Fielded autonomous posture classification systems: design and realistic evaluation

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***Abstract*—Few Body Sensor Network (BSN) based posture classification systems have been fielded to date, despite laboratory based research work confirming their theoretical suitability for a range of applications. This paper reports and reflects on two algorithms which i) improve the accuracy of real-time, multi-accelerometer based posture classifiers when dealing with natural movement and transitions and ii) maximize a wearable system's battery life through distributed computation at nodes. The EWV transition filters proposed here increase the classification accuracy by 1% over unfiltered results in realistic scenarios and significantly reduces spurious classifier output in real-time visualizations. A 200 fold transmission reduction from the on-body system to an outside system was achieved in practice by combining the transition filters with an event-based design. Furthermore, a method of reducing transmissions between on-body data gathering nodes based on distributed processing of the classifier rules (but maintaining a one-way flow of communications during system use) is also described. This provides a 3.3 fold reduction in packets and a 13.5 fold reduction in data transmitted from one node to the other in a two-node wearable system.**

***Index Terms*—body sensor networks, transition filters, distributed computation**

I. Introduction

Knowledge of posture is an important source of information in a diverse range of applications, including monitoring of patients undergoing physical rehabilitation [18], detection of falls in elderly people [17], monitoring the activity of workers in dangerous environments [20], and detecting deviation from daily routine [13]. Generally a wearable posture monitoring deployment has one of two goals: 1) observation of postures (real-time or post-processed) to enable corrective action (in real-time [5] or through longer term interventions), or 2) profiling of the subject's routine over a period of time [23].

A large number of systems and algorithms were proposed in the literature to serve these goals. However, many research questions remain open to date, particularly on the provision of field deployable solutions to address common high-level end-user requirements such as 1) provision of high classification accuracy for natural human movement *in the field* [5], 2) delivery to the remote end-user of an *easy to interpret visual output* throughout usage [6], and 3) sufficiently *long lived* systems (i.e. the wearable system lifetime should match well the length and routine of the deployment scenario).

Based on the authors' past work [5], [10], this paper brings together a number of algorithmic developments to address the requirements stated above. Further, it provides a critique of the field evaluation results obtained with an accelerometer-based postural monitoring system which integrates these developments into a wearable prototype. The resulting system is an event-driven multi-node body sensor network able to classify 8 postures; the system communicates posture to an external base station only when the subject monitored changes their posture.

Specifically, this paper describes two techniques for: 1) increased classification accuracy and system output stability in free movement scenarios which include transitions between postures and 2) longer operating lifetime running on batteries. Transition filters are used to reduce the number of postural update transmissions made by the system and increase the classification accuracy. Furthermore, the classifier used for postural information extraction is distributed at node level to further conserve energy and reduce in-system transmissions between the wearable nodes. The paper is structured as follows: Section II gives the motivation for the work here and an overview of related work, particularly around the area of transitions, Section III describes the case study application and example wearable monitoring system considered here, Section IV describes the need for a method of handling transitions in realistic deployments and provides an evaluation of the method implemented in the system considered here, Section V describes a node-to-node transmission reduction method involving distribution of the classifier model, and finally Section VI concludes on the presented work.

II. Motivation and Related work

A variety of high accuracy classification algorithms for posture have been reported in the literature (as shown in Table I). However, the number of end-to-end systems that have been evaluated via deployment in realistic scenarios is limited. The authors here have found that, when evaluating such algorithms in fielded deployments, their performance is reduced as compared to reported accuracy on truncated data traces. One contributing factor when evaluating in-field is the presence of *transitions* in addition to the well-defined postures monitored. While it has been shown in the previous work by the author and elsewhere in the literature that well-defined postures may be accurately classified (96.3% accuracy for truncated data was demonstrated by Brusey *et al.* [5], for example), transitions impact classifiers negatively in three ways: 1) overall accuracy reduction compared to performance tested on data traces (prior work by the authors demonstrated

Table I
SUMMARY OF SELECTED POSTURE CLASSIFICATION LITERATURE. n =NUMBER OF EXPERIMENTAL SUBJECTS.

