ESANN 2013 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 24-26 April 2013, i6doc.com publ., ISBN 978-2-87419-081-0. Available from http://www.i6doc.com/en/livre/?GCOI=28001100131010.

Sensor Positioning for Activity Recognition Using Multiple Accelerometer-Based Sensors

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EPFL, 2015 Lausanne -Switzerland

Abstract. Physical activity has a positive impact on people's well-being and it can decrease the occurrence of chronic disease. To date, there has been a substantial amount of research studies, which focus on activity recognition using accelerometer and gyroscope-based sensors. However, the sensor position and the sensor combination, which have the best recognition performance with minimum sensor number, have not been investigated enough. This study proposes a method to adopt multiple accelerometer-based sensors on different body locations to investigate this problem. The dataset was collected in a study conducted by the eCAALYX project. Eight subjects were recruited to perform eight normal scripted activities in different life scenarios, and each repeated three times. Thus a total of 192 activities were recorded. The collected dataset was used to find the most suitable sensor-subset for recognizing Activities of Daily Living (ADLs).

1 Introduction

Recently, a substantial amount of research has been performed on using wearable sensor-based systems to recognize and observe various types of activity. Inertial sensors such as MEMS accelerometers and rate gyroscopes are now widely used for this application [1].

There has been significant work on activity recognition using a single sensor attached to different body locations. For example, the authors in [2] proposed an activity recognition system using a waist mounted tri-axial accelerometer (TA) to discriminate ADLs with threshold-based techniques and the authors in [3] used a single chest mounted TA for activity recognition for both young and elderly population. However, two challenges primarily exist in these studies:

- The sensor position, which has the best performance for recognizing ADLs, has not been proposed.
- The minimum sensor number, which can guarantee the recognition performance, has not been investigated.

This study thus proposed a method to explore the recognition performance of sensor combinations under the same experimental setup. The dataset for this experiment was collected from a study conducted in the eCAALXY project [4]. A total of eight subjects, who performed 8 different activities of daily living and three times each, were recorded. Four sensors were attached to the chest, waist, thigh and left under-arm and the accelerometer data was simultaneously recorded from each. The

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dataset thus allows the opportunity to determine the most suitable sensor-subset for activity recognition using multiple accelerometer-based sensors.

2 Data Collection

In this study, eight subjects ranging in age from 70 to 83 (76.50±4.41 years) were recruited for the trial. Subjects were each fitted with four sensors, attached to the chest, left under-arm, waist and thigh, as illustrated in Fig 1. Each subject was asked to perform eight activities as listed as scenario activities in Table1, and repeated three times each. These were recorded in the subjects own home environment. Thus a total of 24 scenarios were recorded from each subject. The tri-axial accelerometer data was sampled at 200Hz and 12-bit resolution, from each of the four sensors simultaneously to a laptop computer via a Bluetooth wireless body area network (WBAN). The University of Limerick Research Ethics Committee approved the trial protocol and written informed consent was obtained from each subject.

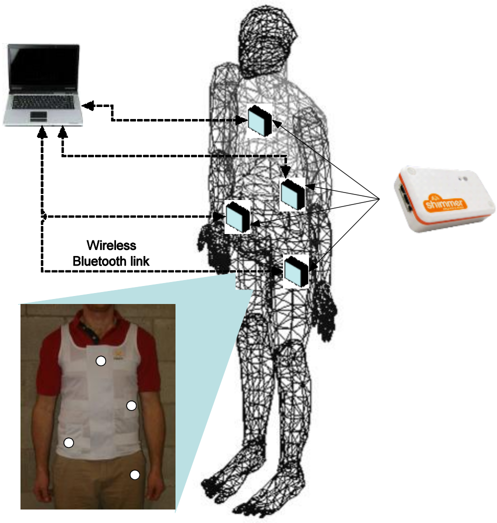

Fig. 1: Subjects were fitted with a garment, to which two sensors were attached at the chest (sternum) and left under-arm. A sensor was attached at the waist (right anterior iliac crest of the pelvis) using a custom carry-case and waist-belt and also at the thigh, in the pocket, where the sensor was placed in a padded box which held the sensor in place (98mm × 42mm × 27mm). This arrangement was thus to simulate the shape and size of a smart phone in a protective case. The Shimmer™ wireless sensor platform [5] was used to record the raw tri-axial accelerometer data.

