Activity classification using a single wrist-worn accelerometer

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Automatic identification of human activity has led to a possibility of providing personalised services in different domains i.e. healthcare, security and sport etc. With advancement in sensor technology, automatic activity recognition can be done in an unobtrusive and non-intrusive way. The placement of the sensor and wearability are ones of vital keys in the successful activity recognition of free space livings. Experiments were carried out to investigate the use of a single wrist-worn accelerometer for automatic activity classification. The performances of two classification algorithms namely Decision Tree C4.5 and Artificial Neural Network were compared using four different sets of features to classify five daily living activities. The result revealed that Decision Tree C4.5 has outperformed Neural Network regardless of the different sets of features used. The best classification result was achieved using the set containing the most popular and accurate features i.e. mean, minimum, energy and sample differences etc. The best accuracy of 94.13% was achieved using only wrist-worn accelerometer showing a possibility of automatic activity classification with no movement constrain, discomfort and stigmatisation caused by the sensor.

***Index Terms*—Activity classification, Accelerometer, Sensor data**

I. Introduction

ACTIVITY CLASSIFICATION is one of the interesting and challenging research areas which aims to automatically recognise different activities of humans. The benefit of automatic identification of human activity makes it appealing for many different domains i.e. healthcare, security, sport and entertainment etc. Understanding the current activity of an individual, a range of personalised services could be offered. For example, knowing a person is currently 'working out', information of energy expenditure, activity intensity level, etc could be used to provide health and fitness guidance. Other monitoring sensors data such as heart rate, temperature, pressure, etc would allow patient to be monitored at home without disturbing their daily activities. In elderly care where falls are major health hazard, activity classification can be used for fall detection and prevention [1]. Other interesting applications are such as smart homes, tracking system, elderly care [2] and sport training etc. Current society issues such as prison management [3], patient falling from their hospital beds [4] could also be resolved by the application of activity classification.

Advancement in current MEMS (Micro Electro Mechanic Systems) resulting in the availability of small, inexpensive and low power consumption sensors. Automatic activity classification using wearable sensors has gained higher research attention as it allows unobtrusive and non-intrusive activity detection. Sensor placement and wearability are one of the important factors in the success of the monitoring system adoption. A number of human activity classification systems have been developed in which sensors are attached on different locations on a subject's body i.e. waist, back and arm etc. However, in a real living environment, these approaches may not be practical as these sensors may obstruct daily activities routine and they could be perceived as stigmatisations for certain persons.

In this paper, an investigation of the use of a single wrist-worn sensor to detect five daily activities i.e. walking, running, sitting, standing and lying was carried out. The sensor is integrated into a sport watch for practical usage. An investigation of features used for activity classification has been carried out where four different sets of feature were used. The performances of two classifiers namely Neural Network and Decision Tree on these feature sets were compared.

II. Related works

A number of research have developed sensor-based activity classification in which a wide variety of sensors have been explored and used to capture physical activities of human. Hong et al [5] fused information from accelerometers and Radio Frequency Identification (RFID) data to detect 18 activities of daily living. Two accelerometers and a Global Positioning System (GPS) were used to detect simple daily activities as well as sport activities such as playing football, cycling on a bike, cycling on a machine and rowing etc [6]. A set of wearable sensors such as accelerometers, compass, temperature, GPS, heart rate, audio and altitude etc were used in [7] to classify seven different activities.

Accelerometer proved to be popular among many activity classification systems. It was shown to be the most information-rich and most accurate sensor for activity recognition as it reacts fast to activity changes and reflects well the type of activity [7]. Accelerometers have advantages over other techniques in quantitatively measuring human movement [8]. Many activity recognition systems used multiple accelerometers to attach to different locations on subject's body such as waist, thighs, chest, arms, back, wrists, foot and angle etc [5]-[7], [9]. However, this approach may not be practical for continuous data collection in a real living environment. Placing many sensors over the body may obstruct daily activities routine. As the result, other studies have investigated the use of only one accelerometer for activity detection. Krassnig et al [10] used data from accelerometer attached to the subject's waist to classify 11 simple activities i.e. standing, sitting and walking etc. A study [11] using a single triaxial accelerometer attached to the chest

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to detect static, transition and dynamic activities. [12] used an accelerometer data worn on the right thigh of a human subject to classify 8 daily activities.

