Abstract

While the quality of life is improving, people care about healthy more than they ever do in the past. Healthcare system and sports management system is useful to everyone. But wearing special instrument is really hard to insist. People carry smartphones everywhere. Accelerometer in smartphones can do activity recognition to support sports management. We use accelerometer embedded in the smartphones to classify five activities: staying still, walking, running, going upstairs and downstairs. People carry smartphones in different positions, such as the pocket of trousers, hands or bags. This work analysis data gathered by accelerometer, extract various features, choose features highly correlated to human behavior, and construct an activity recognition model based on location-independent smartphone. We construct three models: the (behavior, position) vector model, the position-activity model, the activity model. Compare all these models, the activity model gain the highest accuracy and lest time-consuming, which can effectively identify human behavior.

Keywords: Activity Recognition; Position-independent; Feature Extraction

1 Introduction

With improved quality of life, work pressure increases, more and more people need a healthy lifestyle. If we do exercise every day, even running for half an hour, or walking for an hour. Our body shape and blood pressure will get great improvement. Healthcare system and sports management system can urge users to take proper exercise every day, and also provide the user’s heart rate, blood pressure and other healthy information. Specialized medical equipment or wearable sensors can be used for human activity recognition, but it requires the user to deliberately put on some devices. This is really hard to insist. With smart phones, more and more researchers
advocate to do activity recognition without being detected. While people carrying smart phones, their behavior can be recognized and recorded.

The paper first describe the current work in the field of activity recognition and the decision tree method. In Section 3 we propose the frame of activity recognition system, build an activity dataset, which contains five activities when the user wearing the phone in three positions. Analysis behavior data from accelerometer, we extract various features. We construct three models: the (behavior, position) vector model, the position-activity model, the activity model. Experiments are designed to compare all these models to find the best one to classify user's activity. In Section 4 we made a conclusion.

2 Related Works

Many researches have been done in activity recognition. Previous studies is Wearable Computing, people wear sensors at specified position to identify activity and gesture. In 2004, MIT’s Media Lab used five accelerometers worn simultaneously on different parts of the body to identify 20 kinds of everyday common behaviors, Mean, energy, frequency-domain entropy, and correlation of acceleration data was calculated and several classifiers using these features were tested. Decision tree classifiers showed the best performance [1].

With smart phones, more and more researchers started to do activity recognition by smart phones. Gerald Bieber’ team from Germany fixed the smart phone in user’s pocket of the trousers. Microphone was used to capture the sound of friction to identify user behavior severity. They fused sound and acceleration data to identify user’s activity [2]. Lenny Grokop’s team achieve comparable activity recognition performance using smartphones placed in unknown onbody positions including pocket, holster and hand. Results obtained from a diverse data set show that motion state and device position are classified with macro-averaged f-scores 92.6% and 66.8% respectively, over six activities and seven device positions [3]. Yiqiang Chen’s team [4, 5, 6, 7] fused accelerometer and GPS information to recognition traffic patterns [4]. Paper [7] divided people’s everyday behavior to: still, walking, running up and down stairs, falls, etc., Smartphone gather six kinds of behavior data to recognize behavior. Paper [5] considered different wear position of phone, different body parts move in different ways.

Xue Yang’s team build a naturalistic 3D acceleration-based activity dataset to assist researchers in the field of acceleration-based activity recognition and to provide a standard dataset for comparing and evaluating the performance of different algorithms [9]. Paper [10] and [11] extract two kinds of features: interquartile range and Wavelet energy. They can recognize upstairs and downstairs with 95.64% average accuracy when the sensor is in the same location. For a mixed data from all sensor location: waist belt, trousers pocket, and in the shirt pocket, the average accuracy can reach 94.84%. But this work only classify upstairs and downstairs.

3 Position-independent Activity Recognition Model

For helping people to manage their daily sports, we developed a sport management system to classify people’s five different behavior: staying still, walking, running, going upstairs and going downstairs. No matter where they carrying smart phones, in trousers pocket, in the hands or in
the bag, the system can tell what the user is doing and record how long they moved.

