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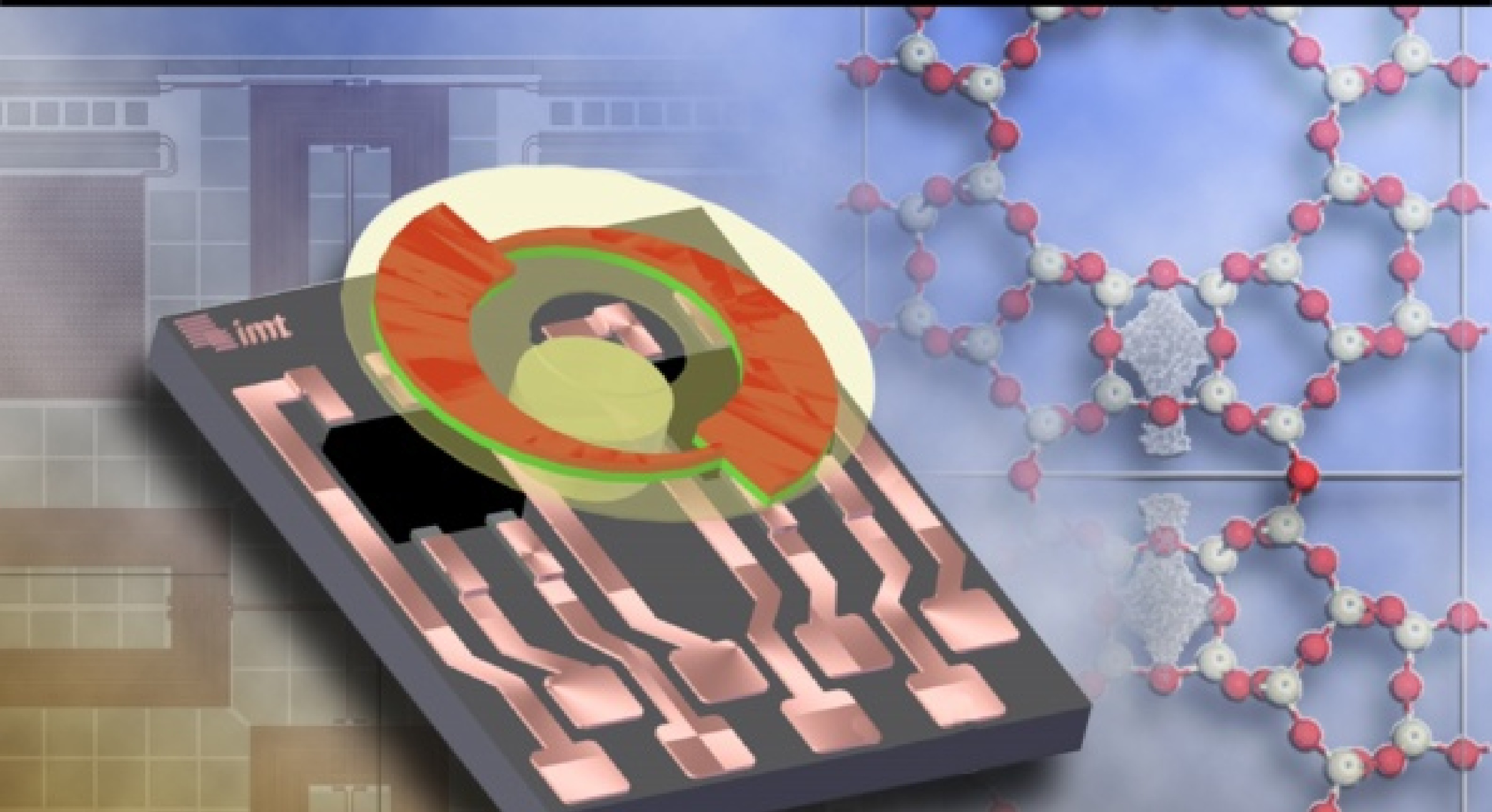

