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HUMAN ACTIVITY ANALYSIS AND DETECTION USING MATLAB AND SMARTPHONE

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Abstract- Human body is a system having links and joints and all together performs activities like walking, bending, lifting, sitting, lying and many more. This activities recognition using hardware or computer vision is at most demand for various applications. Here we proposed the human activity detection using MATLAB and android phone with MATLAB app to record the sensors data. The sensors are 3-axes acceleration and 3-axes gyroscopes from which we will get the raw data and this raw data will be classified into activity using algorithm developed in MATLAB. The human activity detection is having applications as identifying daily activities, the health-care applications, the unsupervised learning method of human activities, etc.

Keywords: *MATLAB, HAR, Health Care.*

I INTRODUCTION

Human Activity Recognition (HAR) research field attracts most researchers nowadays. However, this interest comes from the need of gaining the context-aware data; which in its turn are employed in providing a personal support to the users over a wide diversity of applications sets, such as security, medical, military and life style wise applications. The process of accurate recognition of daily life activities such as walking, standing, running provide a very important feedback to both the user himself and the care provider. For instance, the daily detected observations about patient activities produced by patient's body movements will be quite useful in preventing him/her from performing certain activities which could be considered abnormal or harmful to the health due to the illness or disease history status. Moreover, these daily detected observations could be useful to user health status by providing him/ her comments, tips and reminders over the received analysis about their daily activities performance; which eventually will aid the users enhancing their life style condition. In this work, the data from two types of sensors were used: Gyroscope and accelerometer sensors, which are available in most smartphones nowadays. Accelerometer sensor measures linear acceleration based on vibration. The two axis accelerometer gives in which directionthe gravity is. In general, speed and direction were obtained from accelerometer data after analyzing it. On the other hand, the gyroscope sensor measures the rate of rotation around a particular axis (Angular velocity) by using the key principles of angular momentum, which helps in indicating orientation.

II RELATED WORK

Accelerometers are widely utilized in motion sensing due to their low-power requirement and non-intrusiveness [4]. The body component of the acceleration signal is that the linear acceleration that detects motion of the body itself. Hence, the gravity component is often regarded as noise [12]. However, a recent study showed that the gravity component of the accelerometer aids in discriminating between sitting and standing activities [3]. In fact, the poor performance of gyroscopes in differentiating between the two activities can be attributed to the lack of gravity [3]. The two parameters of the accelerometer signal make use of accelerometers for detecting both body movements and postural orientations [7].

Furthermore, it had been observed during a previous study that linear acceleration is generally sick or on a par with the entire acceleration measurement in terms of motion sensing [3]. To save computational and storage resources, the linear acceleration attribute is omitted in this study. The component due to gravity of the accelerometer output can help in orientation detection [3]. However, since accelerometers are very sensitive, they are prone to noise or

Using the data of motion sensor, like acceleration, gyros and orientation etc., to identity user behavior had been tried before [1] [2] [4]. The experimental setup proposed in various papers [1] [2] assume that the sensors are attached to the subjects waist or back side pocket, which creates a somewhat position and orientation of subject. It has considered real-time based scenario, which assumes cellphone are fixed at hand or its inside pocket, but [4] only achieve 80% of accuracy maximum and in one paper [5] only achieved 91.15% of accuracy due to only acceleration data from sensor. In this experimental setup we'll remove the sensor constraints of attachment. We assume a more real scenario where the user is holding the phone and also using all available cellphone sensor data to do prediction [10].

III PROPOSED SYSTEM

The proposed system is designed using android operating mobile phone with Matlab supported package which will access the sensory data and upload it on cloud as shown in figure 1. The sensors are 3-axes acceleration and 3-axes gyroscopes which will give the raw data. The Data are collected from 3 types of sensor: acceleration sensor, gyro sensor and accelerometer sensor linearity. Each sensor returns three values corresponding to three dimensional x, y, z. The sensor data collection is at 50Hz (collecting 50 values per second speed) to store raw data in sample. Each sample gathers 128 values corresponding to each sample record of 2.56 seconds time.

