subject, was only 0.346. Comparing the above results with those from table 1, it is clear that only using a single gender when training may lead to poor performance when the tree is tested on a different gender. Use of a mixture of genders when training is clearly necessary if the classifier is intended to be tested on a mix of genders.

With regard to the need for a mix of genders in training, there is some possibility that height may play a part (all females were shorter by at least 5 cm than the shortest male) and also weight may be relevant (one of the males (S3) had a weight of 62 kg, which was below the average female weight, and had good results on the female trained tree). Given the nature of the postures misclassified (such as lying face up), a possible reason is differences in leg flexibility. It was noticed that males tended to lie with their knees further off the ground, thus leading to different limb angles.

5.2.3. Dynamic postures. Dynamic activities such as walking produce acceleration values that *at some time instances* cannot be distinguished from static postures such as standing. During walking, the motion of the leg is similar to a pendulum and thus one can expect the acceleration to be roughly sinusoidal along the axis closest to the direction of motion (or forward axis). It is hard to distinguish standing from walking since, for example, standing still produces near to zero acceleration in the forward axis whilst walking motion causes the forward axis acceleration to oscillate, and thus, at some time instances, will be zero.

Examining the results given in table 3, it can be seen that temporal features (WM, MAS, WMS, WVar) generally provide an improvement (compare with 'no temporal features'). Specifically, the tree size is much smaller, and with the exception of WM, mean classification performance improves to above 94%. When dynamic postures are included but when no temporal features are used, classification of static postures continues to be high but standing and walking tend to be confused and this causes most of the reduction in performance of the tree compared to classifying static postures alone. It is interesting to note that for one subject (S3), only WVar produces classification performance above 90%. A strength of WVar is not only the overall performance but also the consistency of results between different subjects. A Welch t-test shows that the mean correctly classified postures over all variants for the WVar feature is significantly greater than that for the WMS feature ($p = 0.032$) indicating that WVar should be preferred. There may be a case for combining the two since, in a few cases, the performance for WVar is worse than for WMS.

Table 3. Performance of decision tree when classifying both static and dynamic postures (which include walking and crawling). The overall result is based on stratified cross validation from the training data. Subjects S1–S4 were not used for training. Classification performances are given as percentages.

	Tree size	S1	S2	S3	S4	Mean
No temporal features	883	82.00	98.10	88.68	80.85	87.41
WM	191	77.02	92.61	80.87	97.86	87.09
MAS ($\alpha = 0.065$)	145	93.89	99.84	86.36	97.63	94.43
MAS ($\alpha = 0.039$)	125	94.02	99.89	84.64	99.59	94.54
WMS	113	98.65	99.88	86.90	99.50	96.23
WVar	95	97.03	98.58	95.66	97.65	97.23
Calibrated WMS	97	96.03	99.85	86.45	99.74	95.52
Calibrated WVar	109	98.47	99.58	90.46	99.81	97.08
Left-side WMS	121	86.01	92.96	95.52	97.75	93.06
Left-side WVar	117	97.44	99.94	98.29	99.79	98.87
Right-side WMS	127	97.79	99.69	86.97	99.64	96.02
Right-side WVar	149	94.53	99.42	93.16	95.41	95.63
Lower body WMS	169	95.65	88.13	84.50	96.44	91.18
Lower body WVar	115	83.70	99.30	89.77	99.79	93.14
Left leg WMS	235	77.89	99.06	88.46	94.36	89.94
Left leg WVar	237	81.82	98.58	97.83	99.72	94.49
Right leg WMS	233	85.41	96.96	85.74	88.11	89.06
Right leg WVar	305	92.95	98.71	89.32	97.38	94.59

5.2.4. Calibration. As previously discussed, calibration is not expected to change the results where no temporal features are used. As shown in table 3 ('calibrated WMS' and 'calibrated WVar'), calibrating sensor values has little effect on the performance even when temporal features (such as WMS) are included. The calibration performed here was a simple linear transform based on measurements for each axis when that axis is oriented to receive $+g$, $-g$ or $0g$. The results show that it is not necessary to calibrate and also that calibration does not significantly alter performance.

5.2.5. Reducing the number of sensors. If either left- or right-hand side accelerometers are excluded, the number of accelerometers used reduces to 5 (from 9) and produces the classification performance results shown in table 3 under 'right side' and 'left side', respectively. For some subjects, performance improves, whilst for others it worsens, depending on temporal feature used. Overall, the degradation in performance is relatively minor.

If only the four lower body accelerometers are included ('lower body'), performance drops below 90% for two of the subjects. With just the left or right leg included, worst case performance drops further. When only the left leg is included, subject S1 is classified poorly with both WMS and WVar, possibly indicating either some peculiarity in the S1's movement or posture, or a problem with the sensors on the left leg. It is interesting to note how much performance improves for S1 when right-hand side sensors are used rather than left-hand ones.

