A Comparative Study of Human Activity Recognition Techniques

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***Abstract*:- Human activity recognition (HAR) from time series sensor data collected by low cost inertial sensors attached to small portable devices like smart phones are increasingly gaining attention in various fields especially for health care, medical, military and security applications. Accelerometer and gyroscope sensor signals are acquired to identify the activities performed by the user. In addition, time and frequency domain signals are derived using the collected signals. In this paper, we have discussed the following techniques used for recognizing human activities using the smart phone sensors. 1) Moving Standard Deviation (MSD) 2) Dynamic feature extraction 3) Histogram of Gradient (HG) 4) Fourier descriptor (FD) 5) Fast Fourier Transform (FFT) 6) HARLIB 7) SVM based RBF Kernel Classifier 8) Convolution Neural Network (CNN) 9) Parameters Adjustment Corresponding to Smart phone 10) k-nearest neighbour (KNN) 11) MEMS (Micro Electro Mechanical System) Cursor Movement Algorithm. It also involves the performance measures of the techniques discussed interms of accuracy.**

General Terms:- Time series, sensors, health care, military, security

Keywords:- Human activity recognition, smart phone,

1. INTRODUCTION

Recent developments of sensor technologies and widespread use of small devices like smart phones, tablets etc., facilitate gathering of huge data from small portable devices of everyday use. The generated data from various high quality in-built sensors of small mobile devices can be collected over a length of time and transmitted by wireless technology to processing computers. Efficient and fast analysis of those time series data provides us with the opportunity of recognition, monitoring of various activities. Activity recognition is also useful in applications such as smart homes, security, transportation & mode detection. Recently smart phone sensor technologies are developing at an incredible pace. Various sensors like GPS, accelerometers, magnetometers, gyroscopes, barometers, proximity sensors, temperature and humidity sensors, cameras and microphones etc. along with Bluetooth and Wi-Fi technologies are normally embedded into mobiles. Human Activity Recognition (HAR) can be achieved by using sensors placed in the environment and the dedicated body-worn sensors. This approach of HAR involves placing wearable sensors at multiple body locations. For example, the bi-axial accelerometer data is collected from sensors placed at four different limb locations and a sensor at the right hip. It also uses two sets of tri-axial accelerometer sensors attached to the left and the right sides of a waist belt. In general, the approaches using multiple wearable sensors achieve high accuracy for activity recognition. However, as mentioned previously, these sensors may become too cumbersome to wear, especially for continuous activity recognition in which users may have to wear the sensors for extended periods of time.

2. LITERATURE SURVEY

A detailed survey on activity recognition using wearable sensors has been explored in this section.

Changhai Wang proposed **"Position-Independent Activity Recognition Model for Smartphone Based on Frequency Domain Algorithm" [1],** which involves analysis of Fast Fourier Transform (FFT) curve of Resultant Acceleration in different mobile positions and different activities. The curve shows that FFT results can be used to distinguish different actions. Furthermore, the highest recognition accuracy is achieved under the condition of 39 lower frequency FFT characteristics. Recognition accuracy can be improved by 5% & time consumed for recognizing activities is reduced by 12.2% using this method.

Hua-Cong Yang proposed **"HARLIB: A Human Activity Recognition Library on Android" [2],** a server application topology, motion recognition & voice recognition system based on Micro Electro Mechanical Systems (MEMS). A cursor movement algorithm is proposed which deals with spontaneous data acquisition from the embedded orientation sensor.

Ankita Jain proposed **"Human Activity Classification in Smartphones Using Accelerometer and Gyroscope Sensors" [3],** an android demo application to test the recognition performance of HARLIB. The limitation of the proposed approach is that there are little difference between sitting and lying, so they are easy to confuse. Stairs is the most difficult activity to classify. It is easy to be confused with walking and jogging.

