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# Automatic Human Activity Recognition Using the Human Computer Interaction System

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**Abstract-**

Smartphone based activity recognition has recently received remarkable attention in various applications of mobile health such as safety monitoring, fitness tracking, and disease prediction. To achieve more accurate and simplified medical monitoring, a patient only needs to carry an ordinary smartphones that contains common motion sensors. This paper proposes smartphone sensors to detect physical activities. The sensors which are currently being used are an accelerometer, gyroscope, barometer, etc. Recently, smartphones, equipped with a rich set of sensors, are explored as alternative platforms for human activity recognition. Automatic recognition of physical activities commonly referred to as human activity recognition (HAR) has emerged as a key research area in human-computer interaction (HCI) and mobile and ubiquitous computing. The goal of activity recognition and Geofencing is to provide information on a user's behavior that allows computing systems to proactively assist users with their tasks.

## 1 INTRODUCTION

The main aim of this paper is to provide facility to monitor the elderly people using location and geo fencing through Android application. Making an application context-aware is one of the best ways to offer useful services to your users. While there are still multiple ways to do this including geofences, activity recognition, and other location services. Google has recently released the Awareness API, which allows developers to create apps that intelligently react to the user's real world situation. The Awareness API combines the Places API, Locations API, Activity Recognition, and Nearby API, as well as adding support for headphone state and weather detection.

Mobile phones or smart phones are rapidly becoming the central computer and communication device in people's lives. Smart phones, equipped with a rich set of sensors, are explored as an alternative platform for human activity recognition in the ubiquitous computing domain. Today's Smartphone not only serves as the key computing and communication mobile device of choice, but it also comes with a rich set of embedded sensors, such as an accelerometer, digital compass, gyroscope, GPS, microphone, and camera. Collectively, these sensors are enabling new applications across a wide variety of domains, such as healthcare, social networks, safety, environmental monitoring, and transportation, and give rise to a new area of research called mobile phone sensing. Human activity recognition systems using different sensing modalities, such as cameras or wearable inertial sensors, have been an active field of research. Besides the inclusion of sensors, such as accelerometer, compass, gyroscope, proximity, light, GPS, microphone, camera, the ubiquity, and unobtrusiveness of the phones and the availability of different wireless interfaces, such as Wi-Fi, 3G and Bluetooth, make them an attractive platform for human activity recognition. The current research in activity monitoring and reasoning has mainly targeted elderly people, or sportsmen and patients with chronic conditions.

The percentage of elderly people in today's societies keeps on growing. As a consequence, the problem of supporting older adults in loss of cognitive autonomy who wish to continue living independently in their home as opposed to being forced to live in a hospital. Smart environments have been developed in order to provide support to the elderly people or people with risk factors who wish to continue living independently in their homes, as opposed to live in an institutional care. In order to be a smart environment, the house should be able to detect what the occupant is doing in terms of one's daily activities. It should also be able to detect possible emergency situations. Furthermore, once such a system is completed and fully operational, it should be able to detect anomalies or deviations in the occupant's routine, which could indicate a decline in his abilities. In order to obtain accurate results, as much information as possible must be retrieved from the environment, enabling the system to locate and track the supervised person in each moment, to detect the position of the limbs and the objects the person interacts or has the intention to interact with. Sometimes, Thus, the supervised person must be located in a smart environment, equipped with devices such as sensors, multiple view cameras or speakers.

Although smart phone devices are powerful tools, they are still passive communication enablers rather than active assistive devices from theuser's point of view. The next step is to introduce intelligence into these platforms to allow them to proactively assist users in their everyday activities. One method of accomplishing this is by integrating situational awareness and context recognition into these devices. Smart phones represent an attractive platform for activity recognition, providing built-in sensors and powerful processing units. They are capable of detecting complex everyday activities of the user (i.e. Standing, walking, biking) or the device (i.e. Calling), and they are able to exchange information with other devices and systems using a large variety of data communication channels.

Mobile phone sensing is still in its infancy. There is little or no consensus on the sensing architecture for the phone. Common methods for collecting and sharing data need to be developed. Mobile phones cannot be overloaded with continuous sensing commitments that undermine the performance of the phone (e.g., by depleting battery power). It is not clear what architectural components should run on the phone. Individual mobile phones collect raw sensor data from sensors embedded in the phone. Information is extracted from the sensor data by applying machine learning and data mining techniques. These operations occur either directly on the phone. Where these components run could be governed by various architectural considerations, such as privacy, providing user real-time feedback, reducing communication cost between the phone and cloud, available computing resources, and sensor fusion requirements.

