RESEARCH ARTICLE OPEN ACCESS

Activity Recognition using Accelerometer and GyroscopeSensor Data

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Abstract:

Smart phones are becoming more sophisticated and consist of many sensors. GPS, vision, audio, light, temperature, direction, and acceleration sensors are few. In smart phones, sensors make human activity recognition better and easier. Accelerometer and Gyroscope are available in most of the smart phones and made data collection easy. In this work twelve different statistical measures are extracted as a feature from the raw data collected by these sensors. LDA and KNN classifiers are used to classify the activity.

Keywords —**Activity Recognition, Accelerometer, Gyroscope, Classifier.**

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I. INTRODUCTION

Activity recognition is one of the most specific technology in pervasive computing. Activity recognition is used in many practical humancentric applications such as human tracking, elderly and youth care. The embedded sensors like Accelerometer, Gyroscope, GPS are used in human tracking activities such as steps taken, stairs climbed, calorie burned, hours slept, distance travelled, quality of sleep etc.

The advancement in mobile sensors helps to recognize human activity but still there are challenges which have come with them. The common challenges in activity recognition using mobile sensors and other factors are mentioned below.

A. Sensor inaccuracy

Sensor data plays a vital part in the inclusive recognition.

B. Sensor placement

Problem could be caused if the sensors are placed or supervised wrongly.

C. Selection of attributes and sensors

To measure the chosen characteristic quality in activity recognition the sensors that measure human activities plays a significant part

D. Resource Constraints

The major factor affecting the size of the battery and sensor nodes are power consumption.

E. Human behaviour

The recognition process make arduous by conducting several human tasks simultaneously.

F. The definition of physical activities

Under inspection and definite attributes are build up a distinct, unambiguous explanation of the activities.

G. Interclass Variability

Different persons conduct the same activity at the same time.

H. Interclass Similarity

Classes that are basically different, but which exhibit analogous characteristics in the sensor

I. Usability:The complex whole can be simpler to assimilate.

J. Privacy:

Private life of the users should not be invaded by sensitive user information.

K. Subject Sensitivity

The precision of activity recognition is extensively influenced by the subjects who participate in training and assessment stages.

L. Obtrusiveness

HAR systems needn't require the user to wear excessive number of sensors nor interact too often with the application.

M. Data collection

Under feasible situation the training data is collected.

N. Flexibility

To help the new users, the system must be flexible that it does not require a re-training system.

O. Processing

Either in the server or in the integration device the task of recognition should be performed.

P. Trade-offs in HAR: To keep the balance against accuracy, system latency, and processing power.

Q. Multiple Residents

In the same environment, several residents can be present. [21]

In recent years, due to the accessibilities of the varieties of sensors a lot of shift has being occurred in mobile phones. The example for such sensors are GPS, accelerometer, gyroscope, microphone and magnetometer. In the case of motion detection sensors provide large opportunity that is very important to detect human activities. [19] Accelerometer and Gyroscope sensor data are used in this research. In the case of human activity prediction, a triaxial accelerometer sensor that proceeds real esteemed estimate of speeding up next to the X, Y and Z axes and the rapidity and dislocation which can also be anticipated. Accelerometers can be used as movement detectors as well as body-position and posture sensing. [3] Gyroscope returns value of revolving along X, Y and Z axis with the gravity. Both of accelerometer and gyroscope areplaced on the left arm wrist and right ankle. Data collected by these sensors are used to guide a set of classifiers which include LDA and KNN along with its generated features. The features are set of statistical measures that provide meaning to the data.

The source of collecting raw data, in activity recognition is sensors. These sensors are divided into three categories:

- Video sensors
- Environmental-based sensors
- Wearable sensors.

