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A Survey on Human Activity Recognition using Smartphone

Vishakha V. Vyas[1]
M.E. 2nd Year, Dept. of CSE
Anuradha Engineering College
Chikhli, India

K. H. Walse[2]
Asst. Professor, Dept of Computer Science and Engineering
Anuradha Engineering College
Chikhli, India

Dr. R. V. Dharaskar[3]
Director
MPGI Group of Institutions Integrated Campus
Nanded, India

Abstract: Human activity recognition is an extensive area of a machine learning research because of its applications in healthcare, smart environments, homeland security, entertainment, etc. Study for human activity recognition observes that researchers are interested mostly in the daily activities of the human. Activity recognition using sensor data plays an essential role in many applications. Earlier, mostly wearable sensors were used to recognize various daily living activities. But, wearable sensors and environmental sensors both are bulky and costly, so switching towards smartphone sensors seems reliable and easier option to researchers and hence smartphone sensors are now-a-days widely used by researchers. In this paper, we review the studies done that implement activity recognition systems on smartphone using various sensors. We also discuss various facets of these studies.

Keywords: Activity Recognition, Sensors, Smartphone, Activity of Daily Living, Aceelerometer, Survey, Processing.

I. INTRODUCTION

Human Activity Recognition (HAR) is an extensive area of a machine learning research refers to the task of measuring the activity of a person via the use of objective technology. In simple words, when a track of sensor signals are given, the activity recognition system predicts a type of activity for the whole sequence. In recent times, human activity recognition (HAR) has been a key component of ambient assisted living (AAL) [1] applications for recognizing activities of daily living (ADL), fall detection [2] and monitoring physical activity levels for sustaining quality of life and independent living among old age people. This task is extremely challenging owing to the complexity and diversity of human activities. Selection of attributes and sensors, Sensor placement over a body, Human behavior: performing complex activities makes the recognition process more difficult, Resource constraints, Usability, Processing, *etc*. are some of the challenges to be considered.

While studying for human activity recognition, it is observed that researchers are interested mostly in the daily activities of the human known as Daily Living Activities, so that they can understand the behavior of present context and generate a Context that can recognize human activities and give a pleasant ease to human life. Walking, running, physical exercise, lying, stair-down/ up, sweeping, cooking are some examples of Daily Living Activity.

The activity can be recognize using various sensors placed on a body of an individual, then that collected raw data is pre-processed and features were extracted from that raw data and then data is classified to accurately recognize the activities. Many Researchers completed their work in this area. This paper shows some work done by researchers in this platform. In this paper, we discuss the Human Activity Recognition process in detail. After that we focus on Activity of Daily Living, human activities, sensors available and used, sampling rates used by researchers for their work. This paper also includes positioning and orientation of sensors for activity recognition along with pre-processing and classification methods used in various work.

II. HUMAN ACTIVITY RECOGNITION

Human activity recognition is the most recently introduced and nowadays widely used term. HAR is an important yet challenging research area with many applications in homeland security, smart environments, healthcare and entertainment. When a track of sensor signals are given, the activity recognition system figures out a type of activity for the whole sequence. Activity recognition from sensor data plays an essential role in various applications. Sensors such as environmental sensors, wearable sensors, in-build sensors are widely used by researchers. Activities can be recognizing using environmental sensors such as Wi-fi, GPS, camera, *etc*. Wearable sensors [3] are sensors which place on different location on the human body. The in-build sensors are sensors of smartphone. Even one can also use the combinations of these sensors for recognizing activities with more accurate results.

Earlier, mostly wearable sensors were used to recognize different daily living activities. However, there has been a shift towards smartphones in recent years, because of the availability of various sensors in these devices. Also wearable sensors and environmental sensors both are bulky and costly, so switching towards smartphone sensors seems reliable and easier option to researchers and hence smartphone sensors are now-a-days widely used by researchers. Examples of such smartphone sensors are gyroscope, linear acceleration, GPS, accelerometer, microphone, gravity sensor, magnetometer, etc. The data to recognize human movement activity from the wearable sensors, and the combination of the compass, accelerometer and GPS sensors are the most commonly used now-a-days [4]. Most of the research on human activity recognition using smartphone is performed offline in different machine learning tools. However, now-a-days, smartphones have become capable of running such recognition systems, so there has been a shift towards an online recognition process. By online activity recognition, we mean that the data acquisition, preprocessing and classification processes are done locally on the smartphone. In some cases, for online activity recognition feature extraction and classification processes are performed either on a remote server or in a cloud.