The most popular sensor location is on waist as it is close to the centre of mass of a whole body and can better represent human movement [8]. The majority of single-accelerometer based approaches have investigated the use of accelerometer attached to the waist [10], [13]-[15], while others placed an accelerometer on specific locations where they wished to study the movements i.e. chest, back and thigh [11], [12], [16]. However, placing the sensor on those locations could restrict and/or cause discomfort in performing daily activities. Also, the sensor could be perceived as a stigmatisation for certain persons. Especially in elderly care where a wireless watch is from a survey finding more preferred [26]. This paper investigates the use of a single accelerometer attached to the subject's wrist in which the sensor has been integrated into a sport watch. It is believed to eliminate the movement constrain, discomfort and stigmatisation caused by the sensor. A relatively small number of researches used data collected from a wrist worn accelerometer to classify different activities [17]-[19]. The activities recognised by these systems are normally activities which have high wrist movements i.e. brushing teeth, scrubbing, aerobic, hitting and swinging etc which [17] also included static postures such as standing and sitting.

A variety of features were used in the accelerometer-based activity classification such as mean, energy, entropy, standard deviation (SD) and correlation etc. Popular features used in a single-accelerometer based activity classification including mean [11], [12], [14], [17]-[19], SD [11], [14], [15], [17]-[19], variance [12], [17]-[19], entropy [10], [11], [15], energy [10], [15] and correlation [10], [11], [15], [17], [18]. An intensive survey was carried out by Figo et al [20] on a range of techniques for extracting activity information from accelerometer data. Three different sensor processing domains were covered namely time domain, frequency domain and discrete representation domain. The authors compared and evaluated the accuracy of different techniques on classification of firstly walking and running and secondly walking, running and jumping activities scenarios. Experiments were conducted on different sets of features deriving from Figo et al [20], also popular features from [11]-[12], [14]-[19] and features selected using CSF evaluation method.

A statistic based activity classification is one of the popular approaches used by many activity recognition systems. Various classification algorithms such as k-Nearest Neighbour (k-NN), Support Vector Machine (SVM), Naive Bayes classifier, Gaussian mixture model (GMM) and hidden Markov model (HMM) have been explored [8]. Using a single-accelerometer based activity classification, classifiers such as Neural Network [10]-[12], Decision Tree [10], [15], [19], Bayes' classifier [15], HMM [12], threshold based [13], [16], as well as combination of classifiers i.e. Neuro-Fuzzy [17] have been investigated. In our experiment, we compared the performance of two classifiers namely Decision Tree and Neural Network using different sets of features.

III. PROPOSED METHODS

An investigation of the use of a single wrist-worn accelerometer to detect five daily living activities was carried out. The main objectives of the investigation were firstly, to investigate in different features used in accelerometer-based activity classification and secondly, to investigate the performance of two classification algorithms to recognise five activities from a wrist-worn accelerometer data. In this Section, selected features and classifier algorithms were described.

A. Feature Selection

In this study, a number of features from both time domain and frequency domain were selected. We compared the accuracy of the classifiers using four different feature sets. Set 1 contains features selected from [20] where two features that had the highest accuracies from each scenario were selected. Set 2 includes features normally used in accelerometer-based activity recognition [11]-[12], [14]-[19]. Set 3 combines features from Set 1 and Set 2. In Set 4, a Correlation-based Feature Selection (CFS) method from Weka [21] was used to select features from Set 3 in which subset features that are highly correlated to the classes but low correlated to other features are selected. All features sets used in the experiment are listed in Table I.

