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An Effective Approach for Human Activity Recognition on Smartphone

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***Abstract*—Activity recognition, which takes the sensor reading from mobile sensors as inputs and predicts a human motion activity using data mining and machine learning techniques. In this paper ,we analyze the performance of two classification algorithm in an on-line activity recognition system working on Android platforms that supports on-line training and classification using only the accelerometer data .First we use the KNN classification algorithm and next we utilize an improvement of Minimum Distance and K-Nearest Neighbor classification algorithms, called Clustered KNN .For the purpose of on-line activity recognition, clustered KNN eliminates the computational complexity of KNN by creating clusters, i.e., creating smaller training sets for each activity and classification is performed based on these reduced sets. We evaluate the performance of these classifiers on four test subjects for activities of walking, running, sitting and standing in on-line activity recognition system. In this paper, we are also interested in the performance of classifiers with limited training data and the limited memory available on the phones compared to off-line .**

Keywords—K-Nearest Neighbor; Clustered KNN; Activity Recognition.

INTRODUCTION

Human activity recognition takes the raw senor reading as inputs and predicts human motion activity. Many main stream smart phones are equipped with various sensors, including accelerometers, GPS, light sensors, gyroscope, barometer, etc .Due to its unobtrusiveness, low/none installation cost, and easy-to-use, smart phones are becoming the main platform for human activity recognition **.**In this paper, we focus on activity recognition using the embedded accelerometers on smart phones. In this paper, we are also interested in the performance of classifiers with limited training data considering the limited memory available on the phones. In the system, training data can be collected only in a few minutes and can be used directly for classification steps which reduce the burden on the users. Being one of the first Android applications used for activity recognition is another important motivation for this study. In the literature, it has been reported that minimum distance classifier does not perform well when used alone. Additionally, KNN results are always better than minimum distance in terms of accuracy. However, KNN is not an online classifier since it requires high computational burden and especially considering the limited resources on smart phone, it does not appear as a preferable method.

II. SMARTPHONE SENSORS

A. Accelerometer

Accelerometer sensors sense the acceleration event of the smart phone. On most modern mobile devices there is a 3-way axis device that determines the phone's physical position. The raw data from the accelerometer is represented in a set of vectors: Acc i =< x i ,y i , z i >,i =(1, 2, 3,...) [1]. A time stamp can also be returned together with these three axes readings. Accelerometer has been used heavily in smart phone sensors based activity recognition. Its popularity is due to the fact that it directly measures the subject's physiology motion status.

B. Compass sensor

Compass is a traditional tool to detect the direction with respect to the north-south pole of the earth by the use of magnetism. The raw data reading from a compass sensor is the float number between 0 º and 360 º . It begins from 0 º as the absolute north and the actual reading indicates the angle between current smart phone heading direction and the absolute north in clockwise. Compass reading can be used to detect the direction change in the human motion such as walking.

C.Gyroscope

A gyroscope is a device that uses Earth's gravity to help determine orientation. Gyroscope measures the phone's rotation rate by detecting the roll, pitch, and yaw motions of the smart phones along the x, y, and z axis, respectively [1]. The raw data stream from a gyroscope sensor is the rate of the rotation in rad/s (radian per second) around each of the three physical axes: Rotation i =<xi ; y i ; z i >; i =(1,2,3,..........) . In activity recognition search, gyroscope is used to assist the mobile orientation detection.

D. Barometer

Barometer is one of the latest sensors equipped on some advanced smart phones .It measures the atmospheric pressure of the environment that the sensor is placed in..

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Thus, barometer reading can be used to indicate the user's position change in localization related activity recognition.

III.CORE TECHNIQUES

A.KNN

K-Nearest Neighbor is a supervised learning algorithm where the result of new instance query is classified based on majority of K-Nearest Neighbor [3] category. It is one of the most popular algorithms for pattern recognition. The purpose of this algorithm is to classify a new object based on attributes and training samples. The classifiers do not use any model to fit and only based on memory. K-Nearest Neighbor algorithm used neighborhood classification as the prediction value of the new query instance.

In pattern recognition, the k-nearest neighbor algorithm (K-NN) is a method for classifying objects based on closest training examples in the feature space. K-NN is a type of instance-based learning and it's function is only approximated locally and all computation is deferred until classification. The K-Nearest Neighbor algorithm is amongst the simplest of all machine learning algorithms: an object is classified by a majority vote of its neighbors, with the object being assigned to the class most common amongst its k nearest neighbors (k is a positive integer, small). If k=1, then the object is simply assigned to the class of its nearest neighbor. The training examples are vectors in a multidimensional feature space, each with a class label. The training phase of the algorithm consists storing the feature vectors and class labels of the training samples. In the classification phase, k is a user-defined constant, and an unlabeled vector is classified by assigning the label which is most frequent among the k training samples nearest to that query point. Usually Euclidean distance is used as the distance metric; however this is only applicable to continuous variables. In cases such as text classification, another metric such as the overlap metric or Hamming distance.

B.Clustered KNN

In clustered KNN, training data is first preprocessed and four features, which are average, minimum, maximum, and standard deviation, are extracted and in the second step classification takes place.

1) Preprocessing in Clustered KNN

In the preprocessing step, our objective is to define activity sets from the training data based on the mentioned features. Instead of comparing all the data in the training set, we compare the test data only with the compact training data set that we selected from the original training set. During the preprocessing step, compact training sets are created for each feature and for each activity. For each feature, except the standard deviation, K data points are selected from the training data. For instance, for the minimum feature set, K "minimum" data points are selected from the training data. Similarly, we create a "maximum" set by selecting the K maximum data points. The average value of the training data is calculated and nearest K data points are included in the "average" set. For the "standard deviation set", standard deviation of training values for each activity is calculated. However, at the same time accuracy of the results are expected to decrease with smaller K, so that there is an important trade off between accuracy and execution time considering the value for K.