## 2 LITERATURE REVIEW

Although the research on activity recognition is beneficial from the mobile sensors' unobtrusiveness, flexibility, and many other advances, it also faces challenges that have brought with them. In this section, review the major, common challenges for activity recognition using mobile sensors, and the corresponding solutions to alleviate them in the current literature.

### 2.1 SUBJECT SENSITIVITY

The accuracy of activity recognition, especially those based on the accelerometer data, is heavily affected by the subjects participated in training and testing stages. This is mainly due to the fact that different people have different motion patterns. Even for the same subject, she/he may have different patterns at different time. The comparative experiments show that training and testing on the same subject achieves the highest accuracy. Training and testing on the same group of multiple subjects has the second highest accuracy. The accuracy decreases when the test data are collected from same subject, but on different days. Thelowest accuracy is in the setting where the training data is collected from one subject on one day and testing is conducted on another subject on a different day. A recognition model trained on such a diversified dataset works more reliably when it is tested on data from new individuals. Deng et al. proposed a cross-person activity recognition model to eliminate the effect of user sensitivity. The model training stage consists of two parts: The initial model is trained off-line and the adaptive model is updated online. Based on this new training data set, the algorithm will update the recognition model to alleviate the subject sensitivity.

### 2.2 LOCATION SENSITIVITY

Due to the property of accelerometer both in wearable sensors and smart phones, its raw reading heavily depends on the sensors' orientation and positions on the subject's body. For example, when a user is walking while holding a phone in his/her hand, the moving data reading is quite different from the data reading if the phone is in his/her pocket. One solution is to address the orientation sensitivity by using another sensor: magnetometer. The magnetic field sensor provides the magnetic vector along three axes of the device's coordinate system in the orthogonal directions. Hence, it could be utilized to derive the devices' azimuth angle. Then the accelerometer reading can be converted to the earth coordinating axes reading. Park et al. presented a device pose classification method based on the regularized kernel algorithm. It provides a way of how to estimate the smart phone's pose before doing any motion data analysis.

### 2.3 ACTIVITY COMPLEXITY

The complexity of user activities also brings an additional challenge to the recognition model. For example, the motion during the transition period between two activities is difficult for the underlying classification algorithm to recognize. People performing multiple tasksat the same time might also confuse the classifier which is trained under one activity-per-segment assumption. In addition, culture and individual difference might result in the variation in the way that people perform tasks, which in turn brings the difficulty in applying the activity recognition models globally. HMM is a natural solution to address the activity complexity by smoothing the error during the activity transition period.

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**2.4 ENERGY AND RESOURCE CONSTRAINS**

Activity recognition applications require continuous sensing as well as online updating of the classification model, both of which are energy consuming. For the online is updating, it might also require significant computing resources (e.g., mobile phone memories). Based on the observation that the required sampling frequency differs for different activities, A3R adaptively makes the choices on both sampling frequency and classification features. In this way, it reduces both energy andcomputing resource cost. It also removes the time-consuming frequency-domain feature calculation.

**2.5 DAILY LIFE MONITORING**

Applications in daily life monitoring usually aim to provide a convenient reference for the activity logging, or assisting with exercise and healthy lifestyles. These devices are equipped with the embedded sensors such as accelerometer, gyroscope, GPS; and they track people's steps taken, stairs climbed, calorie burned, hours slept, distance travelled, quality of sleep, etc. An online service is provided for users to review data tracking and visualization in reports. Compared with smart phone sensors, these devices are more sophisticated, since their sensors are designed specifically for the activity detection and monitor. The drawback is that they are much more expensive. Smartphone applications with activity recognition techniques have been shown up in recent years as an alternative solution. These applications usually have similar roles as above specialized devices.They track users' motion logs such as jogging route, steps taken, and sleeping time. By mining the logged data, they may offer the user a summary on his/her lifestyle and report the sleeping quality.

**2.6 PERSONAL BIOMETRIC SIGNATURE**

A subject's motion pattern is usually exclusive and unique. For example, when people raise their hands, it is almost impossible for two people's hands to share the exact same motion patterns. Even in a successful imitation, the differences still exist because of the difference in the motion related bones and muscles on human bodies. Sensors such as accelerometerscan capture those differences. The activity recognition techniques provide a possible solution for human biometric signature with patterns in motion/gestures. In these applications, pattern recognition methods are used to obtain the unique motion patterns, which are in turn saved in the database. It is convenient and feasible because of the pervasive usage of mobile devices. On the other side, the motion signature could also be used in a malicious way. For example, people could use the learned patterns to crack users' behaviors, such as smart phone keyboard typing, or other spying activities.