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Classifying Transition Behaviour in Postural Activity Monitoring

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Abstract: A few accelerometers positioned on different parts of the body can be used to accurately classify *steady state* behaviour, such as walking, running, or sitting. Such systems are usually built using supervised learning approaches. *Transitions* between postures are, however, difficult to deal with using posture classification systems proposed to date, since there is no label set for intermediary postures and also the exact point at which the transition occurs can sometimes be hard to pinpoint. The usual bypass when using supervised learning to train such systems is to discard a section of the dataset around each transition. This leads to poorer classification performance when the systems are deployed out of the laboratory and used on-line, particularly if the regimes monitored involve fast paced activity changes. Time-based filtering that takes advantage of sequential patterns is a potential mechanism to improve posture classification accuracy in such real-life applications. Also, such filtering should reduce the number of event messages needed to be sent across a wireless network to track posture remotely, hence extending the system's life. To support time-based filtering, understanding transitions, which are the major event generators in a classification system, is a key. This work examines three approaches to post-process the output of a posture classifier using time-based filtering: a naïve voting scheme, an exponentially weighted voting scheme, and a Bayes filter. Best performance is obtained from the exponentially weighted voting scheme although it is suspected that a more sophisticated treatment of the Bayes filter might yield better results. *Copyright © 2009 IFSA.*

Keywords: Posture classification, Evaluation of performance for posture classification instrumentation, Dealing with postural transitions, Data annotation, transitions filtering algorithms and experimental results, Context: case study of bomb disposal missions operatives monitoring

1. Introduction: Motivation and Problem Definition

The aim of this work is to develop a real-time, accurate, energy efficient, posture classification system for a variety of simple postures, based on two or more worn tri-axial acceleration sensors. The set of postures considered are: walking, standing, sitting, kneeling, crawling, lying face down, lying face up and lying on one side. These specific postures are commonly encountered in bomb disposal missions and the monitoring of operatives in such missions provides the motivating application for the work proposed here [1]. The role of the postural monitoring system is to infer the operative's posture and relay this information to a remote observer / base station, in real-time.

Our prior work has shown that a classifier based on supervised learning techniques (specifically, decision trees) complemented by some feature extraction can be designed and implemented to correctly classify the above set of postures on-body and in real-time with 97 % accuracy [1]. The stated performance was obtained when evaluating the classifier system over a test dataset gathered from
4 subjects, performing a 40 minutes activity regime that encompassed all 8 postures considered. While the subjects were asked to move as naturally as possible during the regime and also perform set tasks while kneeling or sitting, for example, the data set was manually truncated for the purpose of the evaluation. The manual truncation process was based on experimental observations and only the classification of clear steady state postures has been considered. Data from the start and end of each activity has been discarded, to ensure that the set contained only representative posture data. (The training dataset was produced following the same process.) When systems such as this are deployed outside the laboratory, however, the remote observer, whilst benefitting from highly accurate classification in steady state, is faced with much postural fluctuation and temporary incorrect classifications during postural transitions.

Much of the work proposed in the literature follows a similar model to that above in designing and evaluating classification systems [2-8]. Consequently, the effect of transitions on the classifier output would be similar for those systems and their associated monitoring application areas.

Thus, improvement in a supervised classifier's performance implies a closer look at the problem of dealing with transitions. In principle, a classifier could be used to identify and label when transitions are occurring. However, several practical problems arise when attempting to train such a classifier (the difficulty of fine grain supervision, the need to train with all possible transitions, the lack of common features between transitions, etc).

In any case, it is not necessarily desirable to identify each transition type. Rather, the aim is to minimise the posture fluctuations during transitions, and to ensure that actual postural transitions are identified smoothly and represented in the output with minimum number of incorrect classifications.

More generically, eliminating fluctuating output during transitions has several key benefits to real-life posture classifiers:

- Reducing the energy requirements of event based wearable systems, and hence extending their lifetime;
- Improving the overall accuracy during natural movement;
- Supporting automated control.