Cameras installed in the fixed places like, at the entrance/exit of the public places are called video sensors. To detect the users' interaction with the environment, environmental-based sensors are used such as WiFi, Bluetooth, and the infrared sensors which are radio based sensors. These sensors are deployed in indoor places like office building and homes. The mobile sensors designed to be worn on human body which are small in size are called wearable sensors. User's physiological states such as location changes, moving directions, speed, etc. can be recorded by them. Magnetometer, Accelerometer, Gravity sensor, Proximity sensor, Ambient temperature sensor, Gyroscope, Light sensor, Barometer, and Humidity sensor are in build in mobile devices. Out of these sensors Accelerometer, gyroscope, magnetometer etc. can be used for human-activity recognition

Accelerometer

An electro mechanical gadget that uses to measure acceleration forces is called an accelerometer. Nonstop energy of gravity, or similar case with a lot of mobile devices, vibrant to sense movement or ambiance are the forces which is static. Time separate accelerations of the measurement of alter in velocity, or speed. [1], [15]

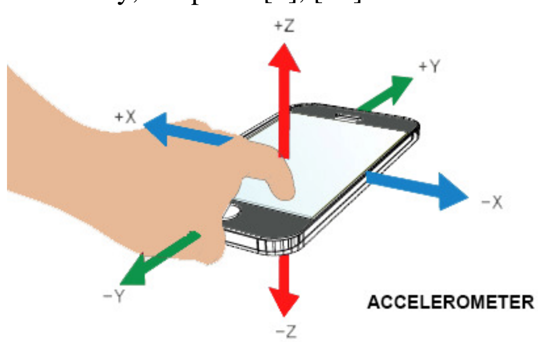

Fig. 1 Accelerometer Used in a Smartphone

Gyroscope

The gyroscope, add an aspect to the information abounding by the accelerometer by tracking turning around or twirling. An accelerometer measures linear speeding up of movement, while a gyro in a way measures the angular revolving speed. [15]

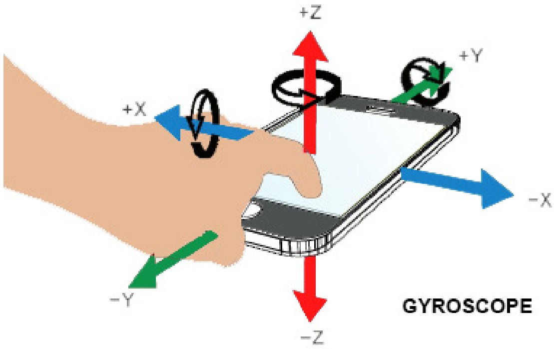

Fig. 2 Gyroscope Used in a Smartphone

II. RELATED WORKS

Activity Recognition using different mobile phones sensors have played an efficient role in the research area. Former researcher's efforts provide a sketch of related appropriate techniques which are listed below in the table 1. The smartphones are becoming better and sophisticated, every day and the sensors used in these phones have many more applications, such as health monitoring, road traffic monitoring, environmental monitoring and human activity recognition [12]. The research works described in table 1, are sensors used, fifty different activities, feature count and machine learning algorithm used are mentioned.

TABLE 1

Comparison of Related Papers

I D	Sensors used	Activities	No of Features	Machine learning algorithms
[1]	Accelerometer	A1, A2, A3, A4, A13,	6	Multilayer perception, SVM, Random Forest, LMT, Simple Logistics, Logit Boost
[2]	Accelerometer	A5, A2, A1, A3, A4, A14, A15, A16	5	Decision Tables, Decision trees, K nearest neighbours, SVM, Naïve Bayes
[3]	Accelerometer	A5, A2, A1, A6, A3, A4, A7	7	SVM
[4]	Accelerometer	A8, A9, A11, A5, A6, A17, A18, A19, A20, A2, A21, A3, A4, A22, A23	8	SVM
[5]	Accelerometer	A2, A10, A3, A4, A9, A5	6	straw man, Logistic Regression, Multilayer Perceptron
[6]	angular velocity sensor, accelerometer, simple digital compass sensor,	A5, A9, A2, A3, A4	3	KNN
[7]	Accelerometer, Gyroscope	A2, A5, A19, A24, A25, A10	5	SVM
[8]	Accelerometer, Magnetometer, Gyroscope	A26, A11, A27, A2, A1, A6	4	C4.5, F1-measure, Levenberg-Marquardt
[9]	Accelerometer, Gyroscope	A5, A9, A8, A3, A4	20	SVM
[10]	Accelerometer, Gyroscope	A12, A8, A9, A2, A5, A8	1	C4.5 decision trees, RIPPER decision rules, Naive Bayes, 3-Nearest Neighbors, Support Vector Machine (SVM), Random Forest, Bagging and Adaboost
[11]	Gyroscope	A28, A29, A2	3	
[12]	Accelerometer, Gyroscope	A2, A1, A3, A4, A6, A7	7	C4.5 Decision Tree, Naıve Bayes, K-Nearest Neighbor (KNN) and Support Vector Machine (SVM)
[13]	Accelerometer, Gyroscope	A30, A3, A7, A8, A1, A9, A5, A2, A31, A32, A33, A22, A34, A35	5	ML Perception, Naïve Bayes, Bayes Net, Decision Table, Best First Tree, K-star
[14]	Accelerometer	A36, A37, A38	3	KNN
[15]	Accelerometer, Gyroscope	A3, A2, A9, A39, A8, A1, A40, A41, A42, A12, A5, A50, A9, A8, A12		The Fall Detection Algorith
[16]	Accelerometer, Gyroscope, Magnetometer	A43, A44, A45, A46	7	KNN
[17]	Accelerometer, Gyroscope, Tilt sensor	A12, A5, A9, A47		Fall Detection Algorithm integrated with DAQ program
[18]	Accelerometer, Gyroscope, Magnetometer temperature sensor	A48, A49	9	C4.5, KNN, and naive Bayes
[19]	Accelerometer, Magnetometer Myroscope	A2, A1, A9, A5, A3, A4	2	Naïve Bayes, Support vector machines, Neural Networks, Logistic Regression, K Nearest Neighbor, Rule Based Classifiers, Decision Trees
[20]	Accelerometer	A2, A9, A5, A1, A6, A8, A3	5	AdaBoost, SVM and regularized logistic regression(RLogReg)

