Real-Time Triaxial Accelerometer-based Energy Efficient Human Activity Recognition using Smartphone

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Abstract—*Activity recognition is formulated as a classification problem. Human activity recognition (HAR) receives more attentions in recent years, due to many of its applications, such as health care, video surveillance and context-aware computing. Human activity are recognized from accelerometer data. Now a days, smartphone are used intensively so the key benefits of using the smartphone accelerometer for human mobility analysis, with or without location determination based upon GPS, WiFi or GSM is that accelerometer is energy-efficient, provides real-time contextual information and has high availability. Using measurements from an accelerometer for human mobility analysis presents its own challenges as all carry smartphones differently and the measurements are body placement dependent. Therefore a novel algorithm is proposed that neutralizes the effect of different smartphone on-body placements and orientations to allow human movements to be more accurately and energy-efficiently identified. We proposed android application AT (Activity Tracker) to collect dataset which runs on android and iOS, record accelerometer data with 40 Hz frequency like 40 samples per seconds.*

Index Terms—*Accelerometer, Classifiers, Human activity recognition, Moving Average, Smartphone*

I. INTRODUCTION

Human activities are inherently translation invariant and hierarchical. Human activity recognition (HAR), a field that has garnered a lot of attention in recent years due to its high demand in various application domains, makes use of time-series sensor data to infer activities. In particular, human activity recognition (HAR) using powerful sensors embedded in smartphones have been gaining a lot of attention in recent years because of the rapid growth of application demands in domains such as pervasive and mobile computing, surveillance-based security, context-aware computing, and ambient assistive living, and the ability to unobtrusively perform the recognition task.

Human activity recognition (HAR) receives intensive attentions in recent years, due to many practical applications, such as video surveillance[14] [15], health care [16][17] and context-aware computing[18][19]. In general, pattern recognition schemes can directly handle the samples which are represented in a vector space. In most neural networks system, such as character recognition[20] and traffic signs recognition[21], the samples can be easily converted into feature vectors after normalizing the size of the input images.

Mobility based services(MBS), in contrast to position or location based services (LBS) focus on mobility in the sense of how someone or something moves in the physical world to a pre-planned destination and covers ad hoc movement away from the current location. The emphasis is on the type of the mobility rather than on the location context, however these two may be combined in a complementary manner. Mobility can be characterized at a low level as the rate of change of location in (x, y, z) directions and velocity with respect to time. At a higher level of abstraction, mobility represents an associated human mobility type of activity such as being stationary versus walking.

Mobility can be determined using smartphone sensors that are of two main types, transceiver based and non-transceiver based. First, transceiver based location signal sensors such as GPS and those based upon Wi-Fi and GSM which exchange data between multiple transmitters and receivers, i.e., to determine the time of arrival (TOA) or received signal strength indicator (RSSI). Second, non-transceiver based sensors that directly measure physical world phenomena that relate to position and/or orientation changes such as an accelerometer, gyroscope and magnetometer. Out of these the accelerometer is the most useful non-transceiver sensor used to provide the data for activity monitoring as it gives more information about movement forces[22]. Also accelerometer has three main advantages over transceiver based location signal i.e., low energy consumption as compared to GPS and Wi-Fi[23], no delay to start the accelerometer while GPS is depend on start mode i.e., hot start or cold start and sensor readings are continuously available with accelerometer as compared to transceiver based sensors that are susceptible to transceiver obstructions and faulty transceiver links. Hence, main focus is on using the smartphone accelerometer for human mobility/activity state classification.

1.1. Challenges for Human Mobility Classification
Mobility activity classification using smartphone is challenging. There are mainly four challenges as follows [1]:

1) Accelerometer measurements of human mobility are body position dependent. It is impractical to require a fixed body placement for the accelerometer in real-world activity classification.
2) There is the issue of accelerometer noise. The two main noise sources are mechanical thermal and electrical thermal noise. A low noise measurement system is useful to achieve a high level of classification accuracy.
3) The issue of energy-efficiency due to limited resources in smartphones. Continuous location updates using transceiver location sensors such as GPS or Wi-Fi can exhaust the smartphone battery within 12 and 46 hours respectively. Depending on the Android sensing mode for non-transceiver location sensors such as the accelerometer the smartphone can be exhausted in approximately 4 hours.
4) Real-time classification is vital for a ubiquitous system, e.g., automatically switching human mobility profiles and adapting travel information services when someone travels and arrives at home or work based upon the travel mode.

