# Wireless sensor networks for activity monitoring in safety critical applications

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## ABSTRACT

The ability to monitor posture is essential to many application areas, including virtual reality, health, and sports applications. The work here focuses on the use of postural monitoring in safety critical missions such as explosive ordnance disposal (EOD) missions. The operatives undertaking these missions are commonly placed under a high level of physical and psychological strain due to the weight of the protective armoured suit and the potential risk of their work. Remote monitoring of posture may allow a better understanding of the operative's status. When combined with additional health information, posture can enhance the accuracy of operative's global state estimation. Previously, a Body Sensor Network - based (BSN) posture monitoring system consisting of nine accelerometers was designed and implemented by the authors here. The system was able to recognise six specific postures (sitting, kneeling, crawling, and three variations of laying on the ground) with high accuracy. However, the system was unable to consistently distinguish between a subject standing, walking or running. In order to counteract this limitation, a new prototype utilising additional sensors and an augmented data processing method has been implemented and evaluated and is reported here.

***Keywords***: Body Sensor Networks, posture, acceleration

## 1 INTRODUCTION AND RELATED WORK

The work reported on here is part of a larger project aimed at enabling detailed physiological measurement and insight into the body's physiological responses when exposed to enclosed and harsh environments. The harsh environment in the application at hand is that induced by heavily armoured suits. Prior research showed that for manned safety critical missions taking place in hot environments, the production of on-line, real-time, accurate human thermal state estimates alongside monitoring of subjects' physical activity is necessary. Such monitoring will enable rapid assessment of hazardous situations at a remote monitoring station and delivery of thermal remedies through control and actuation of cooling systems commonly integrated with armoured suits.

Towards this aim, the authors proposed to use advances in Body Sensor Networks technologies to develop and deploy wearable real-time monitoring instrumentation and enable decision making and actuation. The focus in this paper is the assessment of physical activities such as standing, running, crawling, walking, kneeling, laying on the back, front or sides, in real-time through the use of networked internal devices.

Several attempts have been reported in the literature towards tracking the movement or position of human subjects [5]. The system developed by Biswas and Quwaider [4] for example 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. The system is capable of identifying, through off-line processing and post-analysis a limited set of postures (sitting, standing, walking and running). Using five triaxial accelerometers sampling at 30Hz and a wireless heart rate monitor, Tapia [23] obtained a recognition accuracy of 94.6% and 56.3% using subject-dependent training and subject-independent training respectively, for three activity categories: (1) postures (e.g. lying down, standing, and sitting), (2) activities with multiple intensities (walking, rowing/arm ergometry, and cycling), (3) and other activities (running, calisthenics, move weight, and using stairs). Identifying human posture with inertial (accelerometer and rate gyroscope) and magnetic (magnetometer) sensors was also attempted by Fontaine *et al.* [9], Farella *et al.* [8], [7].

Working towards similar monitoring aims as the above, Jovanov et al. [13] developed the ActiS sensor node, designed to be used as part of a wireless body area network. This node incorporates a bio-amplifier and two accelerometers, allowing the monitoring of heart activity as well as the position and activity of body segments. The main application for their system is monitoring the activity of physiotherapy patients. Other systems exist which detect posture-related events, such as steps while walking (see Ying *et al.* [26]).

The variety of systems and applications reported shows that posture tracking is a relatively well covered research subject with a number of branches and applications: from activity detection [14], [19], to position recognition [15], [6], [4], to real time movement recognition tasks for martial arts [12] and manufacturing environments [21], added to gait measurement [1]. 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 [27], [10], [16] but require different degrees of movement sensing accuracy to fulfil the specific application. Systems such as those above have provided a starting point for the work here.

The remainder of the paper is structured as follows: Section 2 describes the system design and implementation, Section 3 evaluates the prototype produced and Section 4 concludes the paper.

## 2 SYSTEM DESING AND IMPLEMENTATION

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, the need to avoid running wires between the various garment components, and, the overall wearability of the instrument.

