Physical Activity Monitoring with Mobile Phones

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Abstract. The rich sensing ability of smart mobile phones brings an unique opportunity to detect and long-term monitor people's physical activities. However, with mobile phone the application has to comply with people's usage habit of it and thus capture the right moment to recognize activities, which will potentially cause great in-class variances. As a result, the model potentially becomes complex and costs much computing resources in mobile phone. This paper recognize people's physical activities when they place the mobile phone in the pockets near the pelvic region. Experiment results show that the accuracy could reach 97.7%. To reduce the model size, evaluation of each feature attribution contribution for the accuracy is performed. And the result shows that we can cut the feature dimension from 22 to 8 while obtaining the smallest model.

Keywords: activity recognition, machine learning, mobile phone, accelerometer, feature reduction

1 Introduction

Long-term physical activity monitoring of mass population provides rich opportunities for monitoring people's physical active patterns and finding opportunities to changing unhealthy lifestyles. For example, to change the sedentary lifestyles, Sharkra [1], Fish'N'Step [12] and UbiFit Garden [6] use interesting games which adopts people's physical activity (i.e. walking steps) as the input to stimulate them to be physically active. However, currently such systems require additional sensing devices to be attached on human body, which is troublesome and costly for deploying to large population. Mobile phone based physical activity recognition, which embracing the rich sensing power in existing phone platforms, requires no additional devices and no extra spending. And thus it becomes the ideal solution for physical activity monitoring. With this technology, we can easily monitor when and where individuals perform what kind of physical activities, making them more aware of their heath and lifestyle status. Besides, more sophisticated applications can devised to help change the prevailing sedentary lifestyle. For example, not only can we stimulate people to conduct more physical activities by games only running within the mobile phone platform, but also we can also find valuable opportunities from their daily activity patterns, such as encouraging bicycling for short-time driving, or driving to a little further place from the destination and then walking there.

Despite the increasing sensing power of mobile phones, mobile phone based activity recognition still has many difficulties that so far greatly prevent it from mass adoption. We identify three key issues that are critical to mass adoption of such application and are different concerns from previous sensor based activity recognition studies.

I. Complying with people's usage habits. Since people use mobile phones primarily for communications and people have various usage habits, such as placing them in different positions and orientations unintentionally while carrying them, the system has to comply with their usage habits instead of asking them to place their mobile phones in predefined locations and orientations.

II. Finding the right activity recognition opportunity. The fundamental setup of activity recognition is that the sensors can capture discriminative signals of the target activities. However, In the case of mobile phone based activity recognition, not all the deployment of them can be used for activity recognition, such as when people put the mobile on the desk instead of carrying them on, or just sway with their arms when they sit down. Consequently, we have to find the right moment that the mobile phone is able to detect the right body movement signals.

III. The activity recognition application has to be resource saving. Power consumption is a critical concern for mobile phone applications. As the activity recognition program is supposed to be running all along in the background of the mobile phone system, it easily causes battery drain. Besides, large amount of computations also slows the mobile phone and affects the running of other applications, which is not acceptable for user acceptance. And thus the activity recognition application should be small enough to save resources.

However, as the mobile phone may be placed in different body locations with diverse orientations, the signals may reflect movements of different body parts and different sensor orientations. As a result, it leads to the great in-class variance and produces big classification models, which is in conflict with resource saving.

Capturing the opportunities when people put their mobile phones in the pockets around the pelvic region, we recognize 7 typical physical activities that people conduct daily in this paper, including stationary, walking, running, bicycling, ascending stairs, descending stairs, and driving. Our contributions in this paper lie in the following three parts. Firstly, we conduct experiment to examine the opportunities of recognizing physical activities using the accelerometer sensor embedded in the mobile phones in the scenario. Secondly, based on the extracted 22 features, we evaluate the classification abilities of 6 common used machine learning algorithms. The result reveals that Support Vector Machine [4] achieves the best performance at 97.7%. Thirdly, through the proposed feature reduction method, we successfully reduce the feature dimension from 22 to 8, while obtaining the smallest model size.

2 Related Work

In this section we introduce the activity recognition studies that collect sensing data from mobile phones or from sensor platforms that share similar usage pattern. The major concern is that mobile phone has various possible deployment positions and orientations. An earlier work conducted by Lester et al. [11] investigated three representative locations, including the wrist, the waist and the shoulder and found that the general HMM model for all the three locations performs only a slightly worse than that of the separate HMM model for each location. However, the sensor boards in the study are constrained by traps or bags, which limit the orientation freedom of themselves, and also these locations aren't the usual positions for mobile phones. To solve the varying orientation problem when carrying on mobile phone freely, Yang [17] computed the vertical and horizontal components of the sensor reading based on gravity estimation work of Mizell [14]. However, results in [13] showed that the method failed to outperform the method which just adds the accelerometer magnitude as one dimension of the sensor reading. It is probably caused by the inaccuracy of magnitude estimation method. And also it didn't consider the varying deployment positions of mobile phones.