The energy cost of communication is one of the most significant components of wireless sensor design as they typically make use of small batteries or energy harvesting, such as a photovoltaic cell. This low energy budget provides an incentive to use raw sensor values to estimate the system's state locally and transmit only when the state of the system changes. Conceptually, this implies departure from continuously reporting classification systems (which are the norm in most applications) to event-based systems. Assuming that the underlying system state is relatively stable, the benefit of transmitting events is largely dependent on the quality of the system state estimate. If the state estimate fluctuates, it causes many more messages to be transmitted. Take, for example, an activity regime involving 8 possible postures, over 1 minute, monitored using a wearable accelerometer based system sampling at 10 Hz. Assume that 15 posture transitions occur, lasting a total of 10 seconds. The remaining 50 seconds are comprised of 16 periods of steady state posture. In a conventional decision tree-based classification system, such as the one previously developed by the authors here, 600 posture messages are transmitted, of which 100 correspond to transition periods. By only transmitting state *events* (i.e., messages to indicate when the state has changed), a perfect classifier might hope to reduce the number of messages from 600 down to 16. Given the likelihood of some noise in the state signal, particularly during transitions, the number of events might be closer to 100.

A further argument for eliminating fluctuations is the case where automated decisions are taken on the basis of the classifier output. In this case, it is important that the perceived postural state does not fluctuate unnecessarily as this will carry through to fluctuations in the automated control.

In this work, we attempt to resolve the problem of inaccurate and fluctuating classification during transitions using time-based filtering. Several filters have been designed and are evaluated here: a naïve voting scheme, an exponentially weighted voting scheme, and a Bayes filter.

Thus, motivated by the above, this work aims to answer the following two questions:

- Can posture classifier performance be improved by including a post-processing time-based filter?
- Of several approaches, including a naïve voting scheme, an exponentially weighted voting scheme, and Bayes filter, which filter produces the best performance?

The rest of the paper is organised as follows. The following section describes the three sequential filters used to attempt to remove fluctuation from the classifier output. Section 3 details the criteria used for evaluation of each filter. Section 4 contains the results of this evaluation and the paper is concluded in section 5.

2. Sequential Filters

Although posture classification is often treated as a typical supervised learning task where each training tuple is independent and identically drawn, it is clear that, from one moment to the next, posture is not independent. This implies that better performance should be available by making use of the time-based nature of the classification task [9].

In our prior work, adequate results have been achieved without treating the problem as a sequential supervised learning task; using a simple decision tree classifier. In this work, it is proposed that improvement on those results might be possible by using a post-processing filter. A number of options are considered: a simple voting scheme, a weighted voting scheme, and a Bayes filter. These take a time-series of posture classifier outputs and attempt to “smooth” them based on the assumption that posture tends to be static over time. These filters only take as input the estimated posture and do not consider sensor values.

2.1. Voting Scheme

The voting scheme uses a sliding window where the last N classification results are summarised to find the most popular. Given a set of past unfiltered posture estimates $d(t)$, $d(t-1)$, …, the class chosen c^* at time t is given by,

$$c^*_{\text{voting}}(t) = \arg\max_{c \in C} \sum_{i=0}^{N-1} [c = d(t-i)],$$

where the term in square brackets yields 1 if true and 0 otherwise (following Iverson's bracket notation). The set C denotes the possible postures. Although simple and robust, this scheme has the problem that all votes are equal, whereas more recent posture estimates are likely to be a better indicator of actual posture than less recent ones. The following approach takes this factor into account.

2.2. Exponentially Weighted Voting

Exponentially weighted voting (EWV) is inspired by an exponentially weighted moving average (EWMA). This voting scheme attributes greater weight to more recent unfiltered posture estimates. As with EWMA, it can be calculated recursively by tracking the vote weight associated with each class. First, given the current unfiltered posture estimate $d(t)$ and the prior class vote weight $w_c(t-1)$, a vote weight for each class c is calculated as,

$$w_c(t) = w_c(t-1) + \alpha\left([c = d(t)] - w_c(t-1)\right)$$

for all $c \in C$. A constant α controls the relative weight of newer values over old. Second, the class with the largest weight is chosen,

$$c^*_{\text{ewv}}(t) = \arg\max_{c \in C} w_c(t)$$

The voting weights act somewhat like prior probabilities of the class being chosen. This suggests that a more rigorous approach would be to estimate prior probabilities and formulate the problem as a Bayes filter. This is the approach taken in the next section.