Wen Wang proposed **"Human Activity Recognition using Smart Phone Embedded Sensors: A Linear Dynamical Systems Method" [4],** which involves Support Vector Machine (SVM) based RBF kernel classifier that uses confusion matrix to give information about the actual and predicted classifications. The labels of abscissa and ordinate are the names of nine actions considered in their work. Experimental results reveal that different actions obtain different recognition accuracies. For example, Biking and Gym bike obtains higher accuracy (82% and 80%) respectively, but Walking obtains the lowest accuracy (51%). It is often recognized as Bike, Climbing and Descending. The limitation of the proposed work is distinguishing between walking and running.

Kotaro Nakano, Basabi Chakraborty proposed **"Effect of Dynamic Feature for Human Activity Recognition using Smartphone Sensors" [5]**, an approach for dynamic feature extraction from time series human activity data which involves comparison of classification results with dynamic features and static features. Simulation experiments with benchmark dataset with different machine learning classifiers reveal that dynamic features is efficient than static features. Activity recognition using extracted dynamic features can also be achieved by applying Convolution Neural Network (CNN). Though CNN takes higher computational time & memory resources it provides better recognition accuracy for dynamic activity recognition with dynamic features compared to conventional classifiers such as Multilayer perceptron (MLP), Support vector machine (SVM) & K-nearest neighbor (KNN).

M. Sarkar, M. Z. Haider, D. Chowdhury, G. Rabbi proposed **"An Android Based Human Computer Interactive System with Motion Recognition and Voice Command Activation" [6]**, an effective design of an Android-based Human Computer Interactive (HCI) system with voice command activation and gesture recognition to control a computer. The proposed system substantiates remote computing through processing of the orientation readings of physical movement of the phone with a continuous data acquisition from a 3-D Accelerometer sensor embedded into the smart phone. The wrist of human body is attached with Wi-Fi connected sensor. Under certain conditions the proposed work has been tested for performance analysis exhibits its sustainability.

Rong Yang, Baowei Wang proposed **"PACP: A Position-Independent Activity Recognition Method Using Smartphone Sensors" [7]**, Parameters Adjustment Corresponding to Smart phone (PACP) which is a position-independent method improves the performance of activity recognition. The position of the smart phone is recognized by using the features extracted from the data generated by accelerometer & gyroscope. Then the accelerometer data were adjusted with respect to position in order to recognize activities with Support Vector Machine (SVM). Experimental results reveal that the PACP achieves an accuracy of 91% which is better when compared with earlier activity recognition methods.

Kwapisz, Weiss, Moore proposed **"Activity Recognition using Cell Phone Accelerometers" [8]**, activity recognition was performed by using the accelerometer data collected from a smart phone. The subjects kept the phone in the front pocket of their trousers while performing the daily activities such as walking, jogging, ascending stairs, descending stairs, sitting, and standing. To train a model for activity recognition 43 features were generated from the data. The proposed approach gained a recognition accuracy of about 90%.

Bieber, Luthardt, Peter, Urban proposed **"The Hearing Trousers Pocket-Activity Recognition by Alternative Sensors" [9]**, a mobile phone application that detects daily physical activities using the built-in accelerometer. By fusing the information of accelerometer & sound sensor the capabilities of activity recognition was improved.

Harasimowic, Dziubich, Brzeski proposed **"Accelerometer-based Human Activity Recognition and the Impact of the Sample Size" [10]**, where the author classified 8 user activities such as running, walking, going upstairs, going downstairs, standing, lying, turning & sitting. During the recognition of activities the influence of window size was also investigated. Experimental results reveal that the k-Nearest Neighbour algorithm (KNN) provided an accuracy of 98.56%.

Grokop L, Sarah, Brunner, Narayanan, Nanda proposed **"Activity and Device Position Recognition in Mobile Devices" [11]**, which fused the data of the Ambient Light Sensor (ALS), accelerometer, camera & proximity sensor to generate a tuple to classify the device positions and motion states with the respective accuracies 92.6% and 66.8%. It was observed that the accuracy can be improved by increasing the number of sensors but it could result in consumption of resources.