Ref.	Posture set		Algorithm	Accuracy	Evaluation method	n
	Dynamic	Static				
[22]	walk, run, jump, cycle.	sit	Support Vector Machine (SVM)	Accuracy - Up to 86.8% with FFT	LOSOXV, offline	44
[9]	walk, run, jump, fall	sit, stand, lie	Bayesian Network	Prec/recall, > 0.93 except recall for running/jumping and precision for falling	Trained on all, doesn't say how tested, offline	16
[16]	walk, run, cycle	sit, stand,	Artificial Neural Networks (ANN)	95%	40%/60% random split for each subject, offline	10
[11]	run, jump, walk	stand	SVM	97.5%	LOSOXV, offline	11
[19]	walk, run, row, cycle	lie, sit, stand	Decision tree / ANN	86% (DT), 82% (ANN)	LOSOXV, offline	16
[14]	falls	sit, stand, lie	Series of thresholds	90.8%	Real-time node implementation, online	6
[1]	walk, wash, lie, climb stairs, cycle, run, etc	stand, eat, office work, sit	Fuzzy rule based	~75%	10-fold XV, offline	18
[12]	brushing teeth, taking a shower, using the toilet, sleep, walk, wash dishes, iron	sit, driving a car, stand	K-means (and histograms with + nearest neighbour, + SVM), HMM	79.1% with SVM, 91.8% for high-level with SVM	XV using four iterations of the posture regimes	1
[2]	walk, run, stretch, scrub, fold laundry, brush teeth, eat or drink, cycle, etc.	sit, stand still, watch TV, ride elevator, work on computer, read, lie	C4.5 decision tree, IBL, Decision Table, Naïve Bayes	C4.5 accuracy — 84.26 ± 5.178	LOSOXV, offline	20
[8]	walk, run, cycle with an exercise bike, row, play football, Nordic walk, cycle with regular bike	lie down, sit, stand	Custom decision trees, Automatically generated decision trees and ANN	89% classification accuracy on supervised and unsupervised data.	LOSOXV, offline	12
[21]	30 gymnasium activities		C4.5 DT	94.6% subject-dependent and 56.3% subject-independent training	Subject dependent and subject-independent testing	21

a degradation in classification accuracy of 2% for each transition/minute), 2) increased error in systems which take postural information as input, and 3) unstable visualisation (observed by Parkka *et al.* [19] and demonstrated in Section IV-A).

The number of postural transitions performed by a subject differs from application to application and in some cases may be quite high, such as for workers with jobs requiring a high level of physical activity. By comparison, daily activities within the home involve fewer transitions. Dall and Kerr [7] specifically investigated sit-to-stand transitions using the activPAL. They found that the average number of transitions per day for adults was 60 (± 22 s.d.) with a range of 10 to 124 per day—between 0.4 and 5.2 transitions per hour. However, it should be noted that there are likely to be "bursts" of activity during the day, during which many more than the average number of transitions will occur during a short period (cleaning, for example, would involve frequent changes of posture). This demonstrates that while the issues described earlier can be easily demonstrated, the method by which they are resolved is dependent on the application requirements.

In terms of system lifetime, there has been a large quantity of work investigating the power consumption of battery powered sensing devices, along with several commercial systems with quoted lifetime figures, with lifetimes ranging from hours [15] to days or months [3]. Where lifetime figures are given for transmitting raw data and transmitting summarised data/information there is often a significant difference. The manufacturer of the Actial [3] wearable device, for example, quotes a lifetime of 12 days when transmitting all data (at 32 Hz), increasing to 301 days when transmitting energy summaries for 1 minute non-overlapping windows. This demonstrates the utility of on-node data processing and summarisation in increasing device battery life, particularly for high data-rate sensors.

III. CASE STUDY APPLICATION AND SYSTEM OVERVIEW

Realistic evaluation of a posture classification system requires that the system be developed to target a specific application, introducing requirements and constraints as well as defining the applicable postures and activities to be performed by the subject.

The work described in this paper is generic in that the methods for dealing with transitions and extending the system's battery life are neither posture nor platform dependent. However, to better exemplify the issues at hand and evaluate the performance of the proposed algorithms, a case study application is considered —Explosive Ordnance Disposal (EOD) operative monitoring.

