Wearable posture recognition systems: factors affecting performance

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Ramona Rednic, Elena Gaura, James Brusey, John Kemp

Abstract— **This paper presents an investigation into the design space for real-time, wearable posture classification systems; specifically, it analyses the impact of various factors/design choices on classification accuracy when using C4.5 decision trees. The factors can be broadly divided into: 1) system factors (such as sensor sampling rate and number of sensors used) and 2) algorithm and training factors (such as quantity of training data and temporal data features used). These factors are analysed in the context of a case study involving postural activity monitoring of Explosive Ordinance Disposal (EOD) operatives. The case study involves classifying a set of eight postures commonly encountered in EOD missions: sitting, walking, crawling, laying (on all sides) and kneeling. Design guidelines and generic lessons for a wider class of applications can be drawn from the work.**

I. Introduction

High accuracy, autonomous, easy-to-wear, real-time Body Sensor Networks (BSNs) for posture classification can benefit a number of healthcare scenarios. Examples of proposed usage for such systems abound [1]–[5], with rehabilitation [6], Chronic Obstructive Pulmonary Disease (COPD) [3], [7] and classification of daily activities [1] being common themes in the literature.

However, in spite of intensive efforts to date, field-deployed posture classification is not common. Much of the work so far has focused on laboratory-based experimentation, evaluation in controlled environments, and bespoke solutions for narrowly defined application scenarios. Controlled environments allow greater consistency in data gathering, data annotation, and the subsequent analysis, but may limit the range of real-world conditions that are considered in the system design or encountered during system testing/validation. This then potentially limits the suitability of the system for field deployment. Moreover, the little commonality between systems reported in the literature with regard to optimal *sensor sampling rates*, *validation methodologies*, optimal (and minimal) *sensor positioning* or indeed optimal time/frequency based *features* to use for the posture classifiers makes the development effort for new systems/applications considerable. This paper intends to ease the development of new BSN classifiers. It investigates the design space for wearable posture classification systems in terms of the factors listed above and highlights the sensitivity of machine learning based classifiers to these factors.

The application chosen for this investigation is that of monitoring the postures and activities of operatives undertaking Explosive Ordinance Disposal (EOD) missions. In this application, the role of a complex, wearable, safety-monitoring system is to *prevent* the need for healthcare by predicting the onset of Uncompensable Heat Stress (UHS) in the operative. The risk of UHS is high due to i) the oppressive environment created by the suit, which weighs over 40 kg, and ii) the physical exertion typical in such missions, particularly in hot environments. A predictive UHS onset algorithm was developed [8], that takes as its inputs the operative skin temperature at twelve locations on the body, together with the operative's real-time posture and thus activity level. In the EOD mission scenario, the postures most often encountered are crawling, kneeling, sitting, standing, walking, and laying (face down, face up and on one side).

The paper is structured as follows: section II, provides a brief description of two wearable systems used in this research: a real-time classification system produced by the authors and an additional off-the-shelf system also used for high sampling rate data collection. Details of the data gathering process are also provided. Experimental results are presented in section III. Finally the paper concludes with observations drawn from the work.

II. Experimental method: systems and data collection trials

A. Wearable systems—hardware description

Two different systems were used to capture 3D accelerometer data from multiple body locations in order to classify posture and activity: 1) a real-time, in-house instrument and 2) an off-the-shelf, data acquisition only instrument.

The first instrument used (Class-act) is based around the use of Gumstix Verdex XM4-bt [9] devices as the processing and communication platform. A bespoke expansion board allows the connection of several acceleration sensor boards to each Verdex device via a digital I^2C bus. The combination of Verdex device and expansion board is referred to here as a node. The sensor boards were designed as a low-cost, small size, low-power wearable solution based on commodity components, and each consists of a microcontroller, a temperature sensor, and a tri-axial accelerometer (STMicroelectronics LIS3LV02DQ, ± 2g range). Two nodes are used (for the upper and lower body), with up to eleven accelerometers wired to them. The nodes communicate via Bluetooth, both node-to-node and node-to-base station and the data is gathered at 10 Hz per sensor. Data processing and transmission of posture information is routinely performed by one of the body nodes. However, for the work here, it was transmitted and stored for processing.