The Human Activity Recognition process consisting of four main stages these are Data Acquisition, Pre-Processing, Feature Extraction and Classification. The data is acquired using sensors and proceed towards pre-processing; this preprocessed data is further forwarded for a classification process which shows the accuracy of recognition. The human activity recognition process is shown in fig. 1, to better understand its flow:

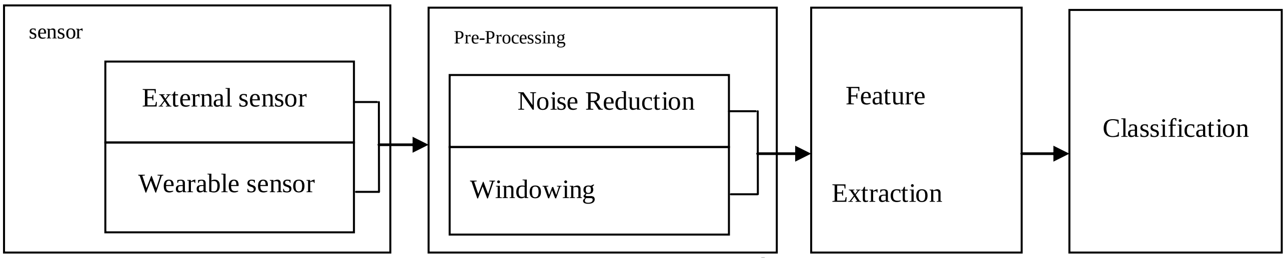

Fig. 1 Human Activity Recognition Flow

- Data Acquisition: Data collection or acquisition is the first and important stage of Human Activity Recognition Process. The data is collected by placing sensors on the body of subjects performing various daily living activities. The sensor data is collected at a specific sampling rate. This collected data or a raw data is forwarded towards the next step.

- Pre-Processing: Pre-processing is the second stage of Human Activity Recognition Process. The raw data collected from subjects using various activities and sensors are further forwarded for pre-processing. Pre-processing is done using two methods; first is noise removal and second is windowing or segmentation. Noise is an unwanted data collected during the data collection process. The noise removal technique is used to prepare a data by cleaning noise from it. Some standard classifiers do not work well on this raw sensor data. Hence it is essential to transform this raw data. This is typically performed by breaking the continuous raw sensor data into the windows of certain duration. Hence, windowing or data segmentation is performed.

- Feature Extraction: This is the third stage of Human Activity Recognition Process. The segmented data is collected as a series of instances containing three values corresponding to acceleration along the x-axis, y-axis, and z-axis. Feature extraction, converts the signals into the most significant and powerful features which are unique for the activity. The features were extracted using various feature extraction tools; one of the examples is MATLAB series software. The features can be extracted in both Time and Frequency domain.

In Jihun Hamm, et.al.[5] simple time-domain features such as zero-crossing rate, mean, autocorrelation, variance, etc and especially frequency-domain features such as spectral entropy, FFT, etc are used for activity recognition using smartphone sensors.

- Classification: Classification process is the final stage of the human activity recognition process where the trained classifiers are used to classify different activities. This stage can be perform either offline in a machine learning tool, or can perform online on the smartphone itself. The classification process involves training and testing. Training is a preparation step to obtain the model parameters. Training can either be done offline on a desktop machine or online on the smartphone itself. After training the classifiers, testing is performed to check whether the activities are correctly recognized or not using various classifiers such as Naïve Bayes, Bayes Net, IBK, J48, Random forest, SVM etc.