2.3. Bayes Filter

A Bayes filter is a general algorithm for filtering on the basis of a Dynamic Bayesian Network model [10]. The Bayesian net model for this filter is shown in Fig. 1 and consists of a time-based dynamic net where the postural state x evolves over time and also affects sensor readings z.

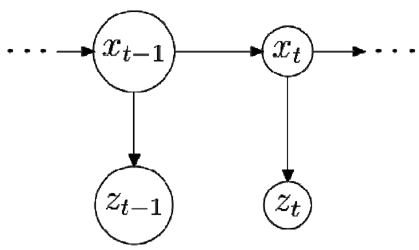

Fig. 1. Dynamic Bayesian net for postural state x over time and corresponding sensor reading z.

The model contains two causal links: First, the posture x causes accelerometer sensor readings z. Second, posture x_{t-1} at time $t-1$ influences the posture x_t at time t. In principle, the intentions of the wearer form a "control" causal link, however it is assumed that this is unobservable and thus is not included in the model. (There may be some point to modelling intention since intermediary postures are gone through when going, say, from kneeling to walking. Therefore, a uniform set of intentions yields a non-uniform distribution between subsequent postures. It is not clear, though, what the distribution of intentions might be.)

In our approach, a further link exists between the sensor values and the unfiltered estimated posture. We collapse the two-stage link between actual posture and estimated posture into a single causal link. The estimated posture at time t is thus denoted z_t from here on. This necessarily ignores some information that would be available by considering individual accelerometer readings.

The key difference between a Bayes filter approach and hidden Markov model (HMM) approaches used elsewhere [2, 3] is that in the Bayes filter, the state (which is hidden in an HMM) corresponds to a known attribute, such as the wearer's posture. In our approach, we start with an existing decision tree-based classifier that infers posture from acceleration sensors readings and that has known classification accuracy.

The filter requires us to identify the set of conditional probabilities associated with changing or keeping posture $P(x_t \mid x_{t-1})$ and those associated with the sensor identifying a posture, given an actual posture $P(z_t \mid x_t)$. These are referred to here as the transition model and sensor model, respectively.

One way to obtain these conditional probabilities is to derive them from experience. In this case, it is important that the environment and behaviour of the subject is as natural as possible. Also, extensive trials are required to produce a good estimate of the true conditional probability distributions. An alternative approach is to use existing knowledge to estimate the transition and sensor model distributions. For example, it is well known that posture does not tend to change. Furthermore, the accuracy of the estimated posture (and thus the associated conditional probability distributions) can be derived from the precision and recall of the classifier.

In this work, we fix the conditional probability of the posture staying the same according to,

$$P(x_t = u|x_{t-1} = u) = p$$

for all postures u. All other cases are set uniformly. The sensor model is set according to,

$$P(z_t = k|x_t = k) = q$$

for all postures k. Again, other cases are set uniformly. Thus the entire set of conditional probabilities is defined by two constants p and q.

3. Evaluation Criteria

Evaluation of classifiers is traditionally based on true and false positives and negatives. For example, precision and recall are both calculated from these underlying metrics. However these do not fully demonstrate the performance of a classifier when used for classifying a sequential process.

An example of a time-based aspect that is important in the system under consideration is the number of event messages that such a system would need to generate and send in order to inform a remote observer of the state. If the state estimate tends to fluctuate, this will cause a corresponding increase in the number of messages that need to be transmitted. Similarly, if the state signal is used for automatic control, then fluctuation in the state will tend to degrade the quality of the control system. On this basis, the number of "events" is a useful metric to consider.