The second system used is based on wireless Shimmer [10] devices which contain 3 Freescale MMA7260Q accelerom-

All authors are with the Cogent Computing Applied Research Centre, Coventry University, England. Corresponding author: Ramona Rednic arabeladear@gmail.com

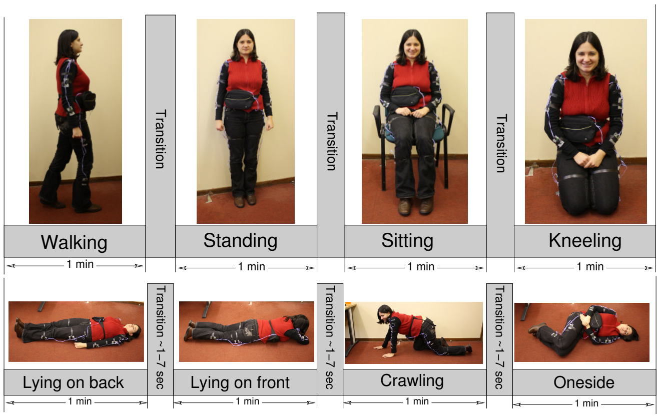

Fig. 1. Regime R1, consisting of the eight postures identified for classification by the system.

eters, along with an MSP430F1611 microcontroller (the integrated gyroscope was not used in this work). Data was gathered at 100 Hz, from up to seven nodes.

B. Experimental trials

Data was collected from subjects performing three different activity regimes, the first of which is given in Figure 1. The other regimes, following the same basic structure, were inclusive of the same set of postures but were task driven (for example loading objects into rucksacks when kneeling) or EOD mission driven. These regimes, along with the justification for their use and the methods of data annotation applied, are described in detail by Brusey *et al.* [11] and Gaura *et al.* [12].

The Class-act system was used for collecting data from 17 subjects (seven female and ten male), between 1.59 m and 1.87 m tall and weighing between 49 kg and 88.9 kg. The Shimmer system was used for collecting data from nine subjects from within the set above. A total of 40 data sets were gathered, representing 6 hours and 20 minutes of data.

For the Class-act system, a total of eleven sensors were placed: symmetrically (left and right) on the calves, thighs and upper and lower arms; on the chest; and on the hip and ankle (right). For the Shimmer system the sensors were placed on the calf (right), thigh (right), upper arm (right), lower arm (right) and chest. Due to a limitation of the Bluetooth protocol, the Shimmer based system was limited to seven nodes plus the base station.

C. Data Processing

The data processing flow for the purpose of the work presented in this paper is shown in Figure 2. 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 was required in order to differentiate static from dynamic postures. In previous work by Brusey *et al.* [11] the need for features is investigated in depth. C4.5 decision trees, as implemented by the Weka toolkit, were used for classification. Leave-One-Subject-Out Cross-Validation (LOSOXV) was adopted as a validation method.

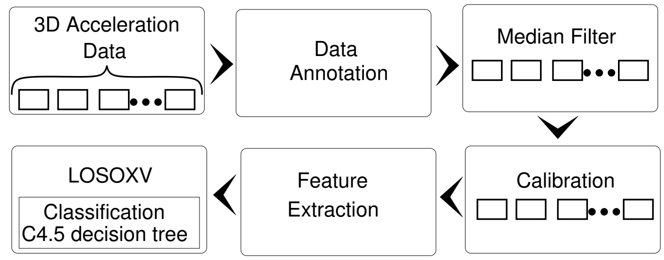

Fig. 2. Data processing flow for system training.