A few studies, like ours, focused on activity recognition with data collected from commercial mobile phones. Kwapisz et al. [10] collected data from mobile phones carried in the front pants leg pockets and recognize similar activities like us with machine learning techniques. However, the mobile phones in in fixed orientations and the pocket locations is specific, which limits the usage in real life. Gerald et al. [2] introduced several aspects of activity recognition with mobile phones, including the wearing positions, sampling rate, activity types and mobile phone requirement. However, it didn't introduce the recognition solutions.

Different from above works, we study the possibility of activity recognition with mobile phones freely placed in the pockets near pelvic region, which is practical for daily usage of such system. Based on the extracted features, we evaluate the performances of different recognition algorithms and the impact of the sampling window length. And feature reduction is performed to get the smallest model size while obtaining high recognition accuracy.

3 Assumption, Experiment and Feature Extraction

3.1 Assumption

As demonstrated in [15], the pelvic region is an ideal deployment position for recognizing various physical activities. And also the pockets of normal clothes are designed around this region (i.e. the front and rear pockets of jeans, the front pockets of the coat as shown in Fig 1(a)). As revealed by [8], over 60% men get used to putting their mobile phones into their pockets. And thus we are trying to seize the opportunity when people place their mobile phone inside their pocket around the pelvic region to recognize their physical activities.

(a) (b)

Fig. 1. (a) Pocket locations. For each pocket shown, there is a corresponding one in the left side of the body. (b) Four phone orientations when users put the mobile phone into the right front jean's pocekt.

Table 1. The sampling time of the each activity during the experimentation

Activity	Station	Walk	Run	Bicycle	Ascend stairs	Descend stairs	Drive	Total
Time(Hour)	10.4	9.8	6.3	6.6	4.6	4.0	6.5	48.2

We choose all the pockets shown in Fig 1(a) as the potential mobile phone deployment positions. Due to the constraints of pocket shapes, we observed that people usually put the mobile phone into each pocket with four typical orientations. For example, Fig 1(b) shows the scenario when people put the mobile phone inside the jeans pocket.

In this paper we choose seven typical physical activities that people conduct daily, including stationary, walking, running, bicycling, ascending stairs, descending stairs and driving. Stationary is the status when people are still, including standing, sitting and lying down. For the activities people conduct while sitting down, the mobile phone isn't suitable to be placed in the rear pocket of the trousers, since it may be crushed by human body.

3.2 Experiment

We conduct experiment to collect the accelerometer data with Nokia N97 at a sampling rate of 40Hz for each activity with each possible combinations of location and orientation. Seven subjects from our campus participated in the experiment. After launching the sampling application, the participants put the mobile phone into the target pocket and conduct the activity for a duration about 5 to 10 minutes. And then they take the mobile phone out and terminate the application, which saves the accelerometer records during this period of time into a file. While residing in the pockets, the mobile phone is completely free to rotate or move. Since the first and the last few seconds of the records are the overhead when people put the mobile into the pocket and take it out of the pocket, they are removed from the official record. Totally we get 48.2 hours training data as shown in Table 1.

3.3 Feature Extraction

As demonstrated in [13], the accelerometer magnitude does help improve the classification accuracy as one dimension of sensor readings. So we add it to the sensor reading and prepare a 4-D raw data set Then we use half overlapping window to separate the data record into a number of equal-sized windows. We evaluate the influences of different window length for the following reasons. Firstly, it's intuitive that long time observation should help to recognize the activities to some extent. So we want obtain the optimized window length to get the best recognition accuracy. Secondly, within the range of acceptance, larger window length implies that the activity recognition frequency is smaller, which could save the energy consumption.

We employ five feature types including Mean, Variance, Correlation, FFT Energy and Frequency-domain Entropy because they have produced good results in previous works [16, 13]. In total, 22 features are extracted from each window (4 features for each Mean, Variance, Energy, Frequency-Domain Entropy, respectively, and 6 features for Correlation) and forms a 22-D feature vector. All the feature vectors forms a feature matrix with each column corresponding to one element of a specific feature type. The data of each column is normalized to [0,1].

4 Result Analysis

In this section we firstly compares the recognition accuracies of different machine learning algorithms and the impact of the window length on the performance. After that, we perform feature reduction to get a small and compact model.

