Energy-Efficient Posture Classification with Filtered Sensed Data from A Single 3-Axis Accelerometer Deployed in WSN

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***Abstract*— Wireless Sensor Networks (WSNs) provide rich and detailed measurements of the physical phenomenon that they monitor. With the sensed data, a variety of pervasive applications can be developed. One category of those applications are classifications based on supervised machine learning, with one example being postures recognition with data from body sensor networks (BSNs). Conventionally for accuracy reason, raw data from the BSN sensors, such as accelerometers or other inertial devices, is transmitted to the central unit for postures identification. It has been well known, however, that in most of the battery powered WSNs, communication consumes most of the energy. This paper explores the possibility of obtaining the same level of classification accuracy with the filtered sensed data to prolong the lifetime of the WSNs. A special case of posture recognition based on Artificial Neural Networks (ANN), Naive Bayes and K-Nearest-Neighbours (KNN) has been studied, and a mechanism for the posture classification based on filtered sensed data has been constructed. Real data from a Shimmer node has been collected and the test results show that the same level of accuracy can be obtained using only two thirds of the raw data. The implementation considerations with some prototypes have also been provided.**

Keywords - Wireless Sensor Network; classification; Artificial Neural Network; Naive Bayes classifier; K-Nearest-Neighbours

I. INTRODUCTION

Wireless Sensor Networks (WSNs) provide rich and detailed data about the physical phenomenon measured by the sensors. With the sensed data, a variety of pervasive applications can be developed in areas such as environmental monitoring, industrial and manufacturing automation, health-care, and military [1]. Among others, one category of the applications are classifications based on supervised machine learning. One example of such a category is posture recognition with data from body sensor networks (BSNs) [2]. Conventionally for accuracy reasons, raw data from the sensors, such as accelerometers or other inertial devices, is transmitted to the central unit for training and then postures recognition. It has been well known, however, that WSNs communication is one of the main factors that contribute to the energy consumption. The cost, measured in energy units, of transmitting a single bit of information is approximately the same as that needed for processing a thousand operations in a typical sensor node [3] [4]. Although recent research efforts focus on energy harvesting which aim to convert the ambient energy from the environment into voltage, current technology is only enough to power the sensor node continuously for 1% to 20% of its operating time [5]. Moreover most of this algorithms is still in experimental and prototype stage [6] [7]. Therefore, before energy harvesting technology become mature, minimizing the amount of communication is still a most effective way of prolonging the lifetime of WSNs.

This paper explores the possibility of obtaining the same level of classification accuracy with the filtered sensed data compared to the raw data. Presented here BSN system, consisting of a single sensor node with one 3-axis accelerometer has been deployed for recognizing four basic postures. These are: standing, walking, running and kneeling. Presented study compares three different machine learning algorithms: ANNs, Naive Bayes, and KNNs. The obtained classification accuracy with raw sensed data for all three algorithms is over 80% what compares favourably with other published results that use single 3-axis accelerometer only. With the same BSN system, a mechanism of classifying using filtered sensed data has been constructed. Real data from test subjects have been collected and the test results show that the same level of accuracy can be obtained using only two thirds of the raw data transmitted from the sensor node.

The rest of the paper is organized as follows. Section II presents background on classification algorithms with filtered and raw data. Section III outlines our BSN system for postures recognition. In Section IV, the mechanisms for classification using both the raw data and the proposed

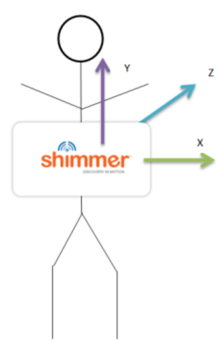

Figure 1. BSN system for postures recognition

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filtered data are described. In Section V test results are evaluated and analysed. Section VI presents ongoing and future implementation works while section VII concludes the paper.

II. BACKGROUND

The classification techniques have been widely adopted in developing WSNs applications. Trabelsi et al. [8] formulated the activity recognition problem from 3-d acceleration data measured with body-worn accelerometers as a problem of multidimensional time series segmentation and classification. They compared supervised and unsupervised classification approaches for human activity recognition using body-mounted sensors

Long et al. [9] used the related Naive Bayes method for posture classification using a single tri-axial accelerometer placed on the waist, obtaining 80% accuracy.