A potential problem with smoothing filters is that they introduce lag. That is, that the state estimate changes too slowly to keep up with changes in the underlying system. Fortunately, for a classifier that is usually correct, the classification accuracy metric is an adequate indicator of the occurrence of lag and therefore no separate metric is used.

Classification accuracy during transition periods is estimated here by assuming that the classifier should output either the prior posture or the subsequent posture. This is not a perfect measure since it is common for intermediate postures to occur that are neither the prior nor subsequent postures, and these may be correctly identified by the classifier. An improvement might be to identify possible intermediate postures and allow those to appear also. For example, between crawling and standing, some short period of kneeling can be expected to occur. However, for the purpose of the evaluation here and also with a view that the essential information to the remote observer is to do with the stable states rather than how the subject moves from state to state, the presumption of prior or post state as an output is sound.

Thus, two measures are used to evaluate the performance of the proposed filters: classification accuracy (including both steady state and transitions), and number of events generated (assuming that a perfect system would generate a single event initially and then one event per actual change in posture).

4. Experimental Results

The instrumentation and experimental set-up supporting the work reported here as well as the results obtained are detailed below.

4.1. The Wearable Instrumentation Systems

A prototype posture classification system has been developed by the authors and described fully elsewhere [1]. For clarity, key elements of the system design and implementation are briefly presented below. The overall design is structured around a mix of wired and wireless communication. Multiple sensing packages are wired to two processing nodes, which communicate with each other and with a base station wirelessly. (This mix of wired / wireless communication is similar to that of the Xsens Moven inertial tracking system [11].) 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).

The acquired 3D acceleration data is processed locally, in-network, at one of the worn nodes, rather than at a remote base station, thus enabling local information based decisions to be taken when the posture classifier is part of a larger sensing and actuation system. The system data flow is shown in Fig. 2.

At a remote base station, a visualiser provides an easily interpretable display of the posture of the wearer. Classification of posture is performed using decision trees. Weka [12] was used to perform all machine learning and the resultant trees were converted to Python to run on the nodes. The Gumstix Verdex XM4-bt devices, shown in Fig. 3, were used as the main processing and communications platform. Several bespoke acceleration sensor boards are connected to each Gumstix device via an expansion board that provides I2C bus connections and connects to the Gumstix via the Hirose connector. Each sensor board consists of a microcontroller, a temperature sensor, a tri-axial accelerometer, and an 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 remote base station receives and displays posture information, either continuously or on an event basis (transmitting only an update when the posture changes). Acceleration readings are taken at a rate of 10 Hz, and postural activity is also assessed at this rate.

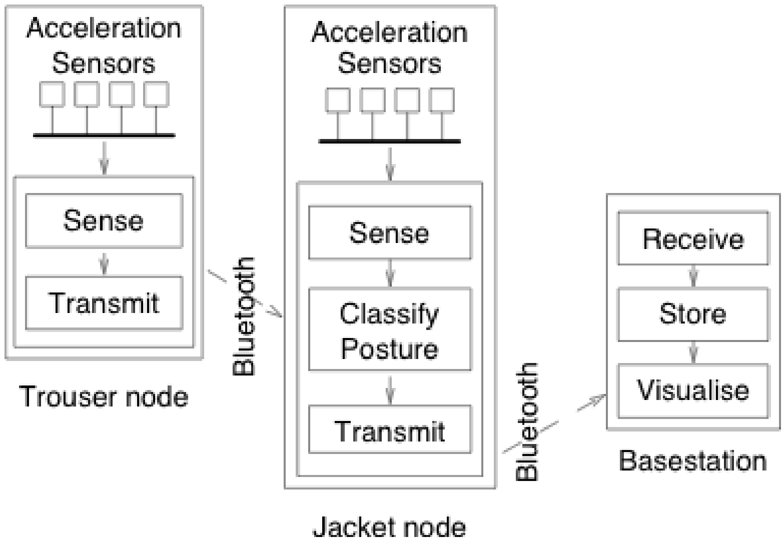

Fig. 2. System data flow.