4.1 Recognition Accuracy Comparison

WEKA toolkit [7] and LibSVM [5] are used to perform the classification with the extracted features. We adopt *10-folder cross validation* to get the final accuracy. All the features are randomly divided into 10 equal-sized folders. Each time we select one folder as the testing dataset and the rest as the training data set. Then the final accuracies is generated by averaging the cross validation results. We also perform grid research to get the best parameters for each classifiers. The classification accuracy of each algorithms with respect to different window length is revealed in Fig. 2. It can be seen that SVM performs the best (97.7%) comparing with the rest algorithms. And following is Random Forest [3] (96.5%), whose performance is almost the same when the tree number exceeds 20. Naive Bayes [9] and RBF Network performs the worst around 70%. When the window length grows from 1 second, the classification accuracy increases for each algorithm. For SVM and Random Forest, it reaches a stable level when the window length is over 6 second. It validates our intuition that with longer time observation, the classification accuracy increases and then reaches a stable level. To save the resource consumption, reducing the classification frequency

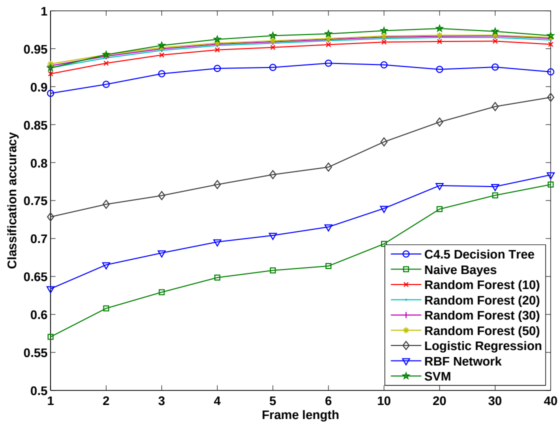


Fig. 2. The classification accuracy of different algorithms with respect to different window lengths.

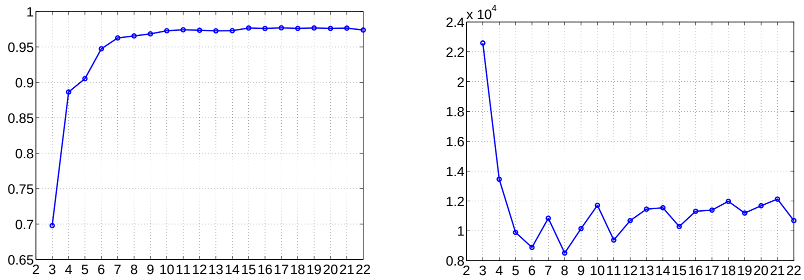
would be acceptable with stable accuracies for some applications. However, the drawback is that the classification granularity would become coarse when the window length increases.

4.2 Feature Dimension Classification Contributions and Reduction

To obtain a compact classification model, we evaluate the feature attribute contribution according to Algorithm 1. We choose the window length as 6 seconds and evaluate the feature contributions with SVM. We show the recognition accuracy with the number of left feature dimensions in Fig. 3 (a). It can be seen that when the feature number exceeds 7, the recognition accuracy become stable. As the computation cost when predicting with SVM model is directly related with the number of support vectors and also the feature dimensions, here we compares the support vector numbers with different attribute numbers of the model in Fig. 3 (b). It's surprising to see that the number of support vectors decreases to the smallest level when there are 8 attributes and then increases with more feature attributes. As a result, choosing these 8 attributes can reduce the number of support vectors and feature dimensions.

5 Conclusion

Mobile phone based activity recognition, which caters to the demand of long-term physical activity monitoring, has to comply with people's usage habits, capture the right moment for activity recognition and save resource. This paper explore the opportunity of recognizing seven typical daily physical activities when people put their mobile phones inside the pocket near the pelvic region.



(a) (b)

Fig. 3. (a), Feature Validation Result. The least contribution feature is extracted in each loop and the horizontal dimension is the number of left contributes. (b), The number of Support Vectors with different dimensions.

Algorithm 1 Feature Contribution Evaluation

DS is the feature dataset T is the feature dimension of DS
while $1 < T$ **do**
  $Acc_{max} \leftarrow 0$
  for $t = 1$ **to** T **do**
    $D_t \leftarrow DS$
    Exclude the t^{th} dimension from D_t
    Perform 10-folder cross validation on D_t and get the average accuracy Acc_t
    if $Acc_{max} < Acc_t$ **then**
      $Acc_{max} \leftarrow Acc_t$
      $MinLossD \leftarrow t$
    end if
  end for
  Exclude the $MinLossD^{th}$ dimension from DS
  T is the feature dimension of DS
end while

Experiment shows that the recognition accuracy reaches 97.7% when people put their mobile phones freely into the pockets. To obtain a compact model, feature validation is performed to evaluate the contributions of each feature attribute and feature reduction is conduct the get rid of the little contribution attributes. Result shows that we can reduce the feature dimension to 8 and meanwhile obtain the smallest model with little loss of recognition accuracy.

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