2.1 Signals Annotation and Segmentation

Each recorded scenario was auto-annotated during the recording phase. Each scenario commenced and concluded with the subject in a standing position for 5 seconds, thus 2 transitions were recorded in each scenario (standing-transition-activity and activity-

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transition-standing). These signals were then segmented into separate activities, which belong to the activity categories listed in Table 2. There are three categories in the target stages: Static, Dynamic and Transition. In this study, it is required to recognize the six activities listed in Table 2: standing, sitting, lying, walking, walking up and down stairs and transition. The transition activities included both up and down transitions. These were not separately distinguished here. The annotated scenario activities were segmented into their separate activities and individually annotated during post-trial data processing and analysis. The reason why the scenario activities are recorded is that the classifiers can be evaluated using the dataset collected in a real-life environment. For example, sitting can be recognized in different scenarios: sitting in a chair, sitting in the bed, sitting in the car and so on. Especially for Case 4 as listed in Table I, the subjects were asked to walk up and down stairs freely. There was no specific routine for this activity to approximate the unsupervised setting. An example of the signal segmentation and annotation can be seen in Fig. 2.

	Description
Case 1	Sitting down and standing up from an arm chair
Case 2	Sitting down and standing up from a kitchen chair
Case 3	Sitting down and standing up from a toilet seat
Case 4	Walking up and down stairs
Case 5	Sitting down and standing up from a bed
Case 6	Lying down and getting up from a bed
Case 7	Getting in and out of a car seat
Case 8	Walking 10m

Table 1: Scenario activities.

<table>
<tr><th>State</th><th>Activity</th></tr>
<tr><td rowspan="3">Static</td><td>Lying</td></tr>
<tr><td>Sitting</td></tr>
<tr><td>Standing</td></tr>
<tr><td rowspan="2">Dynamic</td><td>Walking</td></tr>
<tr><td>Walking up and down stairs</td></tr>
<tr><td rowspan="4">Transition</td><td>Lying-Standing</td></tr>
<tr><td>Standing-Lying</td></tr>
<tr><td>Sitting-Standing</td></tr>
<tr><td>Standing-Sitting</td></tr>
</table>

Table 2: ADLs.

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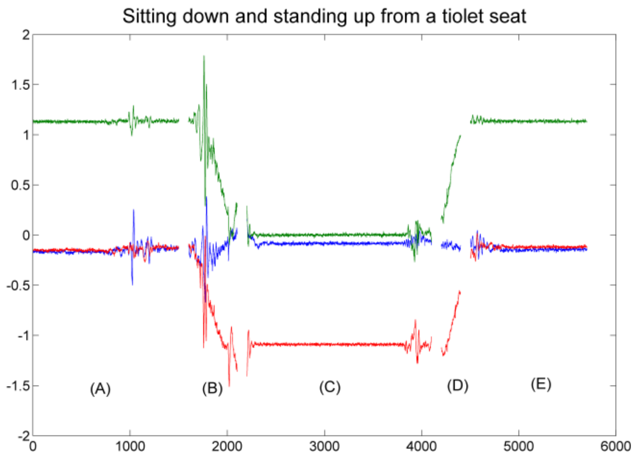

Fig. 2: The process of dividing and annotating a stand-sit-stand scenario is shown. It was (A) standing, (B) transition, (C) sitting, (D) transition, and (E) standing.

2.2 Signal Preprocessing

In this study, two algorithms were used to calibrate the signal dynamically and eliminate the impact of sensor displacement. Further detail on these algorithms can be found in our previous work [6]. The sampling rate of 20Hz and the window size of 1s without overlap were adopted. In this study, only the mean feature was extracted from each sensor for classification. The mean features from multiple sensors can support enough information for classifier. Its sensitivity to the environmental change can be eliminated by the signal preprocessing algorithms.

2.3 Validation Techniques

A 10-Fold-Cross-Validation method was used to evaluate the performance of the activity recognition algorithm. The original dataset of 864 separate activities was randomly partitioned into 10 subsamples. Of the 10 subsamples, a single subsample was chosen as the testing data, and the remaining 9 subsamples were used for training the classifier. This validation process was repeated 10 times, which guaranteed that each of the 10 subsamples was used as the testing data once. The results from the folds then could be averaged to produce a single estimation. The validation process was executed using the WEKA software [7].