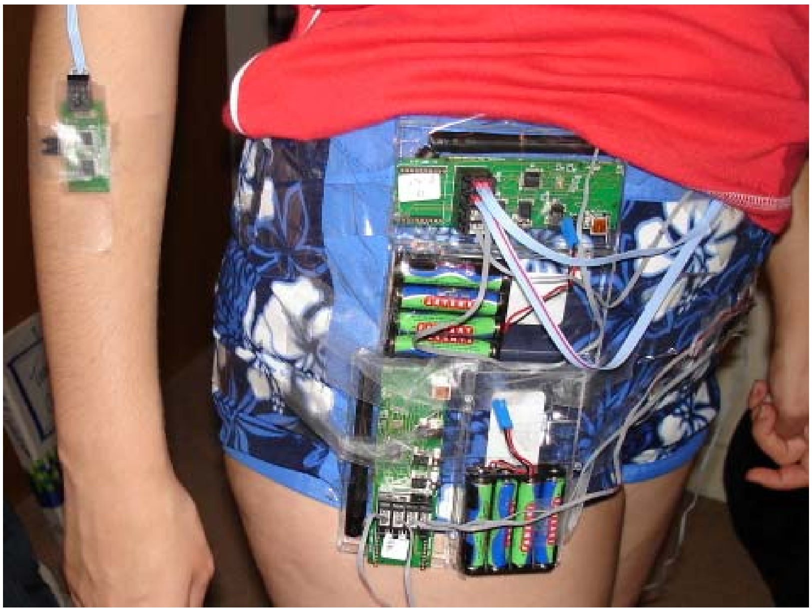

Fig. 3. Two prototype processing nodes being worn.

The sensors were positioned on the subject's body (chest, biceps, forearms, calf's and thighs), as shown in Fig. 4. A single acceleration sensor was used per body segment. The five sensors used for the upper body are connected to one node (jacket node), whilst the four sensors fitted on the lower body are connected to a second node (trouser node; see Fig. 2).

The posture classifier is based on decision trees. A set of windowed variance (WVar) features is also used as input to the decision algorithm together with the sensor data [1]. The window size was fixed to 5 seconds (50 samples).

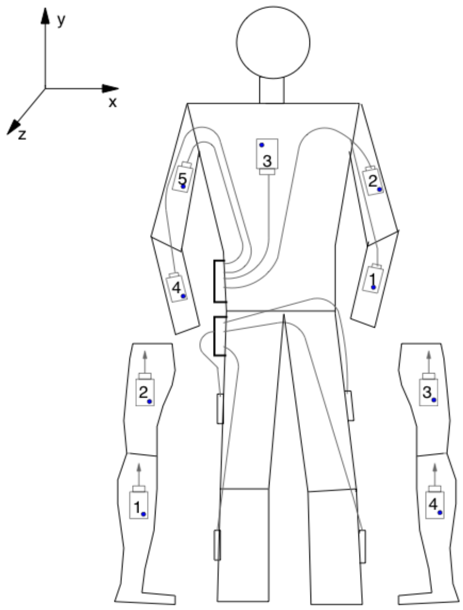

Fig. 4. Sensor positions.

A variety of trees were trained in prior work, of which two were used here for the evaluation of the filters:

- WVar 2 that uses only the subset of two sensors mounted on calf and thigh;
- WVar 9 that uses all 9 body mounted sensors.

Seven subjects and three different activity regimes were used (R1, R2, and R3) for training the above trees. 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 minute, 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). The R2 regime focused on bomb disposal mission-like activities, which included (1) walking (3 minutes); (2) kneeling while putting weights into and out of a rucksack; (3) crawling (2 minutes); (4) arm exercise while standing (4 minutes); (5) sitting (3 minutes); (6) standing (1 minute). 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 minutes of accelerometer measurements over nine tri-axial accelerometers were gathered per subject. Data was truncated for training purposes and only posture representative segments were used. All transitions were eliminated from the training data set.