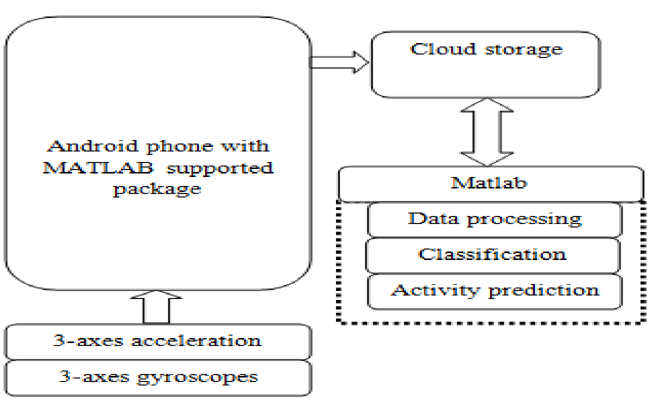

Figure 1 Block diagram of proposed system

Figure 2 Human body with joints and position of mobile phone

We have several challenges when we process data. First challenge is when we identified during data collection is Sensors recording duplicate data samples. The Second challenge is we use different sensors recording which are unsynchronized and the time range is inaccurate. Sample rate collection of sensor is not as exactly 50Hz and not consistent in capturing. The time ranges between the [0.018, 0.022].

Figure 2 shows the orientation of person and mobile phone orientation which is to be considered as standard position and from this we can take sensor data and pridict the results.

IV EXPERIMENTAL SETUP

a- Data Collection

MATLAB Mobile application supports acquisition of data from built in sensors provided in iPhone and Android Phones and also it provides remote access to the written script and data on the laptop/computer with the same MATLAB session and/or MathWorks Cloud. MATLAB Support Package for Android/iOS sensors generally provides the displaying, logging, querying and sending the sensor data. Thus, we acquire or record approximately 15000 seconds of the sensor data sample rate at 50Hz from 4 subjects by taking the following steps:

1. Configure MATLAB Mobile on the mobile device. Connect mobile device to Cloud.

2. Load script as collected to MathWorks Cloud, so the MATLAB Mobile can access to the script.

3. Tag collecting script for the activity before recording.

4. Run the script which initialize a mobile dev object, enable sensors, set sample rate to 50Hz and start recording timer.

5. Save the logging results to Cloud after recording.

b- Data Preprocessing

We have several challenges when we process data. First challenge is when we identified during data collection is Sensors recording repeatedly same data samples. The Second challenge is different sensors recording which are unsynchronized and the time is not accurate. Sensor sample rate is not as exactly 50Hz and not consistent in range. The time ranges inbetween [0.018, 0.022].

To solve these problems, we

Cleaned the sensor data by removing duplicate rows and sort by increasing timestamp.

We can divide each sample into ((0.02*128)=2.56) second segments, and each segment will be used as a data point.

Only select the data sample having overlap time span cross all the sensors.

To make the entire sensor data synchronized at the exact same sample rate, we interpolated and re sampled the data. We had tried few interpolation methods like: Nearest Neighbor, Cubic, Linear and Spline. Spline we assumes gives the best result, because the sample data doesn't over smooth as its in cubic interpolation or sharpen sample data as linear.

V RESULTS

Human activity sensor data contains results derived from sensor measurements recorded from smartphones as shown in figure 3 worn by subject while doing different activities (walking, lying, sitting etc).

The raw data with different positions are as shown in figure 3.and the resultant activities production is shown in figure 4 and figure 5 giving different classes of identification.