Running-A1, Walking-A2, Staires-Up-A3, Staires-down-A4, Standing-A5, Bicycling-A6, Driving-A7,lying-A8, Sitting-A9, Jog-A10, Typing-A11, Falling-A12, Aerobic-dancing-A13, Sit-ups-A14, Vaccuming-A15, Brushing-teeth-A16, Internet-search-A17, Reading-A18, Writing-A19, sorting files on paperwork-A20, Carrying-box-A21, Sweeping-A22, Painting-A23, Smoking-A24, Jacks-A25, Resting-A26, Gesticulating-A27, Sit-to-stand-A28, Stand-to-sit-A29, Biking-A30, Cleaning-A31, Cooking-A32, Medication-A33, Washing-hands-A34, Watering-plants-A39, Parting the Horses Mane-A36, Brush Knee Step Forward-A37, Repulse the Monkey-A38, Jump-A39, Run on staires-A40,Quickly sit down up right-A41, , quickly sit-down reclined-A42, Hummering-A43, Screwing-A44, Spanner using-A45, power-drill-A46, Daily life activity-A47,Full body turns-A48,Arm and leg blows-A49, Bending-A50

III. IMPLEMENTATTION

A. ActivityRecognition Model

Recognising human activity from the raw data is called activity recognition. The activity recognition frame work consists of general data acquisition, signal pre-processing segmentation, feature extraction and selection, training and classification and activity recognition. The activity recognition model is represented in figure 3

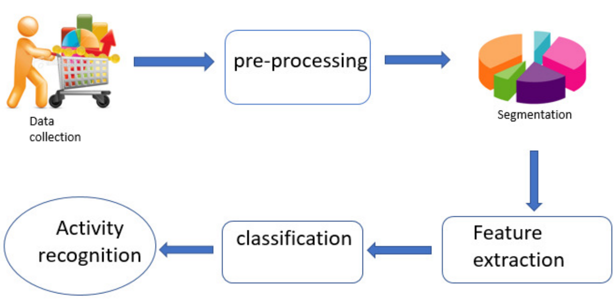

Fig. 3 Implementation model

B. Data Collection

In current years, a shift has been occurred in the case of mobile phones, due to the accessibility for the variety of sensors. The dataset comprises body motion and very important signs recordings for ten volunteers of varied summary as performing 12 bodily actions. Two dissimilar wearable sensors were used for the recording namely Accelerometer and Gyroscope. The sensors were correspondingly positioned on the subject's, right arm and left angle. Multiple use of the sensors help to calculate the motion practiced by device in the body parts, specifically, the acceleration, the rate of turn and the alluring field direction, and therefore one gets improved capture of the body dynamics.

The entire sensing *modalities* are recorded at an example rate of 50 Hz that measured enough for capturing human activity.