Coskun, Incel, Ozgovde proposed **"Phone Position/Placement Detection using Accelerometer: Impact on Activity Recognition" [12]**, which is an approach to classify the activity and position by using an accelerometer. To improve the position recognition accuracy the positions were recognized by using angular acceleration. Experimental results reveal that the recognition accuracy achieved by the proposed method was 85%.

Miao, He, Liu, Ayoola proposed **"Identifying typical physical activity on smartphone with varying positions and orientations" [13],** where physical activity is recognized by placing smart phones in the two front & back pockets on the trousers, two front packets on the coat. Decision tree was used to achieve best performance for classification and recognition. Experimental results reveal that the proposed method results in the recognition accuracy of 89.6%.

Bishoy Sefenet. al. proposed **"Human Activity Recognition using sensor data of smart phone & smart watches" [14],** carried out several evaluations to determine which features and classification algorithm has to be used to increase recognition accuracy and reduce computational complexity. The dataset involving the following information: several fitness exercises and daily activities of 16 participants were analyzed using naïve bayes classifier.

Charissa Ann Ronaoet. al. proposed **"Recognizing human activities from smart phone sensors using hierarchical continuous hidden markov models" [15],** a universal activity recognition method called two-stage continuous HMM classifier which was applied on the data generated by smart phone sensors. Time series data generated by accelerometer and gyroscope were extracted to obtain smaller number of features. The authors also demonstrated that to obtain most useful features from large feature set it is required to have proper knowledge in the domain along with random forest variable importance measures. The coarse classification which involves stationary and moving activities separation was achieved by applying first-level CHMMs. The fine classification employs second-level CHMMs classifies the data into corresponding activity class labels. To determine optimal feature subsets for both fine and coarse classification the Random Forest (RF) variable importance measures were exploited. Experimental results illustrated that the proposed method with reduced number of features provides an accuracy of 91.76%.

3. COMPARISON OF HUMAN ACTIVITY RECOGNITION TECHNIQUES

The table below shows the comparison of different HAR techniques along with their accuracies for recognizing the human activities.

Table 1: Comparison of HAR Techniques

SL.No	Technique	Accuracy
1	Moving Standard Deviation (MSD)	98.6%
2	Dynamic feature extraction, vision based techniques	90%
3	Histogram of gradient (HG)	96%
4	Fourier Descriptor (FD)	90.12%
5	MEMS (Micro Electro Mechanical System) Cursor Movement Algorithm	Walking 87.1% Jogging 77.8% Stairs 65.8% Sitting 75.0% Standing 90.3% Lying 62.3%
6	Fourier Descriptor (FD) Histogram of Gradient (HG)	97.12%
7	SVM Support Vector Machine (RBF Kernel)	80% to 82% but walking is 51%
8	FFT (Fact Fourier Transform)	82% to 87% for FFT39
10	Parameters Adjustment Corresponding to Smart phone (PACP)	91%
11	k-Nearest Neighbor algorithm (KNN)	98.56

4. CONCLUSION

In many fields like disease control, health care, fitness & sports Human activity recognition plays a significant role. In this paper, we have discussed the following techniques used for recognizing human activities using the smart phone sensors. 1) Moving Standard Deviation (MSD) 2) Dynamic feature extraction 3) Histogram of Gradient (HG) 4) Fourier descriptor (FD) 5) Fast Fourier Transform (FFT) 6) HARLIB 7) SVM based RBF Kernel Classifier 8) Convolution Neural Network (CNN) 9) Parameters Adjustment Corresponding to Smart phone 10) k-nearest neighbour (KNN) 11) MEMS (Micro Electro Mechanical System) Cursor Movement Algorithm. It also involves the performance measures of the techniques discussed interms of accuracy.

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