Detecting Accelerometer Placement to Improve Activity Classification

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Abstract—**This paper describes a method to improve the classification of everyday activities through detection of the location of an accelerometer device on the body. The detection of the device location allows an activity classification model, produced using a C4.5 decision tree and specifically tailored for that location, to be applied. Eight male subjects participated within the study. Participants wore six tri-axial accelerometers, positioned at various locations, whilst performing a number of everyday activities. A C4.5 decision tree was also used to detect the location of the accelerometer on the body which achieved an F-measure of 0.63. Based on this approach and applying the appropriate activity recognition model for the detected location improved activity recognition performance from an F-measure of 0.36 to 0.62, for the worst case, when using an activity model trained only one location.**

Keywords—**Activity recognition, accelerometry, sensor placement.**

I. INTRODUCTION

Accelerometers are widely integrated into wearable systems in order to identify various activities. Previous studies have reported accuracy levels of 85% to 95% for recognition rates during ambulation, posture and activities of daily living (ADL) [1-2]. The majority of these studies have incorporated multiple accelerometers attached to different locations on the body. Whilst this provides sufficient contextual information, placing accelerometers in multiple locations can become cumbersome for the wearer and may also increase the complexity of the classification problem. For these reasons, a number of studies have opted to use a single accelerometer. Generally however, using only one accelerometer decreases the number of activities that can be accurately recognized [3].

Incorporation of accelerometer technology is becoming more common in everyday mobile devices such as mobile phones, gaming consoles and digital music players. Due to this, interest in mobile device based activity recognition is increasing.

Bieber *et al.* [4] presented a mobile phone application for identifying physical activities and estimating how many calories were expended. The majority of work on activity recognition from mobile devices assumes that the device is fixed in one location. The classifier is generally both trained and tested in this location. The phone can, however, change location on a day-to-day or much more frequent basis [5]. In such applications, changes in the location of the device may be detrimental to the performance of the classifier. This is due to the classifier no longer being able to accurately classify data from one location when it was trained on data from another [6]. Approaches for dealing with this may include the use of features which are independent of device location or the use of distinct models depending on where the device is located [7].

This paper describes a method of detecting the location of an accelerometer device on the body whilst carrying out a number of everyday activities. The appropriate activity classification model for the detected location is then used for the purposes of activity recognition.

II. METHODS

Eight male subjects volunteered to participate in the study. Subjects were members of staff and students of the University of Ulster. Subjects ranged in age from 24 to 33 (mean 26.25, sd ±2.86). All subjects provided written informed consent to participate in the study. Subjects completed a physical activity readiness questionnaire (PAR-Q) to assess their suitability to take part in the study. The study was approved by the Faculty of Computing and Engineering Research Governance Filter Committee at the University of Ulster. Subjects wore six accelerometers at various locations on the body as shown in Figure 1. Accelerometers were fixed to the body, over clothing, using elasticized strapping and holsters. This is a common method of attachment in activity recognition studies [8].

A. Data Collection

Acceleration data was collected using six Shimmer wireless sensor platforms (Shimmer 2R, Realtime Technologies, Dublin, Ireland). These tri-axial accelerometers had a range of ±6 g and sampled data at 50Hz. This sampling frequency is viewed as being sufficient for the assessment of daily physical activity [8].

Data were transmitted via Bluetooth to a notebook computer where it was saved for offline analysis. In order to achieve synchronization, data was recorded using Shimmer

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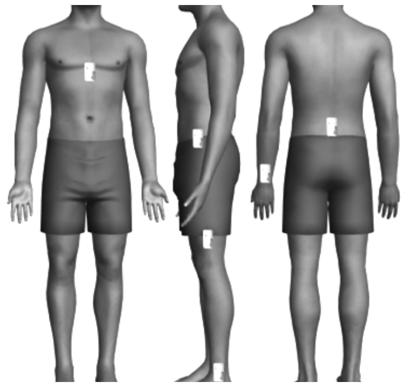

Fig. 1 Illustration showing the selected locations for the accelerometers. These include the chest, lower back, hip, thigh, wrist and foot. Accelerometers were fixed on top of clothing using elasticized strapping and holsters.

sync software (Shimmer sync Version 1.0). This synchronizes time stamp data from each of the six accelerometers. Prior to beginning the study, devices were calibrated using standard calibration techniques as described in [9].