During a typical mission, the EOD operative has to wear a protective suit and helmet (which together weigh over 40 kg)

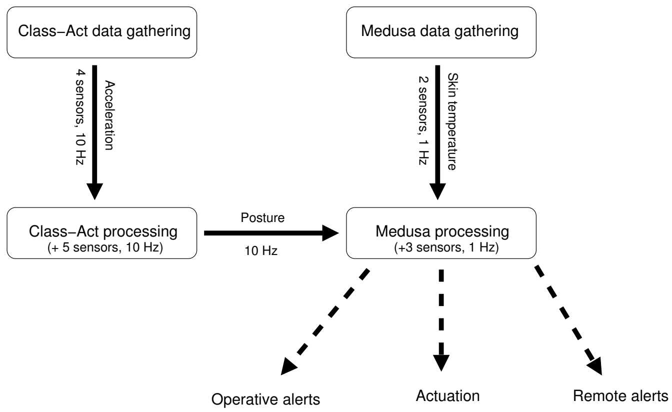

Figure 1. Wearable system wireless communication. Note that the processing nodes of both systems are also responsible for gathering data.

while climbing stairs, crawling, kneeling, lying down, and using specialist equipment. While personal cooling is provided by an in-suit system, the occurence of Uncompensable Heat Stress (UHS) is regarded as a continuing problem due to ineffective control of the system by the operative. The ability to perform corrective actions is thus required, either via a support team making changes to the mission plan or by autonomous control of the providing cooling system.

Previous work by the authors resulted in two interconnected prototype monitoring systems targeted at this application—*Class-act* for classifying posture and *Medusa2* for monitoring parameters such as skin temperature and helmet CO_2 concentration. Figure 1 illustrates the wireless communication occuring between these systems (each with multiple wearable wireless nodes). Class-act provides real-time postural information to Medusa2, which is responsible for several functions including the reporting of high-level information to a remote support team and actuation of in-suit cooling.

The application is challenging in that:

- It requires accurate and stable postural classification. Rapid changes in the classified posture (such as those encountered during transitions) will impact control stability and cause confusion for the support team visualizing the subject's posture. Stable posture output, with minimal fluctuation prior to a new posture being confirmed, is therefore required.
- It requires an operating life well in excess of common mission lengths.
- It relies on opportunistic transmissions from the EOD operative to mission control due to the use of signal jammers; this implies that only relevant information should be transmitted rather than data, to allow for buffering and priorization without informational loss.

When considering a wearable multi-modal sensing and data processing system such as the one outlined here, several difficulties with realistic deployments become apparent, as briefly overviewed in Section 1:

- The system consists of multiple, layered and interconnected components; thus the accuracy of one component (such as posture classification by Class-Act) impacts on the accuracy of successive components (such as heat stress prediction and control action by Medusa2). For example, applying the Monte Carlo method to simulate the effect of a 87% posture classification accuracy resulted in the accuracy of the Medusa2 heat stress prediction (relatively insensitive to posture classification errors) dropping by 0.1%. For other modelling purposes the effect could be much greater.
- The lifetime of the system as a whole is limited by the shortest lived component of the system. Due to the typically higher sampling rate (thus transmission demand) and power consumption of acceleration sensors compared to temperature sensors, this is likely to be the Class-Act system in the architecture described in Section III and specifically the data gathering node (due to the high rate of transmissions to the processing node).

This paper primarily discusses two techniques developed for the Class-Act system in order to solve these problems—transition filtering and data transmission reduction. Transition filtering (Sections IV and IV-B) specifically aids in reducing the number of spurious posture changes in the classifier output, allowing for more stable visualisation or modelling based on the postural information as well as reducing the number of transmissions required by the processing node and thus reducing its overall energy consumption. Reduction in the number of tranmissions required for gathered accelerometer data (Section V) is intended to improve the battery life of the data gathering node by preventing the transmission of redundant data samples.