TABLE I
LIST OF FEATURES USED IN THIS STUDY

Feature Set	Domain		Total Features
	Time	Frequency	
1	minimum, difference x, difference y, difference z	coefficient sum, spectral energy, spectral entropy	7
2	mean, standard deviation, variance, correlation xy, correlation xz, correlation yz	spectral energy, spectral entropy	8
3	*feature from Set 1 and Set 2		13
4	mean, minimum, correlation xy, difference x, difference y, coefficient sum *(Features selected from Set 3 using CFS subset evaluation and best first search)		6

B. Classification

We compared the performance of two classifiers naming Decision Tree C4.5 and Artificial Neural Network.

1) Decision Tree

Decision Tree [22] is a hierarchical model that recursively separates the input space into class regions. It composes of decision nodes and leafs in which each node *m* has a test function $f_m(x)$. Given a node, a test function is applied to the input and depending on the output one of the branches is taken. This process is repeated until the one of the leaves is reached. The learning algorithm of the Decision Tree is greedy where it locally finds the best attribute to split the data and keep repeating until it cannot separate anymore. It aim is to find the smallest tree possible and in order to achieve that it finds the best attribute that would make the data after the split *pure* as possible. The purity is measured by a function called *Entropy*. For K classes, the entropy at node m is calculated as:

$$\text{Entropy}_{(\text{m})} = -\sum_{i=1}^{K} \frac{N_m^i}{N_m} \log_b \frac{N_m^i}{N_m} \quad (1)$$

and the entropy after the split by an attribute A which has n values:

$$\text{Entropy}'_{(\text{m})} = -\sum_{j=1}^{n} \frac{N_{mj}}{N_m} \sum_{i=1}^{K} \frac{N_{mj}^i}{N_{mj}} \log_b \frac{N_{mj}^i}{N_{mj}} \quad (2)$$

Decision tree searches for the attribute that would create the largest reduction of entropy after the split. To avoid overfitting in a Decision Tree, post-pruning is usually performed where a subtree that causes overfitting is deleted.

2) *Artificial Neural Network (ANN)*

ANN utilises the concept of nervous system consisting of several input nodes (dendrites) that connected (through synapses) to several output nodes (axons). The basic processing unit in ANN is perceptron x_i which is associated with a connection weight W_i. The output of the network is calculated from an activation function, usually a sigmoid function i.e. hyperbolic tangent, of the weighted sum of n perceptrons that linked to the output plus a bias weight:

$$output = f\left(\sum_{i=1}^{n} W_i x_i + W_0\right) \quad (3)$$

Adjusting the weight to minimise the error of the output, any relationship between inputs and outputs could be modelled. For activity recognition, a feed forward MultiLayer Perceptrons (MLP) (see Fig. 1) is often used as it can implement nonlinear discriminants. It has been proven that an MLP with one hidden layer can learn any nonlinear function of the input [22].

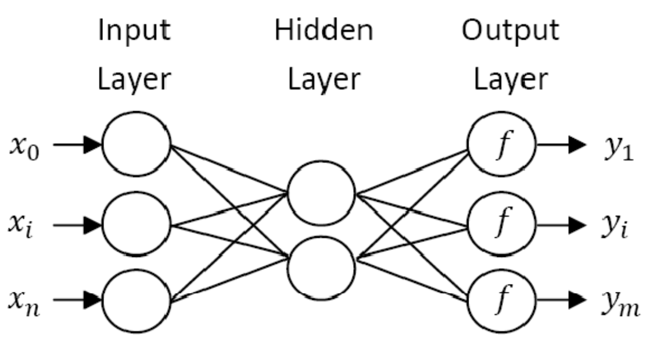

Fig. 1. A conceptual diagram of a feed forward multilayer perceptron with a single hidden layer.

Both decision tree and artificial neural network algorithms have been used successfully in activity recognition with a varying success rate.