1.2. Disadvantages of Existing System

1) Different combination sensors are required for human mobility state classification like GPS, Wi-Fi, accelerometer, gyroscope and magnetometer instead of only accelerometer.
2) Previously, human mobility state analysis systems are unaware of any energy-efficient smartphone based scheme capable of real-time human mobility state classification.
3) Accelerometer signals contains noise so noise filtering is required.
4) Requires Specific smartphone orientation or on-body placement of smartphone.
5) Activity can be recognized only on android platform.

II.   LITERATURE SURVEY

The following surveyed architectures can utilize the embedded smartphone sensor data to promote energy-efficient human mobility state classification, but with low levels of accuracy and noise filtering.

Energy-Efficient Human Mobility Sensing(EHMS) [1] proposed a framework form user generated accelerometer patterns and design of a probabilistic algorithm with a high accuracy. EHMS is proposed without the need for noise filtering and specific on-body placement. To achieve real-time human mobility state by performing all calculations locally within the smartphone. EHMS able to accurately classify accelerometer data from a specialized subset of human mobility states including stationary with no movement e.g., smartphone resting on a table, stationary with slight movements (sitting, lying down, and standing), in-motion (walking, jogging, cycling) and motorized movement including travel by bus, light rail train, underground train, taxi, and car.

Accelerometer augmented mobile phone localization (AAMPL)[2] which detects a user's movement using the mobile phone accelerometer and in-turn places the mobile phone in the right context i.e., specific on-body placement. The AAMPL framework acquires the approximate physical location of a mobile phone using the phones GPS on Google Maps, and augments it with a context-aware logical localization.

Energy efficient mobile sensing system (EEMSS) [3] which uses the mobile phone inbuilt sensors to recognize human mobility states and to detect state transitions. It uses a combination of sensor readings from an accelerometer, Wi-Fi, GPS, and a microphone to automatically recognize the human mobility state defined in three dimensions: motion such as running or walking, location such as staying at home or in a motorized vehicle on a freeway and background environment such as a loud or quiet location. EEMSS has the ability to detect the human mobility state and transition using low energy mobile phone accelerometer sensors.

EnTracked[4] can track mobile devices energy-efficiently and robustly. EnTracked can reduce power consumption and guarantee robustness by calculating an optimal plan, using an accelerometer to decide when to turn on and off sensors such as the GPS. This architecture uses both an accelerometer and GPS to detect a change in the human mobility state and transitions.

Reddy, M. Mun[5] detect transportation modes using a mobile phone with a built-in accelerometer and GPS. The transportation modes includes stationary, walking, running, biking, or motorized transport. They found that a combination of multiple algorithms can lead to higher transport mode detection accuracy.

Khan et al. [6] show that kernel discriminant analysis(KDA) outperforms linear discriminant analysis(LDA) at improving class separation in terms of accuracy. They also use the signal magnitude area to differentiate between static and dynamic activities using 3D accelerometer signals.

Nick et al. [7] classified transportation modes using accelerometer data. The transport modes are travel by car, train and pedestrians. The results showed a higher accuracy using a one-against-one or one-against-all support vector machine as compared to using a naive Bayes (NB) classifier.

EnLoc[8] proposed an energy-efficient localization framework called EnLoc. The framework characterizes the optimal localization accuracy for a given energy budget, and develops prediction based heuristics for real-time use. Evaluation on traces from real users demonstrates the possibility of achieving good localization accuracy for a realistic energy budget.

Ling Bao[9] developed an algorithms and evaluated to detect physical activities from data acquired using five small biaxial accelerometers worn simultaneously on different parts of the body i.e., top pocket, wrist pocket or in hand.

NishkamRavi[10] recognizes user activity from accelerometer data. Author compared the Performance of base-level classifiers and meta-level classifiers and plurality Voting is found to perform consistently well across different settings.

Moustafa Youssef et al.[11] proposed GAC: a hybrid GPS/accelerometer/compass scheme that depends mainly on using the low-energy accelerometer and compass sensors and uses the GPS infrequently for synchronization.

III. PROPOSED SYSTEM

The main objective of proposed system is to classify human mobility state without need for noise filtering and specific on-body placement or smartphone orientation using only the accelerometer on hybrid mobile platform like, Android and iOS.

The proposed system is supported to android studio 1.0 which provides tools for android development and debugging. 'Ionic'is an open source SDK used for hybrid mobile APP development like, android and iOS and 'Cordova'enables software programmer to build application for mobile devices using JavaScript and HTML6. 'Node.js'used for developing a diverse variety of server tools and applications which are open source, cross-platform, JavaScript runtime environment.