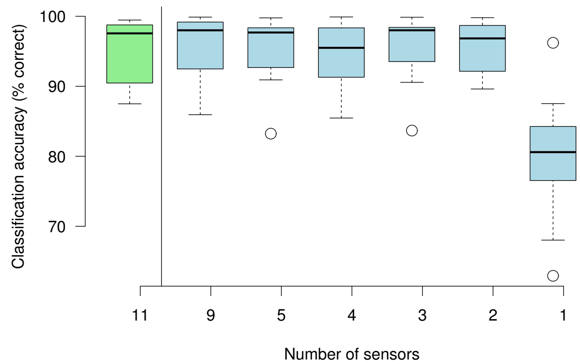

Fig. 3. Multiple sensors classification results.

III. Design Space Optimization

A. Effect of number of sensors

Eleven commonly used sensor positions (as specified in Section II-B) were investigated, and the classification accuracy evaluated, for the set of 8 postures considered here. 17 subjects were used for training, with LOSOXV, for all 9 and below sensor combinations. Four subjects only were used for the 11 sensors combination.

The pruning of the number of sensors was based on signal correlation (eliminating the left-hand side—5 sensors remained), influence of various sensors on overall accuracy (eliminating the arms—3 sensors remained), and application requirements (focusing on lower body only—2 sensors remained, on right thigh and calf). Four sensors variants as well as single sensor variants were also analysed. In all cases, Windowed Variance (WVar) was used as the extracted data feature (see Section III-D) with a sliding window of 30 samples at 10 Hz.

Figure 3 shows the classification accuracy for various multi-sensor combinations. Note that the classifier performance is not significantly sensitive to the reduction in sensor numbers towards a minimal configuration of 2 sensors (right thigh and calf). The performance degrades significantly, however, if only a single sensor is used.

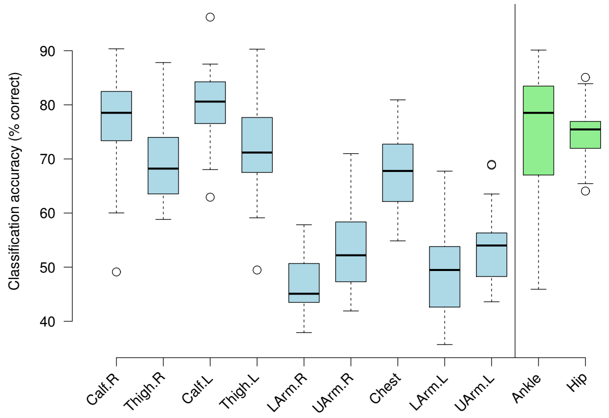

Fig. 4. Overall results for classification using one sensor location.