IV. DATA COLLECTION

The raw sensor data was collected using the eZ430-Chronos watch, which is a fully functional sport watch based on the CC430F6137 microcontroller with the MSP430 CPU and integrated 868 MHz wireless transceiver from Texas Instruments [23]. The eZ430-Chronos includes an on-board 3-axis accelerometer with a measurement range of ±2G and a sampling rate of 33 Hz. The accelerometer actual sampling is 100 Hz, however, the watch is set to transmit only the third data set. The watch can wirelessly communicate with the PC through a USB RF access point. We developed functions on Matlab [24] for collecting sensor data and offline pre-processing. All equipments used in the experiment are depicted in Fig. 2a.

Fig. 2. Data collection illustration of devices and examples of activities performed in the study a) equipments used in the experiment b) the watch with integrated accelerometer c) running d) standing e) walking f) sitting

In the experiment, the participant wore the eZ430-Chronos watch on their non-dominant wrist as shown in Fig. 2b. The experiment was conducted outside in natural environment. Normally the literatures indicated that an individual is given instruction of activity e.g. sit for 2 minutes. In this experiment the participants was given a set of goals (See Table II). For example, a goal to read one poster from a notice board was used for collecting 'Standing' activity data (see Fig. 2d). The participants were given several goals to complete within their own pace allowing activities to be carried out naturally. In this study, 5 activities were included and listed in Table II.

TABLE II
DESCRIPTION OF ACTIVITIES CARRIED OUT IN THIS STUDY

Activity	Description	Example of goal used
sitting	sitting on a chair	walk to the notice board and read one of the posters then walk to the garden and sit on a bench.
standing	standing still	
lying	lying down face up	
walking	walking at subject's normal speed	
running	running at subject's normal speed	

The data was collected from 7 participants performing activities on different days. Two of the participants were females. All participants aged between 27 and 35 years old. The total amount of data collected was 35 minutes containing 69,400 sensor data.

V. EXPERIMENT

The raw sensor data contains noise and signal pre-processing is required. We used weighted moving average and three point differences techniques to filter the outlier data. Example of raw and pre-processed accelerometer data are illustrated in Figure 3. The norm was calculated on each sample i where $norm_i = \sqrt{x^2 + y^2 + z^2}$ which was used later in features calculation. The processed data were divided into windows of 128 samples with 50% overlapping. The size of the window was selected based on Gyllensten where the classifier performance did not increase with window size larger than 128 frames [25]. In total, 1,070 examples were used in this study.

In total, 13 features were calculated and separated into 4 sets as explained in Section III A. For the spectral energy feature, we calculated the energy of signal between 0.3 Hz and 6 Hz as those frequencies include most of the information found in daily activities signal [25]. For coefficient sum feature, the summation of the signal coefficients from 0.5 Hz to 3 Hz were used as it can discriminate between activities like running and walking [20].

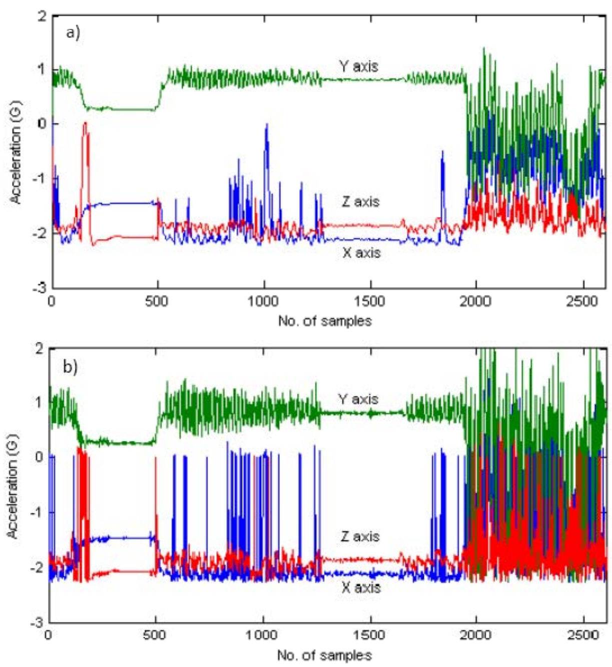

Fig. 3. Example of triaxial accelerometer data on various activities a) processed data b) raw data.

