Review on Recognition of Human Activity through Smartphone Built-In Sensors

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Abstract - **Recently, a lot of development has been done in the area of smartphones which elevates their processing as well as sensing abilities. A smartphone can sense everything ranging from acceleration to a magnetic field acting on it. The human activity recognition using cell phone sensors has enabled the users to keep a track of their daily activities for maintaining their good health. Initially, wearable sensors have been used for these recognitions. However, most of the recent researches have used the smartphone sensors for the same. In many of the current studies, data for recognizing activity is obtained from the inbuilt sensors of a cell phone and this data is then analyzed using the machine learning tools offline. In this paper, the studies that utilize cell phone sensors for activity recognition have been reviewed, discussed their various aspects, limitations and presented recommendations for future work.**

Keywords **: smartphones, human activity recognition, sensors, acceleration, magnetic field, wearable sensors, machine learning tools.**

I. INTRODUCTION

In the hustle and bustle of modern life, smartphones have changed the lives of many people across the world. They offer so many features in one package which made them an essential requirement of millions of people. Almost everything is possible on a smartphone which is truly remarkable. Their hardware and software qualities have facilitated many people's lives in various ways like e-mailing, Internet browsing, reading e-books and magazines, game playing etc. Since 2007, the usage rate of smartphones have accelerated resulting in change of computer industry and routines of people as well. Smartphone applications have endless purposes and usage as they fit in all our needs whether we use it for fun or for work. The smartphone technology has become so successful in few years that people cannot imagine their lives without them even for a day.

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Besides placing calls through a smartphone, they can control a television i.e. can work like a remote control, act as a mirror for the users, prevent users from being caught in the dark again as they have flashlight, scan barcode of a product, acts a mini computer, have millions of applications, wireless sharing of files, WiFi, maps and navigation, applications instead of websites, keeps the user updated throughout the day and many more.

The sensing capability of a smartphone has made them a great assistant of a person. The programmability and portability of the smartphone sensors have made them a device with limitless applications. There are various built-in sensors in a smartphone and are divided into three categories:- motion, environmental and position sensors. The motion sensors measures acceleration and rotational forces along the three axis of a smartphone and these are accelerometer, gyroscope, gravity and rotational vector sensors. The environmental sensors measures environmental conditions and parameters like ambient air, humidity, pressure, temperature and illumination and these are light sensor, photometers, barometer, thermometer, air humidity and harmful radiation sensor. The position sensors measures the changes in physical orientation and position of the smartphone and these include magnetometer and orientation sensors. Some sensors do not come under any of these three categories and they are proximity sensor, heart rate monitor, finger print sensor and so forth.

The release of smartphones with such a rich set of sensors has facilitated the human activity recognition on smartphones. By observing the user's daily activities and their levels enables the recognition of health and wellness of the users which acts as a practical application. This also helps in making a change in the behaviour of the user for a healthier and an active lifestyle. Since 1980s, the research fields based on physical activity recognition using cell phones has grabbed the attention of several artificial intelligence communities as it provides a personalized support for many applications and is connected to different fields like medicine, sociology or human-computer interaction.

The human activity recognition has innumerable applications such as medical, security, entertainment tactical scenario [1],[2]. The sensor data available from smartphones is used in activity recognition. Initially, sensors that can be worn by the users were used for physical activity recognition. However, in recent years, this recognition task has been carried out using a smartphone due to the presence of variety of sensors in them. Such sensors are accelerometer, gyroscope, magnetometer, GPS and microphone.

Most of the studies on human activity recognition have been done utilizing the smartphone sensors and the offline machine learning tools like WEKA. The aim of recognition of activities is to recognize behaviour and actions of the user through the observations of their daily activities. Initially, during the infancy period of the smartphones, its resources are limited like battery (low mAh), CPU utilization and the memory constraints. The use of the sensors results in a major drain in the battery level of the cell phones. Due to this, it was not possible for an activity recognition task to take place for an extended period resulting in the increase in the complexity of the implementation and evaluation of the recognition task using mobile phones.