Djuric-Jovicic et al. [10] designed an ANN based algorithm for automatic recognition and classification of walking patterns with a wireless inertial measurement system.

Archibald and Fann [11] studied the effect of the number of features used on the accuracy of a classification by an SVM (Support Vector Machine). The study is based on a series of classification analyses with two hyperspectral sensor data.

Godfrey et al. [12] demonstrated an application of the scalar (dot) product technique and vertical velocity estimates to detect transitions and their types with only a single tri-axial accelerometer. Activities and postural transitions were accurately detected by this simplified low-power kinematic sensor and corresponding activity detection algorithms. As reported they obtained a sensitivity and specificity of 86–92% for young healthy subjects in a controlled setting and 83–89% for elderly healthy subjects in a home environment.

All the classification mechanisms mentioned above take raw or nearly raw sensed data as their input.

Data filtering in WSNs applications normally refer to low-pass filtering [2] or extended Kalman filters (EKF) [13], etc., that run on the sensor nodes and operate on the current and historical sensed data.

In [1] and [14] the authors used information fusion techniques, more precisely data aggregation techniques, to reduce the amount of data traffic. Moreover, Boulis et al. [14] presented a distributed estimation algorithm that exploits the energy–accuracy trade-off and can be applied to a subclass of periodic aggregation problems. However, in all cases the aggregated data is to be sent to the remote base stations for machine learning based classification.

III. BSN SYSTEM FOR POSTURES RECOGNITION

Postures recognition can be used in many applications for instance to monitor the elderly in order to identify falls or other potential hazards to a person's well-being as a result of restricted mobility or other physical impairments. A simple prototype BSN system used in this study, consists of a Shimmer-2 sensor node equipped with a three-axis accelerometer [15]. The sensor node communicates wirelessly with the remote base station via Bluetooth radio. The device is attached to the subject's abdominal using an elastic band as shown in Figure 1. In this study, four basic body postures were chosen. These are: walking, running, standing and kneeling positions. The first two are dynamic postures, while the latter two are static ones. This set covers the main features of the postures that are of interest for elderly postures monitoring applications.

IV. METHODS

There are many classification mechanisms such as ANN based, Naive Bayes based, KNN based, among others which find their application to posture recognition.

The idea of an ANN is to straightforwardly quasi-simulate the fundamental activity of a network of neurons, which is based on potential build-ups' mechanism for biological neural communication. Therefore, in an ANN there exists a function that governs the signalling of an adjacent neuron in the next phase layer and a random "favouritism" factor in each neuron. Usually, that "signalling" function is chosen in such a way that its "first derivative" is easily computed, typically having a clear association to the original signalling function [16]. Some of the preferred functions are the exponential function or trigonometric functions, especially the sine and cosine that in the complex plane both contribute to the construction of the complex exponential and have easily recognisable derivatives. The weights of the interconnections are computed based on a "learning factor" provided by the user. These are normally within values between 0 and 1. It governs a result given by the multiplication of the previous function, the "learning rate", and a "fault term". These mechanism manages the variation in the values obtained from the test set and the training set as well as the previous results calculated during the training period. The weighting factors should be optimized so that the difference between the outcomes obtained from the unlabelled test set and the facts resulted from the training set is "minimal" [16].

Based on the understanding of set theory and the classical definition of the probability and of the conditional property of it, we could infer Bayes theorem as the ratio of a conditional probability of an event M_1 given an event M_2 and the conditional probability of M_2 assuming M_1 is equal to the ratio between probability for event M_1 and the probability for the second event, presuming that both denominators are not zeroes, otherwise those ratios would be mathematically undefined [17]. This explanation and a basic assumptions are the founding elements of the Naive Bayes classifier. The supposition is that the events that govern each of the samples in the training set are unrelated with each other, which simplifies the calculation of the mutual probability to just the multiplication of the probability for each instance in the training set [18]. KNN algorithm is also constructed on an assumption which corresponds to the principle that the largest quantity of samples, which are

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all labelled under the same class [19] and are closest to the new to-be-classified case, gives the corresponding labelling [20]. For further information regarding ANN classifier, Naive Bayes classifier, and KNN classifier, please refer to [16] [18] and [19].