A. Activities of Daily Living

While studying human activity recognition, it is observed that researchers are interested mostly in the day to day life activities of the human, so that they can understand the behavior of present context and generate a Context that can recognize human activities. This day-to-day life activity of human is known as Activities of Daily Living. Walking, Running, Meditation, Stairs-up, Household work, Stairs-down, jogging, sitting, standing, lying are daily living activities. Different researchers consider a different group of activities for their research. Different activities are recognized by researchers are as shown in table 1. The Activity of Daily Living is divided into two parts such as Low-level or Simple activities and High-level or Complex activities:

- Simple Activity: Simple activity consists of a single repeated action. Simple activity is also known as low-level or logical activity. In simple activities, day to day life activities are considered such as walking, jogging, standing, sitting, biking, cycling etc.

- Complex Activity: Complex activity is the compilation of a series of multiple actions or we can say it is a combination of different simple activities. Complex activity is also known as high-level or physical activity. Some daily living complex activities are cooking, cleaning, watering plants, physical exercise, etc.

Table 1: Types of Activities Recognize

Activities	**Relevant reference**
Simple: Biking, Running, Walking, Climbing Stairs, Sitting, Lying, Standing, Driving.	[6]
Running, Slow Walking, Fast walking, Aerobic Dancing, Stair up, Stair down	[7]
Stay Still, Walking, Running,	[8]
Lying, Sitting, Standing, Walking, Running, Cycling	[9]
Walking, Sitting, Standing, Taking turns	[10]
Down-Stairs, Running, Still, Upstairs, Walking	[11]
Walking ,Rest ,Strength training	[3]
Walking, Standing, Sitting, Driving by bus, by train.	[12]
Ascend, Descend, Cycling	[13]

Stefan Dernbatch et.al.[14] employed 10 individuals to recognize activities with the help of a smart phone for simple as well as complex activities. They consider simple activities such as Biking, Lying, Stairs-up, Stairs-down, Driving, Running, Sitting, Climbing, Standing and Walking; and complex activities such as Cleaning, Medication, Cooking, Watering plants and Sweeping, after that the feature extraction carried out and using machine learning tool classifiers are applied over collected raw data and then the results are drawn. Simple activities recognized with high accuracy of about 93% and complex activities with 50% accuracy [14]. Smart phones support the accelerometer sensor which is used to record to motion of the body, as accelerometer gives the data of estimated acceleration of the body along the three axes *i.e.* x, y and z by which velocity and displacement are also measured.

Akram Bayat *et.al*.[7] took readings on 29 users for these following activities. Running, Slow walking, Dancing, Fast walking, Stairs-up and Stairs-down. Then all the phases of human activity recognition are done like data collection, feature Evaluation, Feature extraction, Classification. They applied classifiers into two sections individually and in combination. Some of them are multilayer Perception, Random Forest and logic boost, LibSVM , Simple logistic and logic boost.

1) Human Activities:

Human Activities does not include very difficult activities. Rather, it includes are specially performed activities. Daily Living Activity of human are divided into two parts i.e. simple and complex activities. Lopez-Nava, Irvin Hussein, and Angelica Munoz-Melendez [15] analyze five complex activities in both structured and daily living environments. The complex activities involved are: eating, mouth care, cooking, doing housework and grooming. The result shows that, eating and cooking are the activities with highest and lowest variability.

In Ioana Farkas and Elena Doran [16] each subject carried out eight different activities. The sequence of activities for the first experiment was: standing, sitting, lying with the face down, kneeling, lying with the face up, crawling, walking and lying on one side. The total time taken is around 9 minutes to complete. For second experiment: standing and moving the hands, arranging things on the table, sitting at the office and working at the computer, kneeling and arranging some boxes on the floor and taking things from the boxes and putting them back, walking and moving hands, crawling. This takes around 15 minutes. For third experiment: cleaning the desk, lying with the face up, sitting in the office and working at the computer, arranging things on the desk, lying with the face down, kneeling and arranging boxes on the floor, crawling, taking some things from the backpack and putting them back, standing and moving the hands and lying on one side. This will takes around 9 minute to complete. Here, walking and crawling postures are considered to be Activity states; whereas sitting, lying with the face down, lying on one side, standing, lying with the face up and kneeling is considered to be Rest states.