- 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 inertial sensing packages are wired to each BSN node. 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 [25]. Hence the system here is designed as a three node body sensor network with three tiers of communication: sensor package to processing nodes

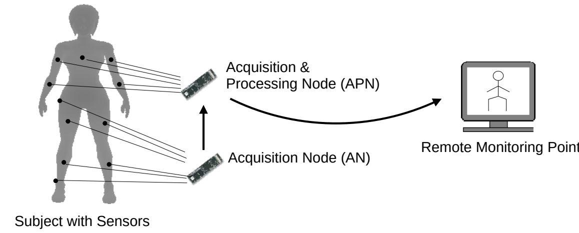


Figure 1: Prototype System Design

(wired); node to node within the suit (wireless); and node to base station / remote monitoring unit (wireless).

The prototype developed processes the acquired 3D acceleration data locally, in-network, at one of the nodes that are worn within the suit (denoted here the APN in order to differentiate from the AN; see figure 1), rather than at a remote base station, thus enabling local decisions. Furthermore, buffering information on the evolution of the operative's physical activity rather than acceleration data removes the burden on the network to store large amounts of data. The high data rate for accelerometers further justifies both the extraction and buffering of information only and a framework that allows in-network processing is needed to support the sensor type used here [20].

A C4.5 (Weka J48) decision tree learning approach [24] is used to infer posture based on the accelerometer readings. This approach was primarily chosen as decision trees are readily generated using available tools and are easily converted into a set of rules for real-time processing. Moreover, previous reported work has demonstrated their successful use for similar activity recognition reseach [2], [3], [17].

Certain activities such as walking and running imply a regular rhythmic motion (particularly of the legs). In order to account for this, the RMS of the data for each of the sensors and each axis is used as a parameter in the tree generation process. The RMS is performed over a sliding 50 sample window, with each value offset by the mean of the window contents.

The BSN prototyped consists of two body mounted nodes (AN and APN) and a base station. The Gumstix Verdex XM4-bt devices [11] are used as the main processing and communications platform. The Gumstix are fully functional single board computers with a footprint of $80 \times 20 \times 6.3$ mm$^3$ and a weight of 8 grams. They contain a 400MHz Marvell PXA270 XScale CPU and integrated Bluetooth communications. This processor board is considerably in excess of the computational requirements for evaluating a decision tree but the added computational power simplifies the prototyping process, allowing, for example, the Linux environment to be used for most of the software development. At the same time, the boards are small and light enough to be easily car-


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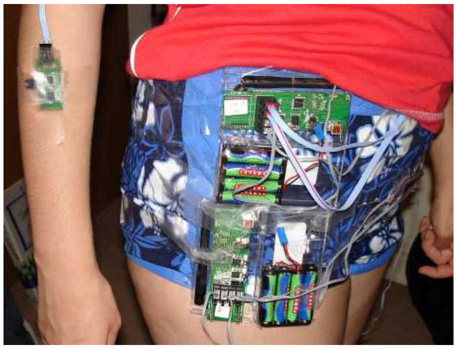

Figure 2: Nodes implementation (packaging open for demonstration purposes)

Figure 3: Sample visualisation

ried in a pouch or pocket.

Several bespoke acceleration sensor boards are connected to each Gumstix device via an expansion board. Each sensor board consists of a microcontroller, a temperature sensor, a triaxial accelerometer, and an $I^2C$ bus extender. The microcontroller is a Microchip PIC 24FJ64GA002 [18], while the accelerometer used is a STMicroelectronics LIS3LV02DQ [22] (see figure 2 for nodes implementation). 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 Functionality) or posture information and acceleration data (in Analysis Mode Functionality) depending on the field or lab use of the instrument.

The sensors were positioned on the subject's body (chest, biceps, forearms, calf's, hip, ankle and thighs). The five sensors used for the upper body are connected to one node (AN), whilst the six sensors fitted on the lower body are connected to the second network node (APN) (see figure 1). At the remote monitoring point, postural information is delivered for real-time visualisation using stick figures (see figure 3 for a sample visualisation).