A. *Postures Recognition with Raw Sensed Data*

As the postures classification in this study is based on supervised machine learning, here we take ANN based classification as an example, and describe the general procedure as follows:

1. Determining the features used for postures classification: in our case, three dimensional accelerations are chosen as the input of the classifier;
2. Assigning values to the four postures as the output of the classifier;
3. Collecting the sensor data that measures the features of the four postures. Two sets of data should be collected, one for training (supervised learning) and the other for testing.
4. Designing the classifier: for ANN classifiers, the structure (or layers) of the neural networks, the connections between the neurons, and the activation function have to be determined. In our case, a three-layer feed-forward back-propagation ANN is adopted with full synapses in-between. The activation function is the sigmoid function.
5. Supervised machine learning
6. Testing the performance of the designed classifier on a group of new subjects;
7. Evaluating the test results: if the performance of the designed classifier is not acceptable, either re-design the classifier or pick up other features for the classification.

Conventionally, both training and testing phases are carried out using the raw sensed data received from the sensor node. Classifications based on ANN, Naive Bayes, and KNN have been adopted and tested respectively. The test results and their evaluation are presented in section V.

B. *Postures Recognition with Filtered Sensed Data*

As data transmission in WSNs consumes most of the energy, the lifetime of battery-powered WSNs will be prolonged if the same accuracy level can be achieved with only filtered sensed data. By studying the data from three-axis accelerometer in time domain, it has been found that these four postures feature significantly differ in amplitudes and frequencies. For example, the dynamic postures (walking and running) and the static postures (standing and kneeling) differ in their frequencies; both the two dynamic postures and the two static postures differ in their amplitudes. Making use of these features we can define the filter conditions on which the sensor node should send or not the data to the central base station. In this study, the conditions are represented by thresholds on the amplitude of the three axial accelerometer. The thresholds are chosen so that the filtered data that is transmitted to the central base station still captures the amplitude features for all four postures. In summary, the procedure for postures recognition with filtered sensed data consists of three stages as follows:

1. During the machine learning stage, raw data from the three-axis accelerometer is collected and the supervised learning is based on the raw data. In practice this is workable as the time for data collection in this stage is short and controllable and thus there is no concern about the lifetime of the BSNs.
2. The second stage is called pre-test stage. This stage is similar to the machine learning stage, i.e., subjects take the four postures respectively in a controlled period of time, and the raw data is transmitted. However, this stage is different in that the sensed data is from new subjects for test purpose. Based on the collected raw data, the thresholds for X-axis, Y-axis and Z-axis are determined based on the analysis and trials on the raw data. In practice, this is also workable with the same reason as in the machine learning stage.
3. The pre-test stage is followed by the test stage. The three-axis accelerometer senses the accelerations, and the Shimmer node filters the data based on the thresholds and transmits the filtered data to the central base station. On the central base station, the classifier recognizes the posture based on the received filtered data.

A case study with detailed recognition process and results is presented in section V.