IV. Event based classifiers: Transition filtering and associated events reduction

A. Transition filtering: overview

There are two main issues that arise when a machine learning based classifier is trained on truncated data containing well-defined postures and is subsequently deployed in a realistic situation: 1) classification accuracy is lower than that expected based on offline testing, and 2) transitions induce rapid fluctuations in classifier output, which can cause confusion when visualised directly. These effects have previously been described by Brusey *et al.* [4] and will be summarised here.

Figure 2 (left) shows a classified sequence of data where the subject transitioned from sitting to lying on one side. During this transition the classified posture changed a total of 11 times, meaning that the user or control system will see 11 different postures displayed over a 6 second interval. An unstable visual output of this type can be unpleasant and can lead to confusion, while use of such output as input to a further model can cause unstable operation or a decrease in accuracy. While the specifics of transition handling will be dependent on the requirements of the application, in the general case it can be considered that adequate filtering of transitions will minimise the occurrence of these problems.

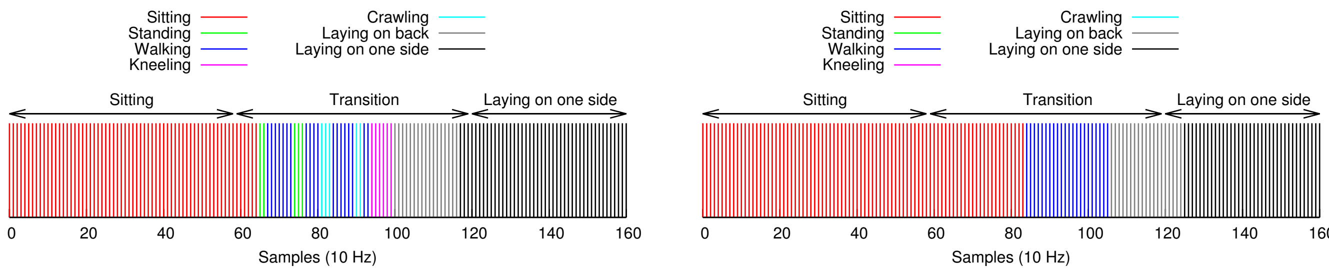

Figure 2. Example of a classification output sequence when transitioning from sitting to lying on one side. Left: without transition filter. Right: with filter. *Labels indicate the correct annotations.*

Furthermore, in many cases it is desirable to implement an event-based system instead of a continuous monitoring one, particularly when: 1) the system's battery life is impacted by the number of transmissions made or 2) the application implies long periods where the classifier output values will be constant. In the case of a battery-powered on-body posture monitoring system, both conditions are true. Thus, an event-based system would be preferable, where only updates to the subject's posture are transmitted instead of every posture classified. The method of handling transitions, particularly in terms of filtering, influences the number of posture change events that will be generated by such an event-based system.

The solution implemented within the system here for handling transitions is based on filters acting on the output of the classifier. Several different filters were evaluated in previous work by the authors [4] and the Expontially Weighted Voting filter (EWV) was selected as the best. EWV, inspired by the Exponentially Weighted Moving Average (EWMA) filter, is based around counting the instances of each posture (votes) in a window, but attributing greater weight to recent postures. This is based on the assumption that more recent posture estimates are likely to be a better indicator of actual posture than less recent ones. Figure 2 (right) visually demonstrates the reduction in events with the EWV filter applied ($\alpha = 0.04$). It can be seen that the number of generated events is reduced from 11 events to 3 events.

Figure 3 shows the effect on classification accuracy of applying the EWV filter to untruncated data. It can be seen that overall there is a gain obtained by applying the filter. However, there are several cases where there is a net decrease in accuracy. While a definite root cause for this hasn't yet been identified, it may be related to short transitions in these datasets, leading to the filter output tending to "lag behind" the actual posture following the transition.

The classification accuracy and number of posture change events generated when using the filter were calculated for a variety of values of α (a parameter controlling the weighting of new samples relative to older samples). The EWV filter increased the accuracy by 1.1% and reduced the number of events generated by around $4\times$ compared to using a basic events filter (transmitting when the posture changed based on the original classifications). The large reduction in the number of events generated mean that both a visualiser display and further modelling would be more stable when the proposed filter is used, particularly during transitions where the majority of the events are generated.