VI. RESULT

The classification was done using Weka software [21]. For the ANN classifier we used feed-forward backpropagation algorithm where different numbers of hidden node were trained and tested for each feature set. For the Decision Tree C4.5, we tested different values of confidence factor used for tree pruning. The optimum neural network models and decision tree models of each feature set were later compared. All of the tests were carried out using 5-fold cross-validation and estimated over 10 runs.

A. Optimal number of hidden neurons

In order to find optimal model, neural network with different numbers of hidden neurons ranging from 2 to 30 nodes by the increment of 2 were trained and tested. The learning rate of 0.3 was used. The performance of the classifier was compared using F-score which takes parameters such as false negatives and false positives into account. The result is shown in Fig. 4. The optimal number of hidden neurons for each feature set was selected where no significant improvement is achieved after that number. The hidden layer sizes of 6, 10, 24 and 8 were chosen for neural network model of feature Set 1, 2, 3 and 4 respectively. The highest accuracy achieved of neural network with feature Set 1, 2, 3 and 4 were 84.65%, 90.42%, 90.57% and 88.87% respectively.

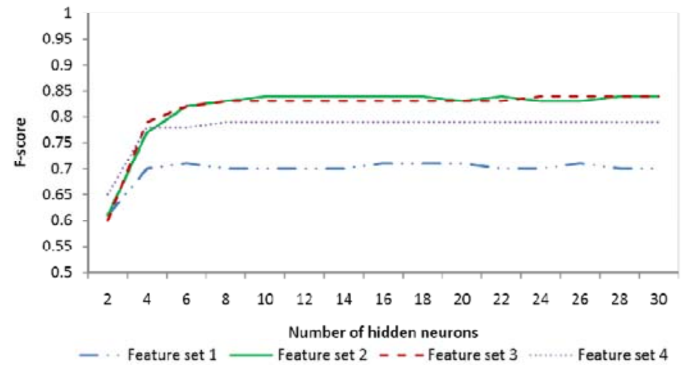

Fig. 4. Neural network models with different hidden neurons of feature Set 1, 2, 3 and 4.

B. Optimal amount of pruning

In order to find optimal amount of pruning of the decision tree C4.5 model, confidence level from 0.1 to 1 using increment of 0.1 were tested. The confidence level is used in Weka decision tree classifier where lower confidence level means higher pruning [21]. The results of the test are depicted in Fig. 5 revealed that there was no significant different in F-score when the confidence level changes. The optimal decision tree for each feature set was selected on the confidence level that achieved highest accuracy. The chosen confidence level for feature Set 1, 2, 3 and 4 were 0.4, 0.2, 0.2 and 0.2 respectively. The decision tree using features from Set 3 achieved 94.13% accuracy which is the highest among all sets.

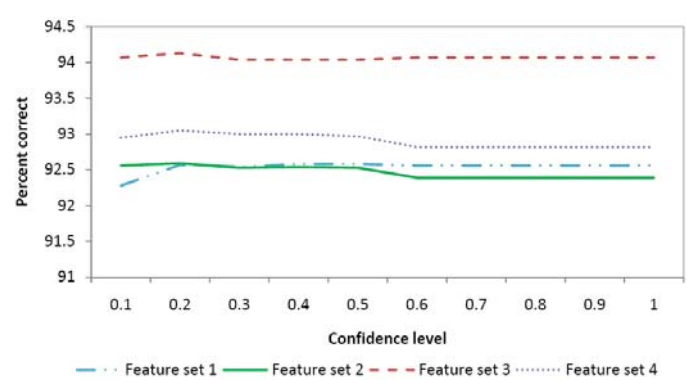

Fig. 5. Classification accuracies of decision tree with confidence level from 0.1 to 1 using different feature sets.

C. Classification accuracy

For each feature set, we selected the best models of neural network and decision tree (See Table III) and compared the accuracies between Decision Tree C4.5 and Artificial Neural Network classifiers. The result was compared using paired t-test with 0.05 significance level and is summarised in Table IV.