For the purpose of gathering the *test dataset*, the architecture of the system described above was modified slightly to enable time synchronization between nodes and base station to be used. In this new configuration, both the lower and upper body nodes acquired and time-stamped the acceleration data and forwarded it to the base station for classification purposes. The NTP protocol was used and data was stamped as acquired by each node. At the base station, the full acceleration vector was formed only if data stamps associated with the lower and upper body readings were sufficiently close together (less than 0.1s). The filters described in Section 2 then process the classification output.

4.2. The Experimental Set-Up

For the purpose of the study here, a test dataset were gathered from one subject, over a 30-minute regime. The regime involved the subject being prompted (with audio and visual signals) at 30-second intervals to move to a randomly selected posture from the defined set. An observer recorded the time when the move to the posture had been completed by pressing a button. All 8 postures studies were however covered at least once during the regime.

The dataset thus gathered contained 58 transitions with a total duration of 2.7 minutes, and 58 steady state postures with a total duration of 28.9 minutes.

4.3. Results

The performance of the two trees, WVAR-2 and WVAR-9 was initially assessed on the basis of a truncated test dataset, with no transitions. The accuracy of the two trees was found to be 94.5% and 97.2%, respectively. When evaluating performance for the whole test set including transition periods, the performance dropped to 86.4% and 84.2%, respectively. This latter performance is based on counting transition period classifications as being correct if they match either the prior posture or the subsequent one.

The output of the two decision trees (WVAR-2 and WVAR-9) was filtered by each of the algorithms described in Section 2, for the dataset acquired following the experimental method described in Section 4.2. The classification accuracy and number of events were calculated for each tree and each algorithm for a variety of parameter values (window size for the voting scheme, α for EWV, and q for the Bayes filter). The results are plotted in Fig. 5.

With the exception of some results where tuning parameters were poorly chosen, all filters substantially improved the performance in terms of classification accuracy. From the graphs in Fig. 2, an optimal window size for the voting filter appears to be around 20 samples (corresponding to 2 s), while peak performance for the EWV filter is given by α of around 0.05. This filter gave the best performance of the three post-processing filters. The Bayes filter gave reasonable performance unless q was set to a value close to unity but generally its performance was still significantly worse than EWV.

The Bayes filter generated more events for WVAR-2 but all filters made a substantial reduction in the number of events compared to the unfiltered data (the unfiltered classifier generated 1130 events for WVAR-2 and 558 for WVAR-9).

It was unexpected that the Bayes filter would perform poorly in comparison to EWV. It seems likely that this was due to the simplifying assumptions made rather than a problem with the technique per se. On the other hand, the Bayes filter appears to be straightforward to tune (p is set according to the likelihood of the posture staying the same, and q is set according to the expected accuracy of the classifier).