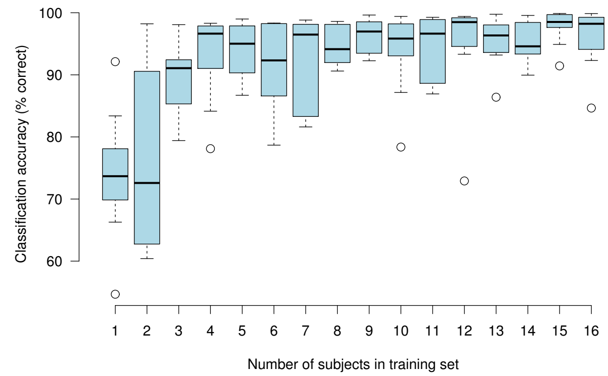

Fig. 6. Classification performance when using different number of training sets

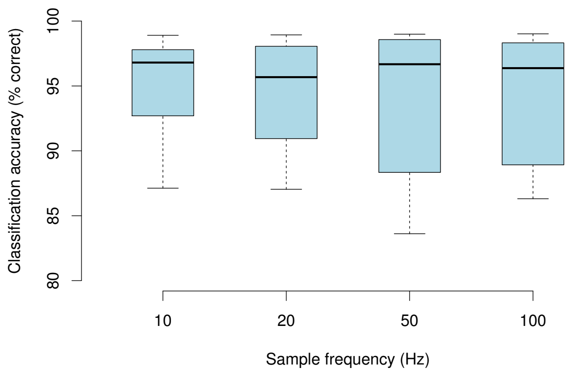

Fig. 5. Effect of different frequencies

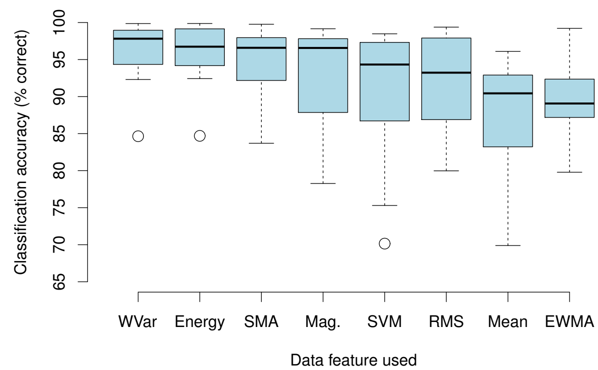

Fig. 7. Classification accuracy when using extracted data features.

The optimal position for a single sensor is the calf (Figure 4), with the arm sensors performing worst for this posture set, as expected. The chest sensor appears to perform less well than expected from the literature. The hip sensor provides adequate (but lower than calf) performance, although in the analysis here only 7 subjects were used for LOSOXV of hip and ankle variants.

B. *Effect of sampling rate*

The most common sampling rates encountered in the literature are 100 Hz and 20 Hz. The sensitivity of classification accuracy was thus analysed for sample rates in this interval (Figure 5). The data was collected using the Shimmer system with a 7 sensor configuration, from 9 subjects performing all regimes described in Section II-B. The window sizes used for feature extraction were adjusted to operate over the same time period in each case. It can be seen that performance appears to be insensitive to sampling rate. Thus, 10 Hz sampling is sufficient for this set of 8 postures.

C. *Effect of training set size*

The effect of training set size was investigated using data collected from 17 subjects using the Class-act system. The feature extracted from the data for this investigation was WVar over a 30 sample window. Nine sensor locations were used, excluding the hip and ankle sensors. Figure 6 shows the results obtained when training the classifier on N subjects (for $1 \leq N \leq 16$) and testing on an unseen subject. This was repeated 10 times with training and test subjects randomly selected (without replacement). It can be seen that there is no significant increase in classifier accuracy when training on more than 8 subjects.

D. *Effect of different features*

The effect of different extracted data features on classification accuracy was investigated at a sampling frequency of 10 Hz. The features considered were: Windowed Mean (WM), magnitude, Signal Vector Magnitude (SVM), Windowed Variance (WVar), Root Mean Square (RMS), Energy, Signal Magnitude Area (SMA), and EWMA [3], [11], [13]. A 30 sample window was used for WM, SVM, WVar, RMS, Energy, SMA. Figure 7 shows the classification accuracy using LOSOXV over 17 sets of data, classifying all 8 postures. The best overall performance was obtained for WVar. The best classification performance for walking, standing, crawling was obtained for WVar feature. While better performance was achieved by EWMA when classifying laying face up, magnitude when classifying laying on one side and magnitude or mean when classifying laying face down. All features performed well when classifying sitting.

IV. Conclusion

There are many factors that can potentially affect the success of supervised learning of posture / activity classification and this paper has examined several key ones. First, the number of sensors can often be reduced. In this case, it was found that for the set of postures examined, two 3D accelerometers were sufficient. Second, sensing frequency can be as low as 10 Hz. Third, while in principle, more subjects will improve the quality of a trained classifier, little improvement was found beyond 8 subjects. Finally, selecting appropriate features is critical. To recognise activities involving dynamic movement, carefully chosen features (such as WVar and Energy) are essential for building accurate classifiers.

The combination of supervised machine learning and MEMS accelerometers provide a powerful solution to automatic posture and activity recognition either as an end in itself or to support a larger body sensing system. The approach is becoming so well established as to suggest that a paradigm shift is occurring. The important research questions are no longer "can such systems be built?" but rather "what guidance can be given to their design?". This work represents the first steps towards providing an answer.

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