Eight activities were studied. These consisted of whole body activities and postures including walking over ground, walking and jogging on a motorized treadmill, sitting, lying, standing and walking up and down stairs. All activities were maintained for a duration of two minutes with the exception of walking over ground and climbing stairs. These activities were carried out over approximately 60 meters and 10 flights of stairs (80 steps). These tasks were repeated in order to capture sufficient data for analysis. For treadmill based activities, users walked and jogged at a self selected comfortable speed. The maximum jogging speed was restricted to 10 km/h given that speeds above this are considered as running [10]. Data were manually labeled offline by a human observer.

B. Feature Extraction

Features were extracted from acceleration data using a window size of 256 samples with 128 samples overlapping between consecutive windows. Feature extraction on 5.12 second windows with a 50% overlap has demonstrated reasonable results in previous works [1]. This window size is capable of capturing complete cycles in repetitive action activities such as walking, running and climbing stairs.

Mean, root mean square (RMS), periodicity (energy), variance and correlation features were extracted from the x, y and z axis signal within each window. This provided a total of 15 features for each window from each accelerometer. These features have been commonly used in activity recognition studies and have been shown to provide reasonable accuracies [1, 11]. The mean acceleration value was calculated by summing the acceleration values within the window and then dividing this by the number samples within the window. The mean was also calculated in a similar manner for both the y $y$and z $z$axis [1].

Periodicity within a signal is reflected in the frequency domain. To calculate the periodicity, the energy feature was calculated [11]. The energy feature, is the sum of the squared discrete FFT component magnitudes of the signal. Normalization was achieved by dividing the sum by the length of the window. The energy feature has been used previously for recognition of certain postures and activities [12].

Correlation is particularly useful for discriminating activities that involve movement in just one dimension [11]. For example, differentiating walking or running from stair climbing. Walking and running involves movement in one dimension whereas climbing involves movement in more than one dimension. Correlation is calculated as the ratio of the covariance between each pair of axes and the product of the standard deviations [14].

C. Classification

Activity recognition on features was performed using a decision tree (DT) based on the C4.5 rule induction algorithm (C4.5 DT) available in the Weka Machine Learning Algorithms Toolkit (Version 3.6.7). The C4.5 DT has been shown to perform well for activity recognition in previous works [1].

The classifier was trained and tested using a leave-one-subject-out protocol. In this method the classifier is trained using features from all but one subject. The classifier is then tested on the features obtained from the subject who was excluded from the training set. The leave-one-subject-out validation was repeated for all eight subjects. Population based training methods have been previously used to classify a number of activities [1]. Having a population trained activity recognition approach is beneficial as it removes the need to train the classifier on a specific individual.

The balanced F-measure was used as the performance index to evaluate the experimental results. For the test results, the F-measure is calculated for each activity at each position. The overall F-measure for the classifier is computed by averaging the F-measures for all subjects.

In order to evaluate the discriminatory power of each location, the F-measure was computed using data obtained from each accelerometer separately. The performance of the classifier at each location is presented in Table 1. Results show that the accelerometer placed at the hip was the most powerful for recognizing the eight activities studied.