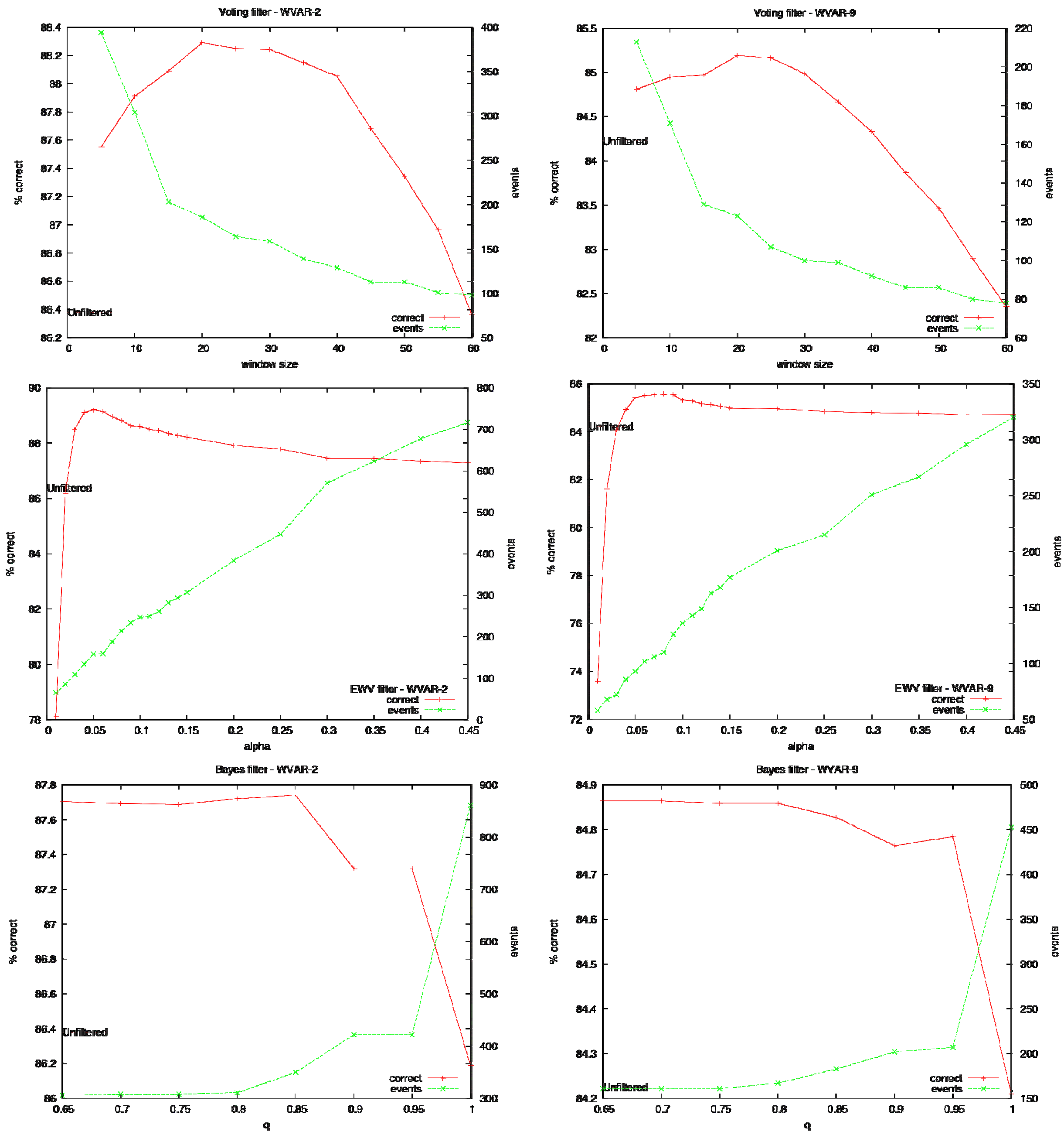

Fig. 5. Performance results for (from top to bottom) voting, EWV, and Bayes filters for postures estimated based on 2 sensors (WVAR-2, shown on left) and 9 sensors (WVAR-9, on right). The graphs show the resulting accuracy (% correct) and number of events generated. The accuracy (only) of the unfiltered classifier results is shown as a dotted horizontal line. For the Bayes filter, p was set to 0.998.

6. Conclusions

This work considers the issue of transitions and their effect on posture classifiers accuracy and subsequent effect on the energy efficiency of a wireless wearable posture classifier.

Transitions pose a problem by decreasing the performance of classifiers trained using supervised learning given that common practise is to use truncated, steady state only data for the training.

Avoiding truncation during training is not, however, the answer to improving real-life performance of classifiers.

Three filters are proposed and evaluated here. All filters improved the performance of the classifier and reduced the number of event messages generated, hence drastically reducing the energy needs of a wearable posture monitoring system.

The exponentially weighted moving average scheme is a simple approach that builds on the voting scheme and proved to give the best results of the filters tested.

The Bayes filter performed less well than expected but this may be due to the simplifying assumptions used in generating the conditional probabilities. It may also be due to it assuming that the state (or posture) has the Markov property. A more thorough exploration of this approach will be performed in future work.

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Guide for Contributors

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