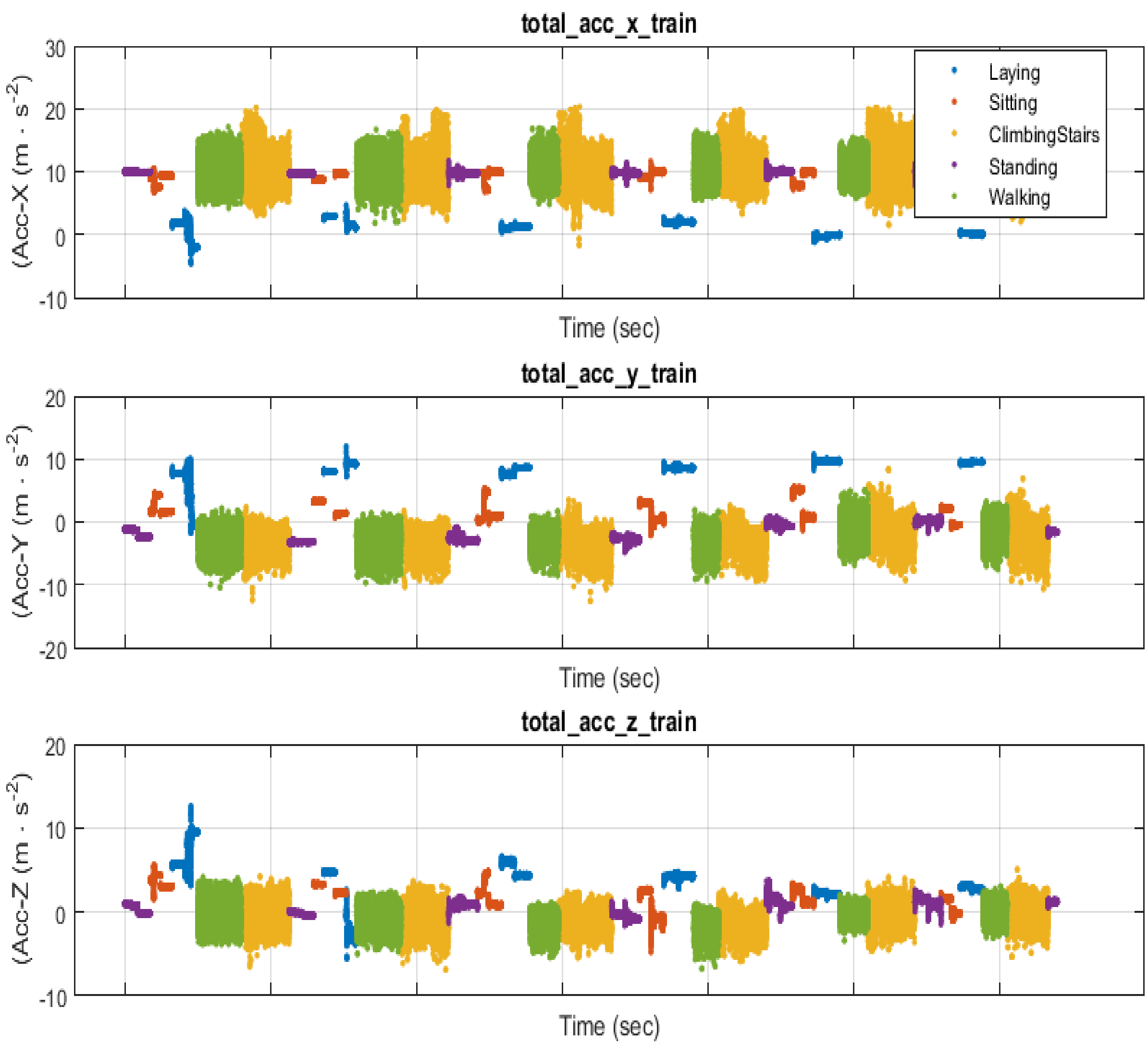

Figure 3 Raw sample data plot in MATLAB from android phone.