C. Feature Extraction

Feature extraction is an important step in the development and accuracy rate of the classifiers. Raw data do not give the best accuracy. For a better accuracy rate some feature extraction has to be done on the raw data.

For the feature extraction, ten different statistical functions are used, such as mean, median, mode, minimum, maximum, kurtosis, skewness, interquartile, percentile and root mean square. These statistical functions have been making the raw data into featured data, the classifiers to give better results.

D. Activity Details

There are twelve different activities used in this work which are performed by ten subjects. The activities are standing still (1), sitting_ and_ relaxing (2), lying down (3), walking (4), climbing stairs (5), waist bends forward (6), frontal elevation of arms (7), knees bending (8), cycling (9), jogging (10), running (11) and jump front and back (12).

E. Classifiers

There are two different classifiers KNN and LDA used in this work. These two algorithms work in two different ways and give different accuracy rate in prediction of human activities.

The K-nearest Neighbours algorithm (or KNN) is a non-parametric process which is used for categorization and weakening in prototype detection. The K nearby training examples for the spaces features is the input of the both cases.

Linear Discriminant Analysis (LDA) is a simplification of fisher's linear discriminant, a technique used in data, model acknowledgment and machine learning to find out a linear mixture of features that characterize or divide more than two classes of objects or events. The resulting combination may be used as a linear classifier or, usually, for dimensionality lessening previous to later arrangement.

IV. RESULT AND DISCUSSION

Table 2
confusion matrix for twelve Activities using KNN

Actual Values

Predicted Values	0	1	10	11	12	2	3	4	5	6	7	8	9
0	821	21	3	0	1	31	0	3	11	12	28	13	5
1	0	0	0	0	0	0	0	0	0	0	0	0	0
10	10	0	17	0	11	0	0	0	0	0	0	0	0
11	5	0	0	25	0	0	0	0	0	0	0	0	0
12	14	0	0	0	8	0	0	0	0	0	0	0	0
2	8	0	0	0	0	0	0	0	0	0	0	0	0
3	12	0	0	0	0	0	24	0	0	0	0	0	0
4	34	0	0	0	0	0	0	16	0	0	0	0	0
5	19	0	0	0	0	0	0	0	16	0	0	0	2
6	8	0	0	0	0	1	0	0	0	14	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0
8	28	0	0	0	0	0	0	0	0	0	0	14	4
9	19	0	0	0	0	0	0	0	0	0	0	2	20

Table 3
confusion matrix for twelve Activities using LDA

Actual Values

Predicted Values	0	1	10	11	12	2	3	4	5	6	7	8	9
0	971	0	4	3	0	12	8	0	0	7	0	0	4
1	29	0	0	0	0	0	0	0	0	0	0	0	0
10	14	0	11	0	11	0	0	0	0	0	0	0	0
11	1	0	0	25	0	0	0	0	0	0	0	0	0
12	6	0	0	1	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	29	0	0	0	0	0	0	0
3	0	0	0	0	0	0	19	0	0	0	0	0	0
4	30	0	0	0	0	0	0	0	0	0	0	0	0
5	19	0	0	0	0	0	0	0	0	0	0	0	2
6	4	0	0	0	0	1	0	0	0	18	0	0	0
7	20	0	0	0	0	0	0	0	0	0	0	0	0
8	28	0	0	0	0	0	0	0	0	0	0	0	0
9	6	0	0	0	0	0	0	0	0	0	0	0	18

Human activities can be recognized with fairly high accuracy using a single triaxial accelerometer located at the arm and angle by using KNN classifier about 85%. Static activities such as sleeping, sitting, standing are much difficult to predict than dynamic activities like running, walking and climbing. It is also found that the activity of one subject is predicted features of one subject; do not give a fair accuracy when applied to another subject. It is also noticed that the larger the training set, the more accurate the result would be. Using LDA classifier for the prediction of activities, gave the accuracy rate up to 76% and the training set decides the accuracy of this algorithm. That is, the result will be more accurate if the training set is larger.

V. CONCLUSION

In this paper the different mobile sensors including gyroscope and accelerometer which are used to recognize human activity are discussed. Simple classifiers KNN and LDA are used to recognize twelve different activities. Result accuracy also discussed.

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