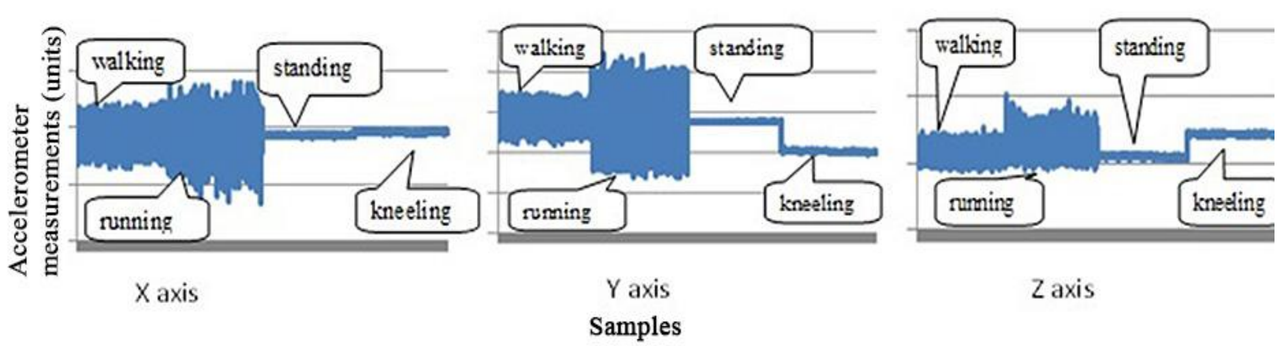

Figure 2. Sensed raw data from SHIMMER board for X, Y and Z axis for four different positions

V. RESULTS

All three classification algorithms were trained and tested with two independent sets of data collected from 12 subjects – data from six subjects with various genders and heights were collected for training and another six subjects were used for testing. In data collection we have used a Shimmer-2 sensor node with a three-axis accelerometer that was attached to the abdominal nearby the navel of the subjects. Each subject was asked to carry out four activities in a row: walking, running, standing and kneeling, with each activity being kept for 3 minutes following Dijkstra et al. [21] and Foerster et al. experiments [22]. Data packets were transmitted via Bluetooth radio to the base station where the data was stored in a Comma Separated Value (CSV) format. Raw data from the three-axis accelerometer for the four postures are shown in Figure 2, where it can be seen that these four postures feature different frequencies and amplitudes on all three axes. The software used in analyses and evaluation stage of this study was RapidMiner 5.2 [23] freely available open-source data mining and analysis system. It provides a cross platform, intuitive drag'n'drop GUI interface, which contains different machine learning and pattern recognition algorithms implemented in Java programming language.

A. *Postures Recognition with Raw Sensed Data*

With the raw data for both the training and testing stage, three classifiers have been constructed. The obtained results measured in terms of accuracy of these classifiers are reported in Table 1. Based on these results it can be seen that with the use of a single three-axis accelerometer, the four postures can be recognised with over 80% accuracy using all these three classifiers. Moreover we can observe that:

- ANN classifier can recognise the four postures, because in the supervised learning process, the features of the postures have been mapped to the weights of the interconnections;
- Naive Bayes classifier can recognise the four postures, because in the supervised learning process the features of the postures have been mapped to the probabilities for each axis
- KNN classifier can recognise the four postures, because in the supervised learning process, the features of the postures have been classified in terms of the distance function chosen which, in our case, is the Euclidean metric.

B. *Machine Learning based Postures Recognition with Filtered Sensed Data*

The procedure for postures recognition with filtered sensed data has been described in section IV.C. During the pre-test stage, raw data from a new subject is collected. After the analysis and some trials, the thresholds for X-axis, Y-axis and Z-axis, denoted as *XThreshold*, *YThreshold* and *ZThreshold* respectively, are shown in below where *avgX*, *avgY* and *avgZ* refer to the

TABLE 1. ACCURACIES OF THE CLASSIFIERS

	Raw Data	Filtered Data
ANN (500 training cycles, 0.8 learning rate, 0.0 momentum)	86.63%	86.51%
Naive Bayes	86.76%	81.67%
KNN (K=10)	82.60%	87.73%

average value of the three-axis raw acceleration data from the training set respectively, and *MaxAmplitudeX*, *MaxAmplitudeY* and *MaxAmplitudeZ* refer to the maximum difference in the value of the three-axis raw acceleration data from the training set respectively:

$$XThreshold = avgX + 10\% \times \frac{MaxAmplitudeX}{2} \quad (1)$$

$$YThreshold = avgY + 50\% \times \frac{MaxAmplitudeY}{2} \quad (2)$$

$$ZThreshold = avgZ + 40\% \times \frac{MaxAmplitudeZ}{2} \quad (3)$$

With these thresholds, 1/3 of the raw data is filtered out. On the sensor node, the only change on the code is to include the condition and action part of the data filtering process, as shown below:

```
With (sensedData)
If (   (sensedData-X > XThreshold)    and
       (sensedData-Y > YThreshold)    and
       (sensedData-Z > ZThreshold))
then   (transmit (sensedData))
```

where *sensedData* refers to the data sensed by the 3-axis accelerometer.