For energy-efficient human mobility sensing(EHMS) inputs are taken as accelerometer signal data from smartphone. By using such inputs human activity is classified.
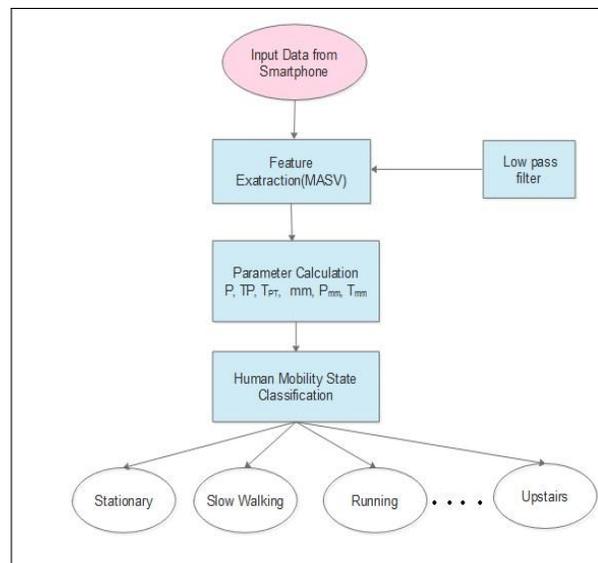
3.1 System Architecture

Fig. 1. System Architecture

The fig. 1 shows the system architecture. First the inputs are collected from the smartphone accelerometer. The input given from the accelerometer is in (x, y, z) format. Second, magnitude of the accelerometer signal vector (MASV) feature isextracted by combining (x, y, z) readings regardless of the smartphone orientation. Given the accelerometer readings (x, y, z) the MASV is calculated using the formula[1],

$$\|V\| = \sqrt{x2 + y2 + z2} \quad (1)$$

Then a low-pass filter is applied, which is a filter that passes signals with a frequency lower than a certain cutoff frequency and attenuates signals with frequencies higher than the cutoff frequency. Kalman filter is used as a low pass filter. The Kalman filter is a parametric model that can be applied to both stationary and in-motion human mobility data analysis[24].

The Kalman filter is suitable due the algorithms ability to efficiently compute accurate estimates of the correct value given noisy measurements. The accelerometer readings provide reasonably accurate data for mobility detection, and for this reason the Kalman filter algorithm is well suited for filtering the Gaussian process and to aid in real-time human mobility state prediction. Then, Peak(P), trough(T),T_{PT}, mm, $P_{mm}$and T_{mm}parameters are calculated by using MASV i.e. $\|V\|$ value. Parameters are calculated by using equations from 4-11. The Proposed system considering only mm parameter to recognize human activity. Finally, by using the calculated parameters human activity is classified as stationary, slow walking, upstairs or downstairs. In proposed system, only 4 activities are considered, in future different activities can be recognized like, traveling in bus, car, cycling, underground train etc.

3.2 Proposed Algorithm

Algorithm 2 shows the pseudo code to determine the human mobility state.

Input: A triaxial (x, y, z) Accelerometer sensor data(A_x, A_y, A_z)

Output: Recognized human activity.

Step 1: $V = A_x^2 + A_y^2 + A_z^2$

Step 2: Magnitude of accelerometer sensing vector(MASV)

$$MASV = \sqrt{V}$$

$$MASV_{sum} = \sum_{i=1}^{4} MASV$$

Step 3: Calculate Moving Average (MAV)

$$MAV = \frac{MASVsum}{i}$$

$$MAV_{sum} = \sum_{j=1}^{40} MAV$$

Step 4: Calculate Peak

$$P_i = \begin{cases} 1, & if\,(Xi + 1 > Xi)\ and\ (Xi + 2 < Xi + 1) \\ 0, & Otherwise \end{cases}$$

Step 5: Calculate Trough

$$T_i = \begin{cases} 1, & if\,(Xi + 1 < Xi)\ and\ (Xi + 2 > Xi + 1) \\ 0, & Otherwise \end{cases}$$

Step 6: Calculate mm

$$mm = Pi_{max} - Ti_{max}$$

Step 7: Human Action

if(($mm \geq d^{mod}_t$) $\wedge$ ($mm \leq d^{mod+1}_t$)) then

state = mod;

end if

$\forall mod \in \{$human mobility states e.g., walking, etc.$\}$

IV. EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Dataset

For analysis and testing purpose data is collected from http://ps.ewi.utwente.nl/Datasets.php website. In which, for data collection four Samsung Galaxy S2 smartphone are used. Using these smartphones, data is collected for six different physical activities. They are walking, running, sitting, standing, walking upstairs and downstairs. Four participants performed these six activities for a few minutes. Each of these participants was provided with four smartphones on four body positions: right jeans pocket, belt, arm, and wrist.