2) Classification in Clustered KNN

In the classification step, during a window with a predefined size we collect test data, in other words we segment the data. After the window is filled, classification starts, and average, minimum, maximum, standard deviation values of the data in the window is calculated. These values are compared one by one with the values in the compact training sets which were created during the preprocessing step. *K* nearest sample to test data is selected from training sets and voting is made by looking at the final list of activities. We label the data in the related window as the activity for which we have maximum amount of data in the final *K* set. The one which is closer to the standard deviation of that window is selected as the recognized activity by the standard deviation feature. At the end, we have four labels coming from voting results of each feature .We label the window as the activity for which we have the highest vote and finalize the classification.

IV.ACTIVITY RECOGNITION IN ANDROID PLATFORM

The clustered KNN classifier and the other classifiers are implemented on Android phones to detect four main activities; which are walking, running, standing and sitting. For this purpose, the process is divided into two phases [4].

At first stage, training data is collected for each activity separately. For this purpose we developed an application called Activity Logger. In this application, user selects the activity to be performed, puts the phone into the packet and starts to perform the related activity. For each activity, the application creates different training data files in which raw data from the 3-axes of the accelerometer is being logged. Low pass filter is applied to raw data for noise removal. Before starting the activity recognition tests, a few minutes of training data for each activity is collected by each subject. In the second stage, activity recognition is performed using the selected classifier. First, the application extracts necessary features of training sets for each activity according to the classification method being used. Depending on the size of the training set and the processor performance of the phone, this step may take a few minutes. The main screen of the application allows the user to select the system parameters, such as the sensor sampling rate and window size.

In order to monitor the recognition performance of the classifier, the ground truth data, i.e. which activity is actually performed by the user, is logged. For this purpose, the application gives voice commands repeatedly to perform an activity. Activity order is predefined in the system whereas activity duration "order interval" is given directly as the user input to the system in unit of seconds. During our experiments each activity is performed for 60 seconds for one cycle. Finally, using these ground truth values, i.e., activity tags, activity recognition performance and other performance metrics of the classifiers are calculated.

V. RESULT AND DISCUSSION

To evaluate the classification performance of clustered KNN for each activity. The confusion matrix for clustered KNN is presented in Table 1.

Compared to the performance of activities of running, standing and sitting, the classifier presents slightly worse performance for walking where it is sometimes classified as running or standing. However, the overall performance for clustered KNN is around 92% accuracy considering all activities.

We are also evaluated the impact of *K* value on the classification performance of clustered KNN. As expected, increasing the *K* value affected accuracy rates positively.

When we consider the overall effect of all system parameters we obtained best results in the case where K is selected as 50, window size is selected as 1 second and sampling interval is selected as 50 msec.

Window size(sec)		0.5			1			2		
Sampling Interval(msec)		10	50	100	10	50	100	10	50	100
K	10	87.9	87.8	87.7	88.4	90.3	89.5	88.6	87.8	89.3
	50	91.1	90.0	91.4	91.9	92.1	90.8	88.9	89.4	91.0

TABLE 1 OVERALL CONFUSION MATRIX

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VI.CONCLUSION

In this paper, we proposed an activity recognition system working on Android platforms that supports on-line training and classification while using only the accelerometer data for classification. On-ine classification performance of KNN classifier is evaluated and a clustered KNN method is used. The clustered KNN method exhibited a much better performance than the KNN classifier in terms of accuracy on mobile platforms with limited resources. We also evaluated the performance of clustered KNN in terms of execution times. As expected, classification execution times are considerably reduced as K parameter is decreased. Moreover, classification times are highly dependent on the device model and capabilities as well.

References

Xing Su, Hanghang Tong, and Ping Ji , "Activity Recognition with Smartphone Sensors" ,tsinghua science and technology ISSN ll1007-0214ll02/11llpp235-249 Volume 19, Number 3, June 2014.

Nicholas D.Lane , Emiliano Miluzzo, Hong Lu, Daniel Peebles,"A Survey of Mobile Phone Sensing",IEEE Communications Magazine • September 2010

Sahak Kaghyan, Hakob Sarukhanyan, "Activity recognition using k-nearest neighbor algorithm on smartphone with tri-axial accelerometer ",International Journal "Information Models and Analyses" Vol.1 / 2012J.

Mustafa Kose, Ozlem Durmaz Incel,Cem Ersoy "Online Human Activity Recognition on Smart Phones"2nd International Workshop on Mobile Sensing, April 16, 2012.

Pekka Sirrtola and Juha Röning, "Recognizing Human Activities User-independently on Smartphones Based on Accelerometer Data",International Journal of Artificial Intelligence and Interactive Multimedia, Vol. 1, No 5.

Jennifer R.Kwapisz Gary M. Weiss, Samuel A. Moore,"Activity Recognition using Cell Phone Accelerometers",sensor KDD '10,july 25,2010 ,Washington,DC,USA.copyright 2010ACM.

Ling bao and stephen S. Intille,"Activity Recognition from User-Annotated Acceleration Data",. Ferscha and F.Mattern (Eds) PERVASIVE 2004, LNCS 3001, pp. 1–17, 2004. Springer-Verlag Berlin Heidelberg 2004.

Won-Jae Yi, Weidi Jia, and Jafar Saniie ,"Mobile Sensor Data Collector using Android smartphone", Department of Electrical and computer Engineering illinos institute of technology 3301 S.Dearborn St.103SH,Chicago IL,USA.