3.1 The frame of activity recognition system

Fig. 1 shows the frame of activity recognition. First collect row data from accelerometers in smartphone. We calculate the resultant acceleration to eliminate the impact of direction. After analysis acceleration data on time and frequency domain, ten features are extracted from each sample. This work classifies activity and the position by decision tree.

3.2 Data collection

Our experiment carried on smartphones with ARM processors, Android2.3 system. We developed a lightweight behavioral data collection system. Experimental designed as follows:

Table 1: The number of samples of different activities

<table>
<thead>
<tr>
<th>Activity</th>
<th>Number of samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stay still</td>
<td>392</td>
</tr>
<tr>
<td>Walk</td>
<td>395</td>
</tr>
<tr>
<td>Run</td>
<td>391</td>
</tr>
<tr>
<td>Go upstairs</td>
<td>392</td>
</tr>
<tr>
<td>Go downstairs</td>
<td>403</td>
</tr>
<tr>
<td>Total</td>
<td>1973</td>
</tr>
</tbody>
</table>

- **User information** We collected 15 user behavior data, the age distribution was: 20 to 30 years old 5 person, 30 to 40 years old 8 person, 2 persons 40 to 50 years old, basically covering smartphone user set;
- **Activity** Behavior information collected is divided into five kinds: stationary, walking, running, upstairs, downstairs;
- **Phone position** For each behavior, the user’s mobile phone wearing position subdivided into three kinds, namely, bag, trouser pocket, hands;
We build an activity dataset **XUPT-AAD** (Xi’an University of Posts and Telecommunications - a human activity acceleration dataset), which contains 1973 samples. Table 1 shows the number of samples of different activities.

### 3.3 Feature extraction

The smartphone is carried in different direction, so the 3-axes acceleration reflects different information. In order to eliminate the impact of direction, we use resultant acceleration. Fig. 2 shows the time domain curve and frequency domain curve of resultant acceleration of five activities.

![Fig. 2: The frame of activity recognition](image)

When users are stay still, the resultant acceleration value is stable at 10, is the gravitational acceleration. Operate the smartphone brings a small amount of jitter. When the smartphone is
carried in hands, trousers pocket or bags, the curve of time and frequency is almost the same. When users are walking, the behavior data cyclical when the phone is in trouser pocket, so the best position of smartphone for behavior recognition is trouser pocket. Users running data is periodicity, the frequency and peak acceleration is higher than walking data, energy is mainly concentrated in 2 Hz, the peak or energy can be used to distinguish between running and other activities. Behavioral data of going upstairs is very similar to walking, so here is a high incidence of misclassification. The acceleration curve of going downstairs is similar to running, but the cycle is longer, the amplitude is smaller, and therefore easy to distinguish.

We extract features from all the samples, including 7 time domain feature and 3 frequency domain feature: mean, median, variance, standard deviation, maximum, minimum, range, RMS (Root Mean Square), fourier transform coefficients and spectral energy.

3.4 The (behavior, position) vector model

People wear cellphones in different positions. According to the foregoing analysis, acceleration data are different when cellphones is carried in different places. To make position-independent behavior recognition, we mix all of the positions and activities of the classification. In determining user behavior, while the placement of smartphone also identified. We build (behavior, location) vector, totally 15 species, ID3 decision tree is used as classification algorithm to construct a model to assigned all sample data to 15 classes.

Using all of the features to build a decision tree. We calculate all the features information gain, and find that the mean is the best feature to do the first classification. After seven level classification, we get 15 classes. When test on the sample set, the rate of miss classification is 26.28%. Then we take cross-validation, which randomly divides the training set into 10 disjoint subsets. Each subset has roughly equal size and roughly the same class proportions as in the training set. Remove one subset, train the classification model using the other nine subsets, and use the trained model to classify the removed subset. The rate of miss classification is 48.18%.