Table 1 F-measure obtained using the leave-one-subject-out validation for each location. Figures presented are average F-measures for all subjects ± standard deviation

Location	Classifier F-measure (sd)	
Chest	0.59	(±0.11)
Foot	0.63	(±0.23)
Hip	0.72	(±0.22)
Lower back	0.45	(±0.13)
Thigh	0.55	(±0.10)
Wrist	0.67	(±0.19)

In order to investigate the effects of training a classifier using data from one location and then the device being moved to another location, a classifier model was built using the C4.5 DT trained on data from the hip. This model was then tested on data from the foot, thigh and wrist. The performance of the classifier was then tested using the leave-one-subject-out validation method. As expected the performance of the classifier decreased with an average decrease in F-measure of 0.47, 0.29 and 0.34 for the foot, thigh and wrist, respectively (Table 2).

Table 2 F-measure for each classifier when trained on the hip and tested on the other three locations; foot, thigh, wrist.

Tested on data from:	F-measure	
Hip	0.72	(±0.22)
Foot	0.25	(±0.12)
Thigh	0.43	(±0.08)
Wrist	0.38	(±0.17)

As previously discussed, the position of the accelerometer can change throughout the day. In an attempt to alleviate this problem, the current approach uses the C4.5 DT to identify the location of the accelerometer on the body. The activity recognition model for that detected location is then applied, on an instance by instance basis, in order to improve the classification accuracy. The same 15 features from the activity recognition study were used as inputs to the classifier. Again, leave-one-subject-out validation was applied.

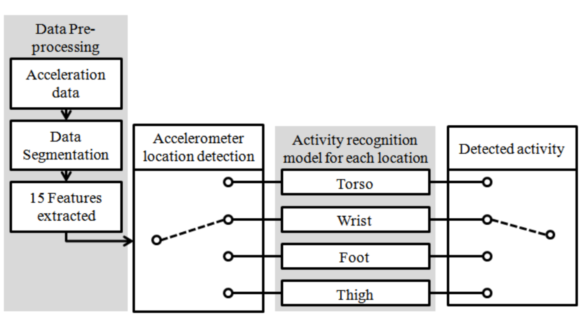

Fig. 2 Flow diagram illustrating the process used to produce and select the appropriate activity classification model.

To test this technique the model from the DT was used to detect the location of the accelerometer from 1440 instances of features from each of the 8 subjects (30 from each location). The activity recognition model from the detected location was then applied to the data on an instance-by-instance basis. For example, if the location DT detected that features were from the hip, then the activity recognition model from the hip was applied to that instance. This process was carried out manually. Figure 2 presents a summary of the approach.

III. RESULTS

This Section presents the results of the C4.5 DT to detect the location of the accelerometer. Following this, results demonstrating the effect of applying the activity recognition model for specifically detected locations will be presented.

A. Detecting Accelerometer Location

The C4.5 DT produced an average F-measure of 0.57 for detecting the location of the accelerometer on the body (Table 3). The confusion matrix, indicates that the classifier confused data from the lower back with other locations such as the hip and chest (Table 4). This may be due to similarities in body acceleration obtained from these locations as they are all located close to the body's centre of mass.

Table 3 Average F-measure of the C4.5 classifier to detect the location of the accelerometer for all six locations studied.

Accelerometer location	F-measure (sd)	
Chest	0.64	(±0.27)
Foot	0.67	(±0.23)
Hip	0.66	(±0.14)
Thigh	0.61	(±0.14)
Wrist	0.52	(±0.27)
Lower back	0.33	(±0.18)
Average	0.57	(±0.23)

Table 4 Confusion matrix from the C4.5 decision tree for classifying the location of the accelerometer. All six locations are used as classes.

Classified as →	Chest	Foot	Hip	Thigh	Wrist	Lower back
Chest	1223	36	224	158	138	181
Foot	53	1312	87	95	97	316
Hip	108	52	1452	58	113	177
Thigh	74	131	58	1166	339	192
Wrist	100	74	287	161	1090	248
Lower back	191	337	244	225	302	661

By amalgamating data from the hip, chest and lower back into one class known as the Torso, the accuracy of the classifier was improved with an average F-measure of 0.63. Therefore, the subsequent activity recognition experiments were carried out using data from four locations; Torso, Foot, Thigh and Wrist, with the Chest, Hip and Lower back data combined under the single location of Torso.