AT(Activity Tracker) android application is created to collect data for proposed system which runs on android and iOS and record accelerometer data with 40 Hz frequency like 40 samples per seconds. The data collection was controlled by an application which is executed on the phone. This application though a simple graphical user interface, permitted user to record the activity, start and stop the data collection, and label the activity being performed. The application permitted user to control what accelerometer sensor data was collected and how frequently it was collected.

4.2 Results

In proposed system four activities are considered: seating, walking, upstairs and downstairs because these activities because are performed regularly by many people in their daily routines. The activities also involve motions that often occur for substantial time periods, thus making them easier to recognize. Acceleration signals from smartphone record data for each of these activities in three axes i.e. x, y and z. The x-axis captures horizontal movement of the user's leg and the y-axis captures the upward and downward motion. The z-axis captures the forward and backward movement of the leg.
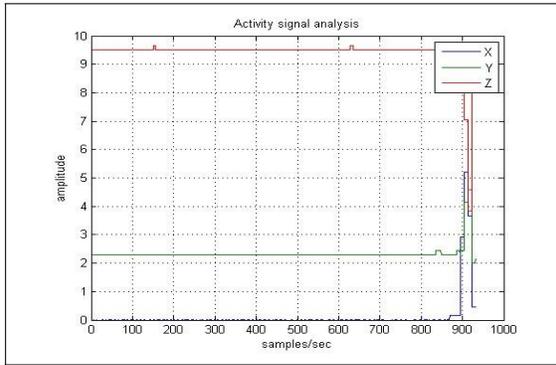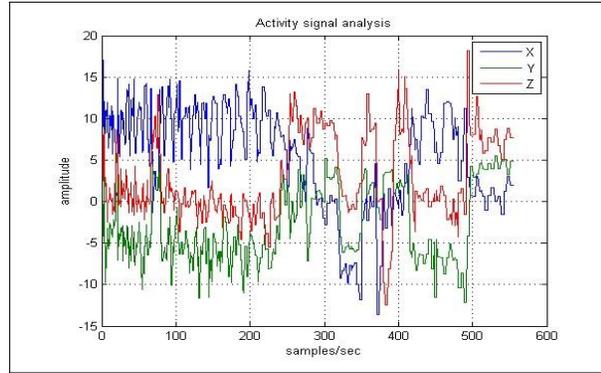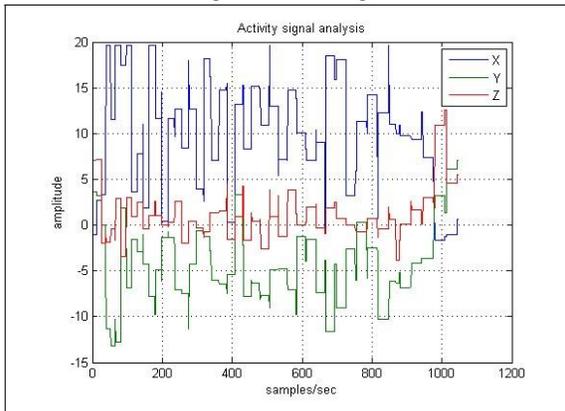
Figure 2. Seating