3.5 The position-activity model

To build a mobile phone position-independent behavior classification model, our idea is to build different models for different locations. First determine the phone’s location, and then determine the user’s behavior by different models. The frame shows in Fig. 3.

![Fig. 3: The frame of position-activity model](image-url)
Build a decision tree to classify the position of smartphone. Of all the features, the best feature to classify the position is the Fourier transform coefficients. The tree shows in Fig. 4. When test on the sample set, the miss classification rate is 20.44%. When take cross-validation, the miss classification rate is 38.69%. The position classification tree can classify all the samples into three data sets.

Three models were constructed according to samples in different positions. The models shows in Fig. 5. When the phone is in the bag, we get the highest accuracy. Combine the 1st and 2nd step, the overall behavior recognition accuracy is 76.64%. The accuracy and time consuming of these models shows in Table 2.

### 3.6 The activity model

Classify activity directly without considering the position of smartphone. Using all of the features to build the tree, which shows in Fig. 6. After pruning, the tree is compact.

The best feature is the maximum value, followed by the variance and range. Sample space of the tree model validation, if the sample set as a test set, then the error rate of 11.68%, if carried out 10 cross-validation, then the error rate of 19.71%.
Table 2: Accuracy and time consuming of the position-activity model

<table>
<thead>
<tr>
<th>Steps</th>
<th>Position</th>
<th>Sample set accuracy</th>
<th>10 fold cross-validation accuracy</th>
<th>Time consuming</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st step classify position</td>
<td>-</td>
<td>79.56%</td>
<td>61.31%</td>
<td>0.8675</td>
</tr>
<tr>
<td>2nd step classify activity</td>
<td>Bag</td>
<td>96.67%</td>
<td>88.37%</td>
<td>0.6759</td>
</tr>
<tr>
<td></td>
<td>Hand</td>
<td>95.92%</td>
<td>85.71%</td>
<td>0.6878</td>
</tr>
<tr>
<td></td>
<td>Trousers</td>
<td>82.22%</td>
<td>80.00%</td>
<td>0.7160</td>
</tr>
<tr>
<td>Position-activity model</td>
<td>-</td>
<td>83.94%</td>
<td>76.64%</td>
<td>1.5607</td>
</tr>
</tbody>
</table>

Fig. 6: The activity model

3.7 Comparison of three models

To sum up, the activity model is more accurate than the position-activity. Both of them is more accurate than the (activity, position) vector model. When making position-independent activity recognition, the same activity in different position cannot be differentiated very clearly. Judge activity and position simultaneously seems difficult. Due to the lowest complexity of the activity model, it has the minimum time consuming and the highest efficiency. The comparison shows in Table 3.

Table 3: Accuracy and time consuming of three models

<table>
<thead>
<tr>
<th>Models</th>
<th>Sample set accuracy</th>
<th>10 fold cross-validation accuracy</th>
<th>Time consuming</th>
</tr>
</thead>
<tbody>
<tr>
<td>The (activity, position) vector model</td>
<td>73.72%</td>
<td>51.82%</td>
<td>0.8813</td>
</tr>
<tr>
<td>The position-activity model</td>
<td>83.94%</td>
<td>76.64%</td>
<td>1.5607</td>
</tr>
<tr>
<td>The activity model</td>
<td>88.32%</td>
<td>80.29%</td>
<td>0.7869</td>
</tr>
</tbody>
</table>
4 Conclusion

In this paper, we gathered acceleration data of five daily behavior, phones were placed in three different positions. Ten kinds of user activity features are extracted. The decision tree based on features has been established. This paper studies three kinds of modeling method, the (activity, position) vector model, the position-activity model and the activity model. Compare all these models, the activity model gains the highest accuracy and lest time-consuming, which can effectively identify human behavior. This model allows the smartphone in a common position, e.g. in the bag, trousers pocket or hands. The classify accuracy of activity can reach 80.29%.

Acknowledgement

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References