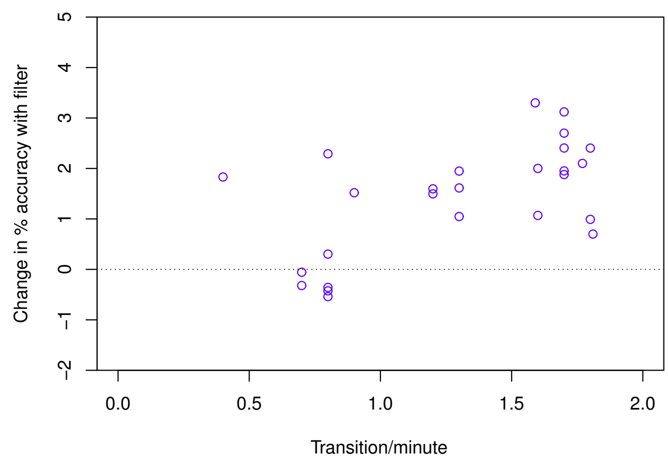

Figure 3. Change in classification accuracy when the EWV filter is applied to untruncated data.

B. Transition filtering: evaluation

This section presents an evaluation of the EWV transition filter based on data gathered from five subjects (three males and two females) performing tasked activities. The specific activities performed were: 1) crawling under a table, 2) sitting, 3) kneeling while moving items out of and back into a box, 4) standing and drawing on a whiteboard, 5) lying face down and using a laptop, 6) lying on one side and moving items out of a box, 7) lying face up and writing on a piece of paper above them. Additionally, the subjects walked between each activity station. The best performing classification tree was selected and deployed on the system hardware to classify the posture of the subjects. Classification accuracy was calculated over both untruncated classifications and truncated classifications (with periods annotated as *transitions* removed). The number of posture change events generated was counted using the untruncated data. The accuracy and number of posture change events was also calculated using untruncated data after filtering using the EWV filter with $\alpha = 0.04$ (determined in prior work to give the best overall performance).

Table II
SUMMARY OF REALISTIC EVALUATION RESULTS FOR FIVE SUBJECTS. A_U *is the overall accuracy loss due to transitions without filtering (comparing truncated and untruncated data) and* A_F *is the overall accuracy loss due to transitions when the transition filter is used.*

Subject	Duration (mins)	Transitions/min	A_U	A_F
1	13.6	1.6	-2.6	-0.6
2	15.7	1.7	-4.3	-1.6
3	14.3	2.7	-3.9	-0.8
4	17.7	1.6	-3.8	-0.5
5	9.6	1.8	-4.3	-2.2

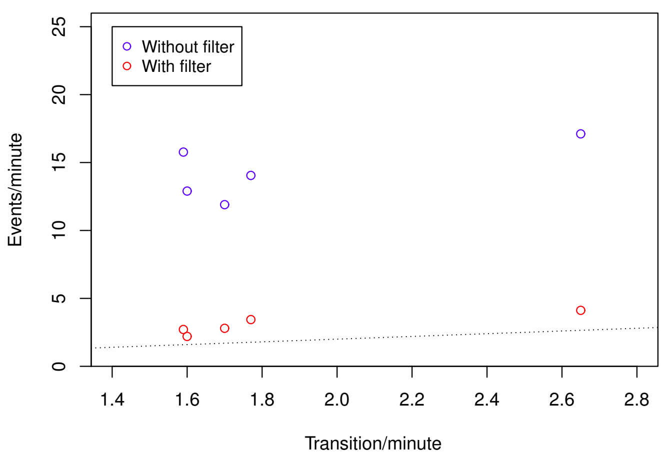

Figure 4. Event reduction when the EWV filter is applied. Dotted line indicates ideal (one event per transition).

Table II presents the results for all five subjects. Additionally, the reduction in transmissions for an event-based system compared to a continuous monitoring system was found to be an average of 42.6× without the filter applied and 204.5× with the filter applied. Figure 4 shows the reduction in generated events obtained by applying the EWV filter. All cases show a decrease in the number of generated events, becoming closer to the ideal value of one event per actual transition. Averaged over all the trials, 7.8 events are generated per transition without a filter and 1.6 events are generated per transition with a filter.