3 Methods

In this study, we adopted the Decision Tree classifier for activity recognition. The Decision Tree classifier is a decision support tool using a tree-like model, which is used to describe decisions, their outcomes and cost. In the training stage, the construction of the decision tree is usually based on the feature selection algorithm. In the testing stage, a tree traversal algorithm is used for classification. In [8], the

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Decision Tree classifier was used to recognize 20 activities with the time and frequency features, and obtained the recognition accuracy of 84% which was the highest among the evaluated classifiers.

In this study, the objective is to find the most suitable sensor-subset for recognizing ADLs. The most suitable sensor-subset is the sensor combination which can obtain the approximately best recognizing performance while using the least sensor number. The dataset was collected from four sensors attached to different positions. For evaluating sensor subsets, the experiment, which is described above, was repeated using different sensor combinations.

4 Results

The results illustrate the maximum and minimum recognition accuracies of sensor subsets for different activities as shown in Tables 3 and 4.

T: thigh, C: chest, W: waist, and S: side of human body, Decision trees.						
Sensor number	Standing (%)	Sitting (%)	Lying (%)	Walking (%)	Up and down stairs (%)	Transition (%)
One	T (92.3)	T (97.4)	C (98.7)	T (72.3)	T (26.1)	T (53.2)
Two	T+W (96.5)	T + S (98.1)	T+W (99.3)	T+W (84.7)	T+W (46.9)	T+C (76.2)
Three	T+C+W (97.5)	T+C+W (98.4)	C+W+S (99.4)	T+C+W (85.1)	T+W+S (51.9)	T+C+S (79.9)
Four	97.5	98.2	99.0	85.5	53.8	80.8

Table 3: Maximum recognition accuracies of sensor subsets.

T: thigh, C: chest, W: waist, and S: side of human body, Decision trees.						
Sensor number	Standing (%)	Sitting (%)	Lying (%)	Walking (%)	Up and down stairs (%)	Transition (%)
One	S (86.7)	S (85.4)	T (91.0)	S (62.6)	W (14.4)	W (42.0)
Two	C+S (93.0)	C+S (94.2)	C+S (98.6)	W+S (76.1)	C+S (30.9)	W+S (64.6)
Three	T+C+S (96.1)	C+W+S (96.8)	T+W+S (98.1)	C+W+S (80.8)	C+W+S (40.1)	C+W+S (74.9)
Four	97.5	98.2	99.0	85.5	53.8	80.8

Table 4: Minimum recognition accuracies of sensor subsets.

The results show that the recognition accuracy increases with the number of sensors used. The effectiveness of adding sensors is notable when the number of sensors increases from one to three. There is a slight increase in the recognition accuracy for the static activities. For example, the maximum recognition accuracy for Sitting only increased from 97.4% to 98.2% when the sensor numbers went from one to four. The dynamic activities and the transition activities are more sensitive to the number of sensors. In addition, the selection of sensor subsets versus accuracy was explored. The acceptable decrease in recognition accuracy was defined as -1%, and the sensor subset with the least number of sensors was selected. The resultant number of sensors in the selected subsets for the static activities was one or two, but the dynamic activities generally required three or four. In addition, the positions of the sensors achieving the maximum and minimum recognition accuracies change

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according to activity. For instance, the combination of C+W+S performed best when recognizing Lying, but it obtained the minimum results when recognizing Sitting, Walking and Up & Down stairs. The positions found through the experimental results with the overall highest and lowest recognition accuracies were T for the maximum recognition accuracy and S for the minimum recognition accuracy. However, the best or worst sensor subsets, which obtain the maximum or minimum overall-recognition-accuracy for all six ADLs, cannot be obtained through these experimental results.

5 Conclusion

In this paper, a study of the sensor selection problem was presented, whose objective is to find the sensor subset with the least sensor number while guaranteeing the recognition accuracy for different activities. However, the results show that the sensor subsets with acceptable recognition accuracy changes according to different activities, not only the sensor number but also the positions of the subset. In the further, the dynamic multi-sensor collaboration for activity recognition will be considered.

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