The average result of about 94.5% for two sensors with the WVar feature corresponds to the posture classification being incorrect for a total of 2.2 min in a 40 min mission, whereas with all nine sensors, the classification would be incorrect for 1.1 min for the same period.

5.2.6. Other classifiers. Several other base classifiers were considered (including Decision Tables and Naive Bayes), of which Naive Bayes was most successful (96.98% mean for unseen subjects with dynamic postures and using the WVar feature). Given that this result is slightly worse than that produced by C4.5 and since there are many practical reasons advantages to decision trees (such as the ease of generating a small machine code program from the tree), decision trees seem preferable for this application.

5.3. Qualitative factors

The bomb disposal application requires a communication range of up to 100 m, hence, further work will look at replacing Bluetooth-based communications with a longer-range radio such as IEEE 802.11 (WiFi).

Bandwidth payload requirements in 'mission' mode are relatively small at 4 kbit s^{-1} (12 bytes per accelerometer by four sensors over 1 hop plus 1 byte over the subsequent hop by ten samples per second). In 'analysis' mode, this increases by 12×9 bytes per packet for the second hop giving a total of 12 kbit s^{-1} to allow raw samples from all nine sensors to be transmitted to the base station. The system as developed includes some further overhead per packet to transmit debugging information. Also, the use of UDP, Bluetooth Network Encapsulation (BNEP), and L2Cap protocols adds additional overhead per packet.

Bharatula *et al* [4] indicate that no significant information is contained above 15–20 Hz and sample at 40 Hz on this basis. The prototype here provides the end user with the option to set the sampling rate between 10 Hz and 60 Hz although all of the results presented are based on a 10 Hz sampling rate.

If the system is used in isolation, as done in experimental trials, it is not comfortable to wear for long periods. There is the need to ensure that the accelerometers are firmly attached and aligned with the limb or torso. Each sensor must be individually applied to the body and this can be time consuming. When stitched into the suit fabric, however, it is expected that the system will become relatively invisible to the wearer. The suit fabric itself is quite stiff and thus not subject to the problems associated with fixing accelerometers onto loose clothing.

Conclusions and further work

In this work, the problem of accurately classifying posture or activity based on measurements from multiple accelerometers positioned around the body was explored. The context of this work is that of providing warnings of the onset of heat stress for explosive ordnance disposal operatives. The need for postural measurement was identified in earlier work since, although it is clear that posture or activity alone does not cause heat stress, posture has an effect on both cooling efficiency within the suit and measurement of skin temperatures. This context provides an opportunity to use multiple sensors around the body to ensure the best possible classification performance. Since sensors can be stitched into the fabric of the suit and since the suit itself is quite stiff, the wearability issues of using so many sensors are reduced.

The key results are as follows: it was found that, using C4.5, static postures can easily be identified to a high degree of accuracy (99.93%) using only raw acceleration readings. If dynamic postures (walking and crawling) are included, performance drops (87.41%), mainly because instantaneous accelerations of dynamic movements are often indistinguishable from those of static postures. Inclusion of temporal features improves performance considerably (with the best performing feature—windowed variance—yielding 97.23% correct). Unlike position estimation, postures can be classified based on inexpensive, factory calibrated accelerometers. If included, linear calibration does not impact performance significantly. The basic system used sensors on both sides of the body but this requirement can be removed if a small loss of performance is allowable (worst case performance was 93.16%). Performance continues to be reasonably good with just lower body sensors or just one leg, although distinguishing between such postures as lying down and sitting up (with legs straight) suffers—as might be expected.

In the context of the overall application, communication of acceleration measurement over a large number of accelerometers would make poor use of the wireless communication link. By converting raw acceleration data into posture, and further, by only communicating 'posture change events', the use of the wireless link is substantially reduced.

A key aspect of this work is the tight focus on a specific application and this has lead to useful simplifications and optimizations, such as relaxing wearability considerations (since sensors can be integrated into the suit), and the focus on a specific set of postures (that are both found in the missions and relevant to the task of estimating thermal state). Although the design of the posture classification system has made use of features that are specific to EOD suits, a similar approach to that used here might be used to derive posture for other types of suits.

In future work, it is planned to perform comparative trials with the sensor integrated into the outer fabric of the EOD suit. Furthermore, the output of the posture classification system will be integrated into the thermal state modelling tool. Also, given the relatively high performance obtained with simple temporal features, it is planned to port the classifier to one of the PIC processors or a similar, low-power embedded device to make it suitable to be further developed as a commercial product.

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