V. NODE-DISTRIBUTED CLASSIFICATION

As discussed previously, wireless communication is a significant user of energy for a battery-operated sensor node. However, it is clear that with typical on-body accelerometer sampling rates of tens to hundreds of hertz, there will be a high level of auto-correlation between samples, particularly during periods of a single sustained posture. Furthermore, the nature of decision trees means that the readings for each accelerometer will be able to vary within the defined thresholds without changing the output. Drawing on the concept behind the Spanish Inquisition Protocol [10], transmissions from the Class-Act data gathering node to the processing node can be reduced by transmitting only samples that could cause a change in classifier output[1].

Table III
NUMBER AND SIZE OF TRANSMISSIONS USING THE PROPOSED METHOD OF ACCELERATION DATA REDUCTION.

	Full data		Reading updates		Threshold updates	
	Packets	kbits	Packets	kbits	Packets	kbits
Trial 1	9,932	586	2,932	77	2,932	52
Trial 2	10,703	631	2,705	53	2,705	32
Trial 3	10,551	623	3,765	83	3,765	52
Overall	31,186	1,840	9,402	212	9,402	136

Table IV
REDUCTION IN NUMBER AND SIZE OF TRANSMISSIONS USING THE PROPOSED METHOD OF ACCELERATION DATA REDUCTION.

	Reduction (reading)		Reduction (threshold)	
	Packets	kbits	Packets	kbits
Trial 1	3.4×	7.6×	3.4×	11.3×
Trial 2	4.0×	12.0×	4.0×	19.8×
Trial 3	2.8×	7.5×	2.8×	11.9×
Overall	3.3×	8.7×	3.3×	13.5×

As the basis of classification is a decision tree, the condition under which the output could change is clear: a reading crosses over one of the thresholds defined within the tree. Each sensor therefore is only required to transmit a reading if it crosses one of these thresholds. Further, the actual value of the reading is unimportant—classification only requires knowledge of whether the reading is above or below each threshold. Therefore, the sensor can simply transmit an update that identifies a particular threshold and provides an "above" or "below" status.

Detail of individual items within the transmitted packet structures is not detailed here, but to summarise the size of transmitted data in the prototype monitoring system developed, each sensor provides three axes of acceleration data plus a feature (windowed variance) calculated for each of these. The lower body node gathers data from four sensors resulting in a total size per transmission of 59 bytes. Each transmission is assumed to be contained within one packet. The two methods of transmitting threshold-crossing updates are as follows:

- Transmission of individual readings after a threshold crossing would require 11 bytes per updated reading.
- Transmission of a threshold update (as implemented here) would require 6 bytes per update.

In order to realistically judge the transmission savings from this method, data was used from three posture trials and the transmissions that would be made with this method were counted. Tables III and IV summarise the results. It is assumed that multiple reading or threshold updates at a given time instant are "batched" into one packet. The number of packets sent for reading updates and threshold updates is therefore the same. It is important to note that posture

[1]To avoid the need for two-way communication, it is assumed here that only the node performing classification is capable of knowing the current posture, and therefore transmission is required for all readings that *could* cause the classifier output to change. If this constraint is relaxed then transmissions can be further reduced by only transmitting readings that would *definitely* cause the output to change, though this would then require two-way communication.

classification accuracy was not affected by this transmission reduction method.

It can be seen that, while the data reduction method demonstrated is relatively simple, it provides a large reduction in transmitted data by considering the intended use of the data (posture classification) rather than applying a more general compression algorithm.

VI. Conclusions

This paper discussed two core problems with the deployment of wearable posture monitoring systems: 1) reduced accuracy and output stability caused by transitions and 2) high rate of transmissions between nodes due to the typically high sampling rate of accelerometers. A previously devised method for handling transitions was evaluated in a realistic deployment with data pre-processing, posture classification, and transition filtering occuring on the on-body nodes. The results showed that the performance matched that expected based on offline testing. Furthermore, a method of significantly reducing node-to-node transmissions was presented and evaluated, giving a $3.3\times$ reduction in packets and a $13.5\times$ reduction in total data transmitted. These algorithms thus provide solutions to two of the major problems in deploying posture classification systems.

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