Table 5 F-measure for the C4.5 decision tree in classifying the location of the accelerometer. Hip, chest and lower back classes are combined into one class referred to as torso.

Accelerometer Location	Average F-measure (sd)
Torso	0.76 (±0.06)
Foot	0.69 (±0.24)
Thigh	0.60 (±0.12)
Wrist	0.48 (±0.28)
Average	0.63 (±0.21)

B. Activity Recognition

For the 11,520 instances tested, the detected location was the same as the actual location 67.96% of the time. Table 6 presents a summary of the classifier F-measures obtained using the activity classification model from the detected and actual locations, as well as that from each of the four investigated locations.

The F-measure obtained using the detected location was comparable to that obtained using the actual activity recognition model for that location. Using the DT to detect the location of the accelerometer improved the activity classification in comparison to always using the model from the same location (i.e. always using a model built with data from the torso, foot, thigh or wrist). The classifier F-measure improved from 0.36 when using only the thigh activity model to 0.63 when using the model for the detected location.

Table 6 Average F-measure of the activity recognition using the model for the detected location, the model for the actual location and the model for each of the four locations.

	Average F-measure					
	Detected	**Actual**	**Hip**	**Foot**	**Thigh**	**Wrist**
Stand	0.74 (± 0.10)	0.72 (±0.12)	0.65 (±0.11)	0.59 (±0.19)	0.72 (±0.06)	0.81 (±0.08)
Walk free	0.43 (±0.13)	0.46 (±0.11)	0.29 (±0.11)	0.21 (±0.12)	0.18 (±0.11)	0.13 (±0.12)
Walk tread	0.40 (±0.19)	0.42 (±0.16)	0.29 (±0.16)	0.33 (±0.15)	0.16 (±0.16)	0.19 (±0.18)
Stairs Up	0.47 (±0.10)	0.52 (±0.09)	0.38 (±0.09)	0.30 (±0.12)	0.33 (±0.12)	0.31 (±0.12)
Stairs down	0.56 (±0.14)	0.58 (±0.14)	0.47 (±0.16)	0.35 (±0.14)	0.23 (±0.14)	0.36 (±0.10)
Run	0.93 (±0.09)	0.93 (±0.07)	0.70 (±0.04)	0.30 (±0.16)	0.69 (±0.05)	0.35 (±0.13)
Sit	0.59 (±0.20)	0.60 (±0.12)	0.43 (±0.21)	0.42 (±0.25)	0.18 (±0.15)	0.36 (±0.09)
Lying	0.81 (±0.10)	0.79 (±0.14)	0.79 (±0.09)	0.82 (±0.06)	0.37 (±0.21)	0.50 (±0.25)
Avg	0.62 (±0.19)	0.63 (±0.17)	0.50 (±0.19)	0.41 (±0.20)	0.36 (±0.23)	0.38 (±0.21)

IV. CONCLUSION

This work investigated the use of the C4.5 DT algorithm to detect the location of an accelerometer on the body. The aim of this was to improve the performance of activity recognition by applying the appropriate activity classification model for a device placed in that location. Results showed the performance of the C4.5 DT in correctly identifying the accelerometer position (F-measure 0.63). This improved the activity classification, also using a C4.5 DT, when compared to using a model from only one location. It must be noted, however, that in this case the orientation of the accelerometer is fixed. When the accelerometer is housed within a mobile device, it can change orientation in addition to location. This further complicates the ability to detect the location of the accelerometer. One solution may be to examine the use of features which are not affected by device orientation such as those associated with the magnitude of acceleration. Results within this paper are of particular interest for activity recognition using accelerometers within mobile devices taking into consideration that for mobile applications, the position of the accelerometer can change throughout the day.

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