## 3 EVALUATION

Several volunteers of different builds were used for acquiring tree training and testing data. The volunteers group was mixed males and females with heights between 1.6m and 1.83m and weights between 60kg and 89kg. Experiments were conducted with both skin taped sensors and sensors fitted over light clothing. Acceleration readings were taken at a rate of 10Hz, and postural activity was also assessed and displayed at this rate. Three activity regimes were studied (*Regime 1, Regime 2* and *Regime3*). Over all, the subjects undertook sitting, standing, walking, kneeling, crawling, lying on one side, lying down on their front, lying down on their back, and running. Each posture was maintained for either 1 minute or 3 minutes depending on the particular posture and regime. In *Regime 1* the subjects were asked to maintain exactly each posture described for 1 minute. For *Regime 2* the subjects maintained each posture in the context of a mission-like protocol (for instance kneeling while putting weights into and out of a rucksack, or standing while performing arm exercise). *Regime 3* expanded on this by adding natural movements to the activities performed (such as lifting weights while standing, packing things into a box while kneeling or sorting cutery from one bowl to another). This progression from strictly controlled postures to natural movements allowed a variety of data to be used for tree training and a thorough evaluation of the prototype. Data from seven volunteers performing the regimes described was gathered. Four data sets were used for tree training and three data sets for tree testing. Time-constraining each activity simplified annotation of the data set.

The accuracy of postural activity information produced by the prototype is evaluated below according to the precision and recall per posture type. *Precision* represents the percentage of instances that the classifier identifies a posture correctly out of all instances that were identified as that posture. Conversely, *recall* represents the percentage of instances a posture is classified correctly over all instances which should have been identified as that posture.

A tree (denoted Trms_l) was trained on the data from the 11 accelerometers coupled with RMS values. The precision and recall as shown in figure 4 (averaged over the set of 3 test volunteers) are sufficiently high for all 9 postures to confirm the accurate performance of the prototype over a variety of body builds and hence its suitability for the application at hand. An average correct classification of 97% to 100% for all postures was achieved. This improves considerably on previous results (averaging 69.7% accuracy over a set of 4 volunteers and all postures) obtained by using only 9 sensors (as per Figure 1 but without hip and ankle sensors) and only instantaneous data.

While the evaluation discussed above was performed with subjects not wearing the bomb disposal suit, additional trials with the suit being worn showed that tree Trms_l produced comparable results, averaging 95% ac-

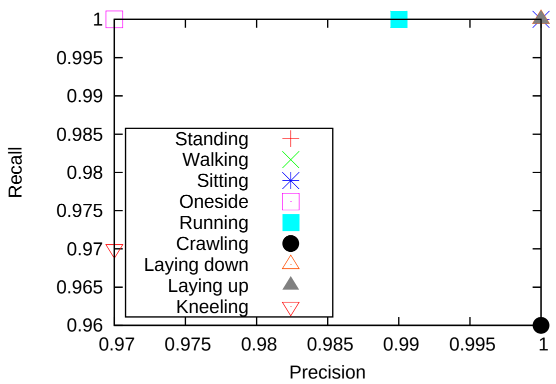


Figure 4: Overall precision versus recall for Trms_l tree

curacy for one test volunteer, over a 15 minutes bomb disposal like protocol. This means that training of the system can be performed without the bomb disposal suit, hence avoiding strain on the subjects. The error observed was entirely for periods when the subject was moving from one posture to another. For these transition, the system tends to output a succession of different unstable classifications in a very short space of time. This effect will be further quantified and studied and may be resolved using some form of smoothing or by implementing a simple rule to display posture only when a certain number of consecutive classifications of the same posture have been produced.

## 4 CONCLUSION

The paper reported on the design, implementation and evaluation of a posture monitoring prototype for manned safety critical missions. Based on inertial devices and exploiting wireless networking, the prototype is able to differentiate between nine activities commonly undertaken by operatives in bomb disposal missions. The postural information is infered locally, within the worn network of devices, and relayed in real-time to a remote mission control unit. Both instantaneous and historical acceleration data is taken as input to the decision tree running on one of the worn nodes. Experimental evaluation with several volunteers has shown that the prototype is robust, can be worn within the protective suit over light clothing or directly on the skin, and maintains the correctness of postural information delivered for a wide range of subjects undergoing mission like activities.

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