B. Sensors Used for Activity Recognition

These studies use different types of motion sensors in the leading role in the activity recognition process. The accelerometer was a dominant sensor in all of these studies. In most of the cases it is used individually, and in some cases, in combination with other sensors, such as gyroscope, Magnetometer and sensor of smartphone. Even one can use accelerometer sensor in combination with environmental sensors and wearable sensors. The majority of earlier research on activity recognition used wearable sensors and embedded systems [17, 18, 19, 20, 21, 22] or used external or environmental sensors such as object-attached sensors, surveillance cameras or microphones and RFID tags [23, 24, 25].

Sahak Kaghyan and Hakob Sarukhanyan [4] uses accelerometer sensor in combination with wearable sensor such as GPS for activity recognition. The data is collected using accelerometer and GPS sensor for collecting some simple activities. SQLite database is used for data storage. Kadian Davis et.al.[1] employed 31 healthy volunteers, from 14 countries, received 5744 samples from them and merges with public dataset for HAR using smartphones and collected 16043 samples together. The data were collected using Accelerometric and gyroscopic sensors. Linear acceleration is a sensor that can be used to measure acceleration without considering the gravity component and the gyroscope is a sensor that can provide orientation information as well, but with greater precision. Dean M. Karantonis et.al.[26] uses tri-axial accelerometer for ambulatory monitoring. The tri-axial accelerometer measures acceleration (a rate of change of velocity) along its three axes *i.e.* in smart phone; it is used to determine a device's orientation along its three axes (X, Y and Z-axis).

1) Sampling Rate:

The sampling rate plays a considerable role in the HAR process. The sampling rate is typically expressed in samples per second, or hertz (Hz). The choice of a selecting a sampling rate is an important decision taken by considering some factors such as the type of data features being used, desirable accuracy and the available resources for activity recognition. Higher the sampling rate, better the accuracy of classification. The rates within the range of 2 Hz to 125 Hz are suitable for human activity recognition. Different researchers use a different sampling rate for their work as shown in table 2.

Jihun Hamm et.al.[5] uses a sampling rate of 16 Hz with tri-axial accelerometer and 11,025 Hz in 16 bits PCM format with an audio sensor for collecting naturalistic data from smartphone, and present the multisensory bag-of-words framework for automatic annotation of daily activity. Whereas, in Ioana Farkas and Elena Doran [16] each subject performed eight different activities with the sampling rate of 10Hz (10 samples per second).

Table 2: Sampling Rate Used in Activity Recognition

Sampling Rate(Hz)	Relevant Study
100	[7,11,27,28,29]
80	[14]
40	[12]
30	[13]
32	[30]
10	[31,28]
5	[32]
50	[33,34,35,36]

2) Positioning of Placing Sensors in Activity Recognition:

Position of Placement of sensors on the body plays an important role in the data collection process. Wrongly placed sensors on the body may results in an inappropriate collection of samples. So it is essential to consider a better position for placing different motion sensors on the body and also the environmental condition is considerable. In the paper of Ioana Farkas and Elena Doran [16] three different experiments were conducted in which four male subjects with age ranging between 23 to 27 performed a sequence of specific postures and movements. Subjects wore the tri-axial accelerometer on their right part of the hip. Pattern recognition neural network machine learning algorithm was applied and the accuracy of activity and rest state was found 94.1% and 97.1% respectively.

Lars Schwickert et.al. [37] used inertial sensors to explain the kinematics of lie-to-stand (LTS) transfer patterns of younger and healthy older adults. Many aged people lack the capacity to stand up again after a fall. Here different features of standing up from the floor after a fall have been analyzed. Fourteen younger subjects with age between 20 and 50 years out of which 50% are male and 10 older subjects with age 60 years and above were included and they were recurrently stand up without help. Each subject perform four LTS starting from different initial lying postures on the floor such as lying on the back, lying on the front, lying on the left and right hand side with sensors worn at a trunk. In Lopez-Nava, Irvin Hussein, and Angelica Munoz-Melendez [15] wearable inertial sensor were worn by three young users on three positions of their upper limbs: in the center of the sub-scapular fossa; 10 cm up to the right elbow joint, in the lateral side of the upper arm; and 10 cm up to the right wrist joint, in the posterior side of the forearm for recognizing some complex activities.