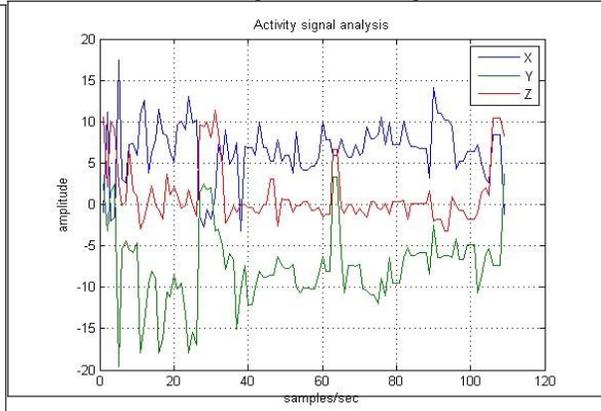Figure 3. Walking

Figure 4. Upstairs

Figure 5. Downstairs

Figure 2-5 plots the accelerometer data for a typical user, for all three axes and for each of the four activities. For different activity there are different signal patterns according to peak and trough value. The periodic patterns for walking, upstairs, and downstairs (Figure 3-5) can be described in terms of the time between peaks and by the relative magnitudes of the acceleration values is nothing but activity is detected while testing. mm is nothing but difference between maximum of peak and trough values for each activity.
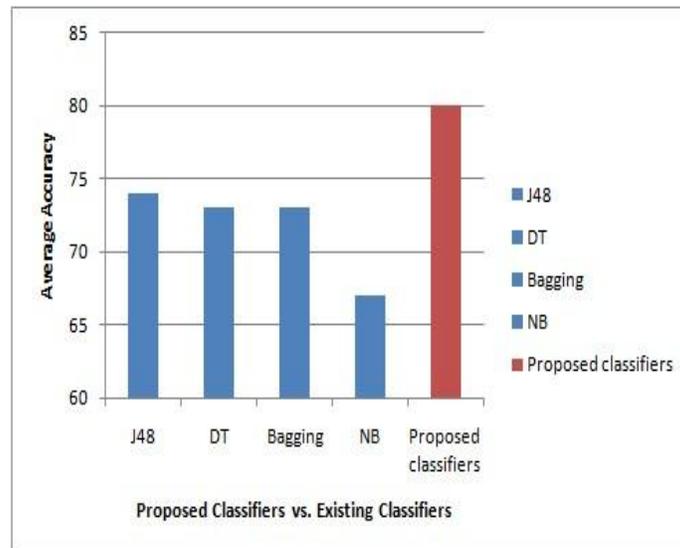

Figure 6. Average accuracy of proposed classifiers vs. existing classifiers

The following metrics used to evaluate the classification performance: accuracy, precision, recall, and F-measure. Accuracy indicates as the sum of correct classifications over the total number of input instances.

TABLE I
HUMAN ACTIVITY AND MM VALUE

File name	Actual Activity	Detected Activity	mm
Seating10	Seating	Seating/Stationary	0
Seating45	Seating	Seating/Stationary	-0.00
Walking57	Walking	Slow Walking	5.281
Downstairs89	Downstairs	Downstairs	19.374
Upstairs67	upstairs	Slow Walking	6.93

TABLE II
HUMAN ACTIVITY AND MM VALUE

Sr. No.	Parameters	AT	Google Activity Recognition
1	Battery	0 %(0 mAh)	1% (13 mAh))
2	App Size	3.80(including assets)	6.47
3	Sensor used	Accelerometer	Accelerometer, GPS, GSM, Body Sensor
4	Activity Detection Time	16 sec	187 Sec

The precision is the percentage of documents that are correctly classified as positive out of all the documents that are classified as positive, and the recall is the percentage of documents that are correctly classified as positive out of all the documents that are actually positive. The metrics of precision and recall are defined as

$$Precision = \frac{TP}{TP \times FP}(2)$$
$$Recall = \frac{TP}{TP \times FN}(3)$$

Where TP denotes the number of true positive, FP denotes the number of false positive, and FN denotes the number of false negative. To combine precision and recall as one single measure, the F-measure is one of the most popular, which is defined by

$$F - measure = \frac{2 \times Precision \times Recall}{Precision \times Recall}(4)$$

Fig. 6 shows the classification accuracy results comparison of proposed system with existing classifiers like, J48, DT, Bagging and Naive Bayes (NB). The average classification accuracy was calculated from the predictions of unknown samples. Accuracy indicates as the sum of correct classifications (the actual classes at the time of data collection and detected classes at the time of testing are same) over the total number of input instances. The Proposed classifiers is gives 7% more accuracy than J48. The proposed classifiers i.e. EHMS outperformed existing classifiers with a weighted average accuracy of 80 percent. For Proposed system Precision, Recall and F-measure is 1.

The propose system is energy efficient because it require simple and less mathematical computation and EHMS recognizes human activity without using GPS, Wi-Fi or GSM so it requires less battery power.

V. CONCLUSION AND FUTURE WORK

Human activity recognition useful for different applications such as video surveillance, health care, and context-aware computing. This system has some challenges like specific body dependent, energy efficient, noise filtering and real time classification. The proposed energy-efficient mobility sensing(EHMS) helps to fulfill these challenges. The proposed system is used for hybrid mobile platform like, Android and iOS. In future, it is also possible to add more activities like in car, bus, cycling etc., also possible to use this system for creating personal human diary which can logging all daily activities.

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