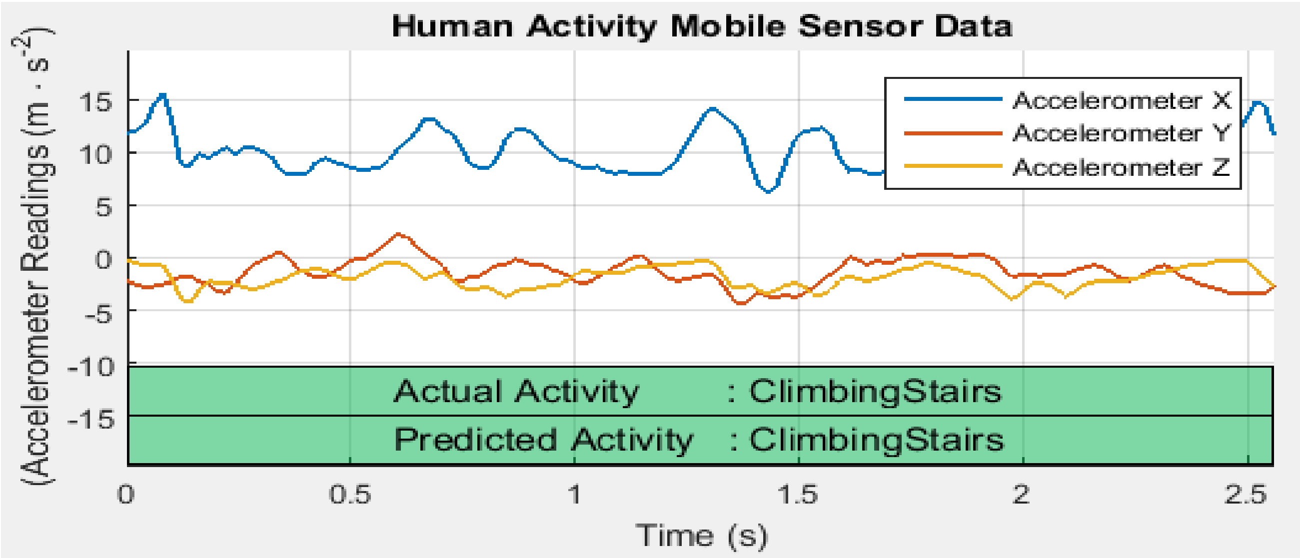

Figure 4 Accelerometer data for result prediction

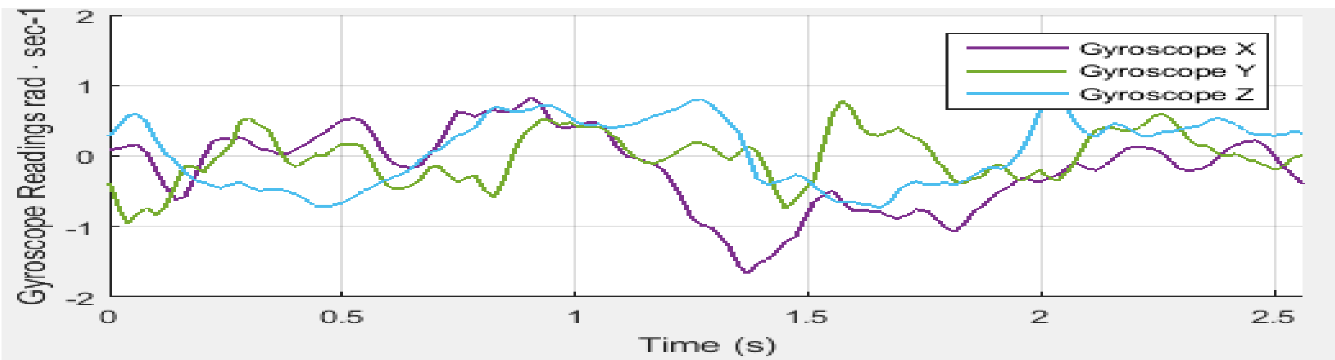

Figure 5 Gyroscope data for result prediction

VI CONCLUSION AND FUTURE WORK

The results above show that it is possible to identify subject behavior while the subjects are holding phones in their hands. However, from this project, following points required improvements as

1) Adding more data will increase the accuracy as the error margin will decrease.

2) Well classified activities would improve the results and easily identifiable. We can adopt the multiple activities tagging concept, since some activities can also be done simultaneously.

3) Collection of sensor data from different types of phones can be significantly differ. The reason for this could be the sensor calibration methodology and precision can be different for each phone. We suggest the data from the same phone.

4) There is an unique activity pattern for each user/subject. It is not possible to pridict the activities to another person or subject to another subject or person. Personalized predictive system for each user might improve the classification accuracy. We will try to solve these problems in the future.

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