When the filtered data is investigated, it is found that all the data for the standing posture is filtered out. So in the classifying process running on the base station, the default posture is set as 'standing' and the classifying algorithm presents as follows:

```
currentPosture = 'standing';
/* set a timer named postureTimer with the
period being 1 second */
//timeout routine for postureTimer is
{currentPosture = 'standing'}
//main algorithm
while (classifying)
{  with (receivedData)
   do
   {  currentPosture=Classifier(receivedData);
      reset (postureTimer)
   }

}
```

Table 1 illustrates the classification results for the ANN classifier, Naive Bayes classifier and KNN classifier with filtered data respectively, from which it turns out:

- With filtered data, all these classifiers are able to recognize the postures with accuracy being over 80%.
- It is noticed that when using 10-NN, the accuracy with filtered data is higher than that with raw data. This is because those filtered measurements do not represent the features of the postures, thus the relative accuracy has improved.
- 1/3 of the raw data is filtered out in this case. As data for standing posture (around 1/4 of the raw data) is filtered out, this posture is not identified by the classifiers but by the algorithm described above. For the rest of the data that is filtered out, it had little effect on the accuracy of the classifiers as it doesn’t contain the information on the features of the postures.
- In practice, for different subjects, the thresholds may be different. This requires that the middleware for the sensor nodes should enable on-line parameters (such as the thresholds) re-configuration.

VI. FUTURE WORKS

As mentioned above, to make this filtered data based postures recognition practical, the underlying WSN middleware should facilitate on-line re-configuration, i.e., setting the thresholds for the three-axis accelerometer. Rule Execution and Event Distribution (REED) middleware has been developed that employs a rule-based paradigm to allow sensor networks to be programmed at run time. Setting and resetting thresholds can be implemented via updating the condition part of the rules that run on the sensor nodes. REED has been implemented on the Gumstix™ GS400K-XM, as shown in Figure 3 [24]. So far, with this platform a simple rules based test bed has been simulated on the Microchip PIC18F4520 that implements the automatic control of the temperature based on the higher and lower thresholds. In addition, a publish-subscribe service has been implemented enabling notification conditions, expressed using thresholds, to be tuned by the subscribers. Future work will focus on implementation of the ANN and Naive Bayes classifiers for real-time postures recognition with use of REED framework. The future works will include real-life testing, further study on the mechanisms of effective classification with filtered data, and application of the research results to other applications such as energy monitoring in manufacturing environment.

VII. CONCLUSION

In battery powered WSNs, data transmission consumes most of the energy. In this paper, a mechanism for postures recognition with filtered data is proposed. A WSN system consisting of one sensor device has been

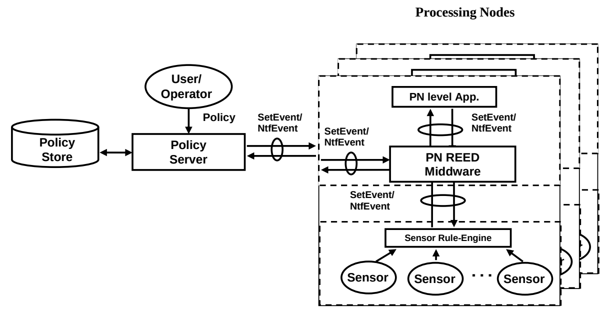

Figure 3. REED based system architecture

deployed and acceleration data is collected from real subjects. Classifiers based on ANN, Naive Bayes and KNN have been constructed using RapidMiner. Classifiers were trained with raw training data set. Postures recognitions with unfiltered and filtered testing data were carried out respectively. Results show that with appropriate thresholds, postures recognitions with filtered data achieve the same level of accuracy over 80% when compared with unfiltered data. So far the underlying WSNs middleware that enables on-line parameters such as thresholds configuration has been implemented on some sensor node platforms. The full implementation of the real-time classifier based on ANN, Naive Bayes and KNN is still in progress.

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