TABLE III
CONFIDENCE LEVEL AND NUMBER OF HIDDEN NEURONS SETTING FOR EACH FEATURE SET

Feature Set	Setting for C4.5	Setting for ANN
	Confidence Level	Number of hidden neurons
1	0.4	6
2	0.2	10
3	0.2	24
4	0.2	8

Overall statistically, the decision tree C4.5 performs significantly better than neural network regardless of the feature set used. Models using feature from Set 3 showed the best result in which 94.13% is achieved using decision tree and 90.45% using neural network. In contrast, models using feature from Set 1 gave the lowest accuracy. The decision tree model using feature from Set 3 showed the highest f-score suggested that the model is not over sensitive to any specific class. The result revealed that Lie activity is often confused with Stand activity.

TABLE IV
ACCURACY AND F-SCORE OF DECISION TREE C4.5 AND NEURAL NETWORK MODELS USING FOUR DIFFERENT SETS OF FEATURE

Feature Set	Accuracy		F-score	
	C4.5	ANN	C4.5	ANN
1	92.58	84.65	0.88	0.71
2	92.59	90.42	0.89	0.84
3	94.13	90.45	0.91	0.84
4	93.05	88.41	0.89	0.79

VII. DISCUSSION

Our experiment results suggest that using only one wrist-worn accelerometer can adequately identify user's activities. Using only a minimal number of sensors in wearable activity recognition system is a key success in system acceptance. The study investigated several combinations of features used for activity recognition. Our findings suggest that using 13 simple features from Time and Frequency domains can achieve high recognition accuracy of 94.13%. Comparing to different feature sets, Set 1 and Set 2 achieved relatively similar accuracy where as Set 3 showed higher accuracy. This can be implied that important features are found in both Set 1 and Set 2 hence Set 3 which is a combination of both set achieved better result. Features from Set 4 also gave a comparatively high accuracy as they include features with highly correlated to the classes meaning important features were selected.

Decision Tree C4.5 and Neural network were compared in many activity recognition studies but to the best of our knowledge not in a single wrist worn activity recognition system. The experiment showed that Decision Tree C4.5 gave better result which is similar to other study [27] that compared these two classifiers. In addition, the performance achieved by Decision Tree is also comparable with other classifiers for single wrist worn activity recognition systems such as [10]-[12].

Although one wrist worn accelerometer can be used to identify activity of a user, only simple activities can be detected. This is due to that fact that the data obtained from the accelerometer mounted on wrist cannot provide enough information for complicated or high level activity. Also, there are many activities involve the use of hand e.g. eating, washing, reading, etc and by using only one wrist worn accelerometer to predict those activities can be complicated. Our suggestion is to use other sensors to provide additional context information to reduce ambiguity from an accelerometer.

VIII. CONCLUSION AND FUTURE WORK

The aim of this paper is to investigate the use of a single wrist worn accelerometer for activity recognition. The study investigated four sets of features commonly used in single accelerometer based activity recognition (Set 1: top performance features from [20], Set 2: popular features from [11]-[12], [14]-[19], Set 3: combination of features from Set 1 and Set 2, Set 4: selected features of Set 3 using CFS evaluation). A search for optimal models of decision tree and neural network of each feature set was carried out. The result showed that decision tree C4.5 using features from Set 3 achieved the best performance of 94.13% while neural network using features from Set 1 gave the lowest accuracy of 84.65%. Highest accuracy of both decision tree and neural network were achieved by using features from Set 3. The best accuracy is comparable with other single wrist-worn accelerometer based activity recognition models [18]-[19].

The result shows the potential of using only a single wrist-worn accelerometer for activity recognition. The placement of sensor is important in the success of adoption of activity recognition of human daily living in free space environment. The use of a wrist-worn sensor would reduce problems such as movement constrain, discomfort and stigmatisation caused by the sensor. However, using only one wrist-worn sensor could recognises some basic activities, in future work we will investigate in other wearable sensors which will be combined with accelerometer in order to recognise more daily activities.

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