**2.7 ELDERLY AND YOUTH CARE**

There is a growing need in elderly care (both physically and mentally), partially because of the retirement of the baby Boomer generation. A major goal of the current research in human activity monitoring is to develop new technologies and applications for elderly care. Those applications could help prevent harm, e.g., to detect older people's dangerous situations. Architecture on the smart phone is developed with the purpose of users' fall detection. Activity recognition and monitor sensors could help elders in a proactive way, such as life routine reminder (e.g., taking medicine), living activity monitoring for a remote robotic assists. The youth care is another field that benefits from the activity recognition research. Applications include monitoring infants' sleeping status and predicting their demands for food or other stuff. Activity recognition techniques are also used in children's (ASD) detection.

**3 PROPOSED SYSTEM**

Smartphone based methods have been gradually recommended as a substitute for wearable sensor-based methods on because the latter may deploy redundant and complicated sensor devices on human bodies. Modern smartphones usually have various built-in motion sensors such as accelerometers, gyroscopes and magnetometers, which makes it much easier to capture users' activity data and recognize their activities in real time using an ordinary smartphone.

Network location providers have been recommended as a substitute for GPS location provider. This provider determines location based on availability of cell tower and Wi-Fi access points. Results are retrieved by means of a network lookup. Requires either of the permissions:

-android.permission.ACCESS_COARSE_LOCATION

-android.permission.ACCESS_FINE_LOCATION

By using this scheme, a patient only need to carry an ordinary smartphone which contains motion sensors for recognize the activities. Network location provider is less accurate than GPS but it works both indoors and outdoors. It works faster and uses less battery power.

Design is the first step in the development phase for any techniques and principles of defining a device, a process or system is sufficient detail to permit its physical realization.

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The design activities are the main importance in this phase, because in this activity, decisions ultimately affecting the success of software implementation and its ease of maintenance are made. These decisions have the final bearing upon reliability and maintainability of the system.

A system architecture or systems architecture is the conceptual model that defines the structure, behavior, and more views of a system .An architecture description is a formal description and representation of a system, organized in a way that supports reasoning about the structures and behaviors of the system.

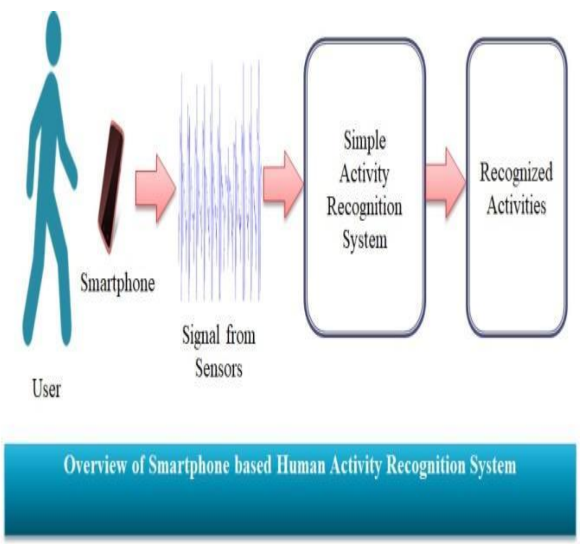



Fig. 1: HAR System

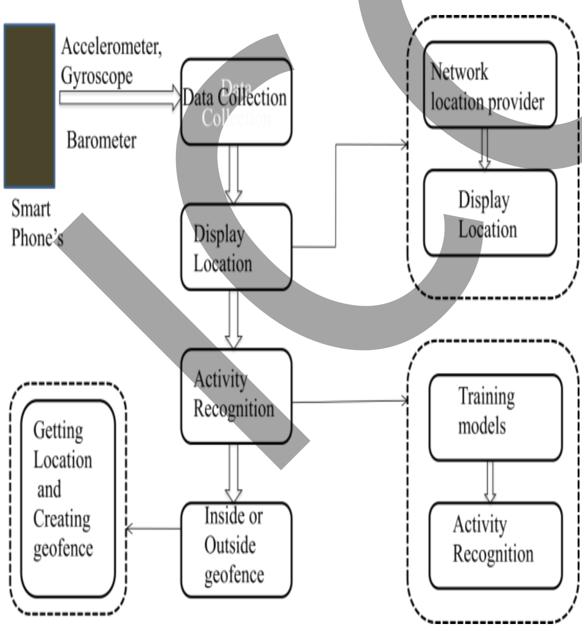