While smartphones provide high computation power, communication and sensing bandwidth and storage, it's resources are still limited. The smartphone sensors consume a lot of battery and other resources. There are different requirements for different applications of a smartphone. There are also a number of studies where there is smartphone based activity recognition for real time processing. The studies show that online activity recognition is carried out on smartphones with the available resources while others develop an application where there is a record of the user's activity is kept such as mobile dairy or a fitness tracker [3]. There are many surveys which reviewed the work done so far in this area [1],[4]-[7]. These covered online activity recognition partially as the focus was mainly on offline analysis. Moreover, they were studies covering different aspects of context-aware applications of smartphones or wearable sensors. The process of online activity recognition includes data collection from mobile phone sensors, preprocessing and activity classification is done on a mobile phone locally.

In this paper, there is focus on the work in which the human activity recognition task has been carried out using the built-in sensors of a smartphone online or offline. The studies that have recognized different physical activities like sitting, standing, walking, jogging, climbing stairs are reviewed. The studies have been compared that are based on different criteria like training and classification methods, experimental setups, position and orientation independence, user independence, sensor selection, evaluation methods, sampling frequency and resource consumption analysis.

The rest of the paper is organized as follows: In Section II, we briefly discussed the related work. In Section III, the process of different online and offline activity recognition studies are discussed and compared. In Section IV, the possible improvement in the current work and future recommendations are discussed. In Section V, finally, the paper is concluded.

II. RELATED WORK

The recognition of human activity based on wearable sensors or the smartphone sensors is becoming a widely researched area. The work of [1],[6],[10] gives the outline of the related research and techniques which are applicable on them. These surveys include all the recognition tasks using the wearable sensors. In contrast, this paper surveys the human activity recognition using the smartphone based sensors. It has many applications like monitoring good health, monitoring road and traffic, the environmental conditions and human behaviour recognition [11]. The work in [4] focuses on physical activity recognition using smartphones. These studies include offline processing of the cell phone sensor data. A survey done in [12] focuses on the current smartphone sensing algorithms, applications and systems. All these studies discussed the various emerging smartphone sensing algorithms and provided an architectural framework for discussing the open issues including challenges emerging in the area of the same. In [4], a review on the activity recognition systems that use fusion of smartphone sensors that target personal health and well being applications and have focussed on classification of the existing work. In [18], there is a review of the studies that implement online activity recognition systems in real time. Also various aspects of reviewed studies are discussed (such as their experimental setups, training and classification methods, feedback in real time, position and orientation independence, sensor selection, sampling frequency and analysis of resource consumption) including their drawbacks and present various recommendations for the future work. In [19], the survey of current research approaches of activity recognition systems is done by introducing a framework of mobile centric user context recognition system. Also, lessons learned from previous works are presented as motivation for future work. Our paper focuses entirely on the studies based on physical activity recognition using smartphone built-in sensors. Moreover, our goal is to evaluate the potential of the smartphone sensors to help in activity recognition both online and offline.

III. ACTIVITY RECOGNITION APPROACH

The online physical activity recognition includes six steps: Sensing, preprocessing, segmentation, feature extraction, training and classification. The steps are described in detail as follows:

1) Sensing: Acquisition of the sensor data at a fixed sampling rate using the accelerometer of a smartphone. Here, the smartphone is attached to the subject's body when the subject is performing the activity.
2) Preprocessing: The raw sensor data can be erroneous, containing background noise, drift and the z-value of the accelerometer has the extra gravity. In this step, there is removal of such errors

from the raw sensor data using different preprocessing techniques depending on the error to be removed such as high and low pass filter or band pass filter.

3) Segmentation: A windowing scheme is applied to divide the data into small segments for feature extraction.
4) Feature extraction: In this step, features like time and frequency domain, informative features are extracted for further process. These are average, skewness, median, mode, maximum, minimum, angular velocity etc.
5) Training: The activity classifiers are required to be trained before the classification process. Training provides the model feature to be used by the classifiers. Training can be done offline on a desktop machine or online on the smartphone itself. In offline training, raw data is obtained from the sensors and then it is used to obtain model parameters and training and classification is done on desktop machine. In online training, the raw sensor data is directly processed for training and classification. The obtained observations are used for further activity recognition.
6) Classification: It is the final step in which the trained classifiers are used to recognize the different physical activities. A classifier is a supervised function used to classify the different types of activities. This step can be done offline on the machine learning tool like WEKA or online on the cell phone itself.

In this paper, we have reviewed studies that have done activity recognition online and offline. There are many different approaches for online and offline activity recognition. These different approaches are discussed in the following aspects:-

A. Offline classification methods.
B. Online classification methods.
C. Data features extracted for classification.
D. Position independent activity recognition.
E. Orientation independent activity recognition.
F. Fusion of smartphone inbuilt sensors.
G. Performance of various classifiers.
H. Sensors and platforms used in activity recognition.
I. Fixed and adaptive sampling.

A. Offline recognition methods:-

In offline activity recognition, the acceleration sensing by the sensors is done on the smartphone itself, then, these collected signals are sent to a desktop machine for further processing such as preprocessing, segmentation, feature extraction, training and classification. This method acts as a client-server approach, in which the smartphone acts as a client and the desktop machine as the server for the real time processing. The offline recognition may or may not require an internet connection during the time of sending the signals from the cellphone to the desktop machine. This method is used to carry out the computationally expensive steps at the desktop machine because of the limited resources of the cellphone.

B. Online recognition methods:-

In online activity recognition, all the recognition steps are done on the smartphone locally. Here, there is no transfer of the acceleration signals from one device to another. The collected data is directly used for the real time processing on the smartphone itself by implementing an activity recognition application on the smartphone. This method may or may not require internet access for activity recognition task depending on the type of application implemented. The Table I outlines all the studies of offline and online activity recognition methods.

Table I. Activity recognition (offline vs. online).

Recognizing activity	**Related studies**	**Total related studies**
Offline	[4],[9],[10],[16],[17],[21]-[25],[28],[30]-[33]	15
Online	[3],[5],[8],[13]-[15],[20],[26],[27],[29]	10

C. Data features extracted for classification:-

There are mainly two types of features that were extracted for the classification i.e. time and frequency domain. The time domain feature consists of average (Avg), mean, median, variance (Var), standard deviation (Sd), skewness (Sk) and root mean square (Rms). The frequency domain features consists of frequency of steps, speed of motion, angular velocity (Av), fast fourier transform (FFT) and discrete cosine transform (DCT).These extracted features are then used by the classifiers for classifying the type of activity performed by the user. In most of the studies, the time domain features were extracted more commonly than that of the frequency domain as the former is cheaper than the latter one i.e. the time domain features are more easily extracted and evaluated than that of the frequency domain features. The studies in which activities and features extracted to recognize them are displayed in Table II.

Table II. Recognized activities and extracted features.

Study	Activities	Extracted features
[8]	St,W,R,L,US,DS	Mean,Sd, median,Sk
[15]	Si,St,J,W,R,L,US, DS	Avg,Median,Sd,Sk
[16]	Si,St,L,Jo,W	Min, Max, Median,Sd
[17]	US,DS,R,J	FFT,DCT,Sd,Mean
[20]	W,DS,US	Var,Max
[22]	St,Si,US,DS,Jo	Avg,Mean,Median
[23]	St,W,R,US,DS	Av,Sd,Sk,Mean,Median
[25]	W,L,US,DS,Si,St	Av,Linear acceleraton
[29]	W,Jo,Si,L,St,US,DS	Avg,Sd,Mean,Var
[30]	W,Jo,Si,St,L,US,DS	Sd,Avg,Binned distribution
[31]	W,R,Dancing	Avg,Rms,Min,Max
[32]	J,W,R,US,DS	Var,Mean,Max,Min
[33]	W,R,Jo,Si,St,US,DS, Biking	Mean,Median,Var,Sd, Rms

Activities :- Standing-St;Walking-W;Running-R;Laying-L,Upstairs-US;Downstairs-DS,Sitting-Si;Jumping-J;Jogging-Jo.

D. Position independent activity recognition:-

As the smartphone sensors can sense any change in body position, the position independent activity recognition is a challenge to overcome. Most of the studies kept mobile phones at different body positions and different recognition rates are obtained for the same. Some studies [14],[27] have minimized the variations in these recognition rates resulting in a position independent activity recognition system. The various positions for placing the smartphone on the subject's body are front and back pockets of shirt and trousers, waist and both arms. An efficient and effective activity recognition system should recognize the human activity independent of these body positions with considerable accuracy rates and keeping an account of the resource consumption during activity recognition.

E. Orientation independent activity recognition:-

The smartphone sensors like accelerometer and gyroscope are sensitive to the orientation changes in the phone which affect the activity recognition results i.e. for a small change in orientation, there will be a large change in the sensor signal. This large change will affect the sensor data as well as the recognition rate. The activity recognition system should be orientation independent otherwise, the users will be required to place the smartphone in a particular orientation for successful activity recognition. The studies [14],[23] have presented an orientation independent recognition systems along with considerable accuracy rates. The various orientations of the smartphone can be straight, upside down and tilted positions.

The studies with orientation and/or position independence recognition by using the sensors along with their accuracy rates are displayed in Table III. From the table, it is clear that for an activity recognition system to be position and orientation independent, the two sensors i.e. accelerometer and gyroscope are enough to measure the changes in the position and orientation of the user.

Table III. Position/Orientation Independent recognition, utilized sensors and their accuracy rates.

Study	Independence	Sensors	Accuracy
[27]	Position	Ac,GPS,Audio tool,WiFi	92.43%
[23]	Orientation	Ac,Gy,Ma,Pro,Li	89.6%
[14]	Position & Orientation	Ac,Gy	85.2%

Sensors:- Accelerometer-Ac,Gyroscope-Gy,Magnetometer-Ma,Proximity-Pro,Light-Li

F. Fusion of smartphone inbuilt sensors:-

The studies utilize the smartphone motion sensors for activity recognition systems. Among all the sensors, the accelerometer is the dominating one which is used individually in most of the studies and in few cases, it is used with combination of the other sensors. In some studies, there is fusion of sensors at low level whereas in other studies, the fusion is done at high level depending on the objective. The results show that the accelerometer is enough to sense any acceleration in the subject's body. If the accelerometer is only used for activity recognition, it will give considerable recognition rates and consume less resources of the smartphone as well. Table IV displays the studies with the fusion of smartphone motion sensors.

Table IV. Fusion of sensors for activity recognition.

Study	Fusion of sensors
[8],[9],[13],[16],[17],[21],[22], [26],[29]-[32]	Ac
[14],[24],[25]	Ac , Gy
[15],[20],[33]	Ac , Gy, Ma
[28]	Ma
[27]	Ac,GPS,WiFi,Audio tool
[23]	Ac,Gy,Ma,Pro,Li

G. Performance of various classifiers:-

In activity recognition process, the classification step is the most important. In the activity recognition task, the classification is considered as an instance of supervised learning in which the classifiers learn from the training set of correctly identified observations obtained during the training phase. There are many classifiers that are used for activity recognition process. Some studies [15] used the combination of two or more classifiers resulting in a hierarchical or multilayer classification. While the other studies have compared many classifiers on the basis of accuracy [29],[31],[32]. Table V shows the studies implementing various classifiers along with their accuracy.

Table V. Performance of various classifiers.

Implemented Classifier	Accuracy	Related Studies
Support Vector Machine (SVM)	96%	[8],[29],[16],[24],[26],[31]
Sequential Minimal Optimization (SMO)	89.6%	[23]
k-Star	99%	[29],[16]
Naïve Bayes	90%	[29],[23],[16],[25]
Bayes Net	96%	[26],[29],[16]
Logic Boost, Simple Logistics	91.5%	[30],[31]
K Nearest Neighbour (KNN)	90%	[29],[21],[22],[13],[16],[25],[26]
Decision Tree (J48, Random Forest)	96%	[20],[29],[23],[16],[31],[25],[26],[30]
Minimal Distance Optimization (MDO)	90%	[32]
Variance Contribution Ranking (VCR)	92.87%	[32]
Hierarchical Classifier System	95.03%	[15]
Vector Space Model (VSM)	85.2%	[14]
Neural Networks	99%	[17],[16],[31],[30],[26]
Quadratic Discriminant Analysis (QDA)	94%	[13]
K means Clustering	96%	[25]
Gaussian Mixture Model	92.43%	[27]

H. Sensor and platforms used in activity recognition:-

The recognition task has been carried out on different mobile phone platforms having different built-in motion sensors. Among these platforms, Android is the dominant one. While some studies have done the activity recognition on other platforms like Symbian and iOS. All the various android phones have android operating system, the iPhones have iOS platform and the Nokia 98 has the Symbian platform. The Table VI gives the description of the mobile phone platforms and their sensors used in activity recognition. The table shows that for activity recognition the accelerometer is the most essential and effective sensor as compared to the other ones.

Table VI. Mobile phone platforms and their sensors used in activity recognition.

Platforms	Sensors	Related studies
Android	Ac,Gy,Ma,Pro,Li, GPS	[8],[9],[13]-[17],[20]-[23],[25]-[27],[30]-[33]
iOS	Ac	[9],[29]
Symbian	Ac	[13]

I. Fixed and adaptive sampling:-

For the higher accuracy of the activity recognition the sampling rate at which the acceleration data is collected plays an important role. The sampling rate or sampling frequency is the samples per second i.e. average number of samples obtained in one second. Some studies have done the activity recognition at a particular (fixed) sampling rate while some studies have used a range of sampling rate (adaptive) to find which of them is most appropriate for their recognition system. A higher sampling rate gives more accurate results but in turn consumes battery and other smartphone resources a lot. Table VII gives description about the sampling rates of the activity recognition studies. The table shows that sampling rates 100 Hz, 50 Hz and 25 Hz are most commonly used for activity recognition.

Table VII. Sampling rates for activity recognition.

Study	Sampling Rate (Hz)
[9],[20],[31]	100
[29]	80
[28]	60
[8],[21],[24]-[26],[33]	50
[13]	40
[14],[15],[23]	25
[17],[30]	20
[16]	10

IV. DISCUSSION

In the previous section, the various aspects of online and offline activity recognition were presented. As all these studies use different classifiers, training methods, experimental setups and evaluation methods as shown in tables I-VII, it is very difficult to compare them in terms of performance and resource (battery, memory and CPU) consumption.

Most of the studies have implemented only one classifier while some studies [15] used the combination of two or more classifiers creating a hierarchical or multilayer classification. Some studies have compared many classifiers on the basis of accuracy [29],[31],[32] in a standard experimental setup. This helps in deciding which classifier is most appropriate for activity recognition as required by the researchers in the future.

It is found that many studies have not done the resource consumption analysis like memory, battery and CPU usage during activity recognition. For an activity recognition using the smartphone sensors, the resource consumption analysis of the smartphone is a very important factor to evaluate the feasibility of the recognition system whether online or offline. In the studies carried out online, there is only one classifier used and there is no comparison of it with the other classifiers while in the offline activity recognition studies, different classifiers were compared in different simulation steps based on their recognizing accuracy only. To report a classifier or data feature set as most appropriate for online or offline activity recognition system, the trade-off between the accuracy rates and consumption of resources should be taken into account.

In some studies, as shown in Table 4, there is fusion of smartphone sensors but each sensor's contribution in the recognition and consumption of the resource is not evaluated. Also in these studies, this blind fusion is not actually that helpful. It should be clear that how much the fusion of a sensor increases the recognition rate and what amount of resource consumption making it useful to decide when to fuse sensors for activity recognition.

The selection of suitable features to be extracted for activity recognition is very important during the design decision. It should be evaluated that an addition of a new feature how much affects the system's performance and at what resource consumption cost. As shown in Table 2, many features were extracted without evaluating each of their contributions to the recognition.

Most of the studies were done offline as shown in Table 1, making the recognition process static. The lack of personalization in these systems prevents them to be adaptable to different users. Old people walk slowly as compared to the younger people. The same behaviour can be seen while using stairs, running, dancing, biking, jumping etc. This differentiated behaviour of users affects the recognition rates of the systems which are statically trained and tested on same type of users. These systems become user dependent. This user dependability can be removed by training the system online making them more personalized.

We found that many studies have placed the smartphones in a fixed positions and orientations and only few studies as shown in Table 3, have made their system position and/or orientation independent. The fixed position and orientation of the phone limits the freedom of the user to use the phone as and when required. This makes the system less attractive and less practical for the users.

Although, there is significant work done in this area, but it is still in its infancy which provides a room for the future work. Hence, the following recommendations for future work have been presented helping in making design decision for such systems in the future:-

A. There should be feedback in real time to make the recognition systems more user interactive and effective. Here, the mobile phone can be used as the feedback interface or device. The mobile phones can send a message to the user about how much calories they have burnt or how many steps they have taken. The feedback can also include the type of activity which is most appropriate for the user at that point of time.
B. The activity recognition should be carried out in an energy-efficient way. For this, adaptive sampling and duty cycling methods can be used. The recognition system should not consume all of the smartphone's battery.
C. For activity recognition systems to be feasible, there should be no blind fusion of the sensors and extraction of useless data features which do not contribute to the activity recognition in any way. The selection of sensors and features should be simple and easy as possible. The activity recognition system should use the minimum number of sensors as possible for activity recognition.
D. The resource consumption analysis should be considered during the activity recognition. There should be a good balance between the consumption of the resources and the recognition rates during the recognition process. Most of the smartphone battery is utilised by the sensors used in activity recognition.
E. The activity recognition system should be adaptable to every type of users with differentiated behaviour. The system should not depend on the type of users on which it was trained and tested. The recognition system should be so accurate that it can recognize activities of any person with considerable recognition rates.
F. The recognition system should be position and orientation independent making the users free to use their mobile phones in their own different ways. For activity recognition to be position and orientation independent, the smartphone must have an accelerometer and a gyroscope.
G. The activity recognition systems should be more personalized so that the users can train the systems according to them with an ease. This can be done by making the whole activity recognition process more user interactive and online on the smartphone itself.

V. CONCLUSION

In this paper, the studies that worked on human activity recognition using the smartphone sensors are surveyed. There is review of the studies of online or offline activity recognition which have done classification locally on mobile phone itself or at some desktop machine respectively. 33 such studies have been reviewed that have recognized multiple activities performed by a set of subjects for a particular duration to time. Here, all these studies have been compared on the basis of various aspects and discussed their limitations. Some of the aspects are:- setup for their experiment, classifiers used, training process, sensors and mobile phone platforms used, position and orientation independence, sampling rates, extracted features and accuracy rates. Moreover, some of the improvements that can be done in the current work are discussed. Lastly, various recommendations for future work have been presented for conducting future studies on the recognition of human activities using smartphone sensors.

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