3) Orientation of Smartphone in Activity Recognition:

Activity recognition results are sensitive to some of the sensors orientation changes. Most of the time, placing the smartphone in a specific orientation, restricts the freedom of subjects to use the smartphone. Therefore, in to have an empirical activity recognition solution, mostly smartphones are placed orientation independent. The three axes of acceleration sensor such as x, y and z axis are affected by the earth's gravity [38] depends on the orientation of the smartphone. As a consequence, the orientation of smartphone can even alter the calculated results. Bozidara Cvetkovic, Vito Janko, Mitja Lustrek [9] proposed a method for recognizing activity and estimating human energy expenditure with a Smartphone. Here, the orientation of smartphone is placed normalize.

C. Preprocessing Method Used for Activity Recognition

In pre-processing the collected raw data are processed in two ways: Firstly, noise is removed and secondly, the windowing or segmentation method is applied. Stefan Dernbach et.al.[14] experimented for simple and complex activities of daily living with one, two, four, eight, twelve and sixteen seconds time windows. Numbers of features were extracted to encode each window. The result shows that, the accuracy for simple activities remains above 90% for each of the different window lengths. Whereas for complex activities, shorter window frames gives better performance over longer one.

Kadian Davis et.al.[1] employed 31 subjects performed six activities for one minute in a semi-naturalistic environment. The features were computed on a fixed length sliding window of 2.56 sec with 50% overlap. Sliding Window (SW) is divided into two parts i.e. overlapping and non-overlapping sliding window. In this method, data segment is extracted by moving a window over the time series data to use these segments in the other activity recognition stages. The size or length of this window affects the accuracy of recognition.

D. Classification Methods Used for Activity Recognition

Classification is a process of grouping together documents or data that have similar properties or are related. In a classification stage, machine learning tools are used to classify collected data. For classification, one can apply a single classifier or combination of classifiers on dataset and can be done in offline and online mode [7]. This method includes training and testing of data. Kadian Davis et.al.[1] applied Support Vector Machine (SVM), a hybrid of Hidden Markov Models (HMM) and Support Vector Machine (SVM-HMM) and Artificial Neural Networks (ANNs) classifiers on collected dataset. The results show high classification performances for all three classifiers. Specifically, the SVM-HMM hybrid classifier gives the best classification performance.

In Stefan Dernbach et.al.[14] six different classifiers were tested such as Decision Table, Multi-layer Perceptron, Bayesian network, Best-First Tree, Naive Bayes and K-star for recognizing both simple and complex activities. The accuracy of the classifiers was tested using a ten-fold cross-validation method. The default parameters are associated with each of the classifier. The result shows that, the classification accuracies for simple activities remain consistently above 90% except for Naive Bayes. And for complex activities, the performance of all the classifiers seems uniform. The best accuracy noted for complex activities was 50% with the use of Multi-Layer Perceptron. Also, earlier work done by Gaganjot Kaur *et.al.* [39] proposed a new approach for predicting the diabetic patient from their medical records. The modified J48 classifier used to increase the accuracy of activity recognition. The experimental result shows that J48 classifier can achieve the accuracy up to 99.87%.

III. CONCLUSION

In this paper, we reviewed the work done so far on human activity recognition using smartphone. We studied smartphone sensors, a sampling rate, position and orientation of smartphone. Moreover, these studies focus on recognizing number of activities and different classification methods used for the recognition process. We discuss different challenges and facets of these studies. We also discussed the areas that need further improvements.

IV. FURTHER WORK

There remains plenty of work to do to improve the accuracy of activity recognition. To improvise accuracy, researchers should use a combination of sensors or combination of sensor types. Researchers may use combination of sensors for recording complex activities for higher accuracy. Also determining efficiency of classification with a lower sampling rate is an area of further research with the goal of reducing the power usage of smartphone. Researchers may investigate other algorithms for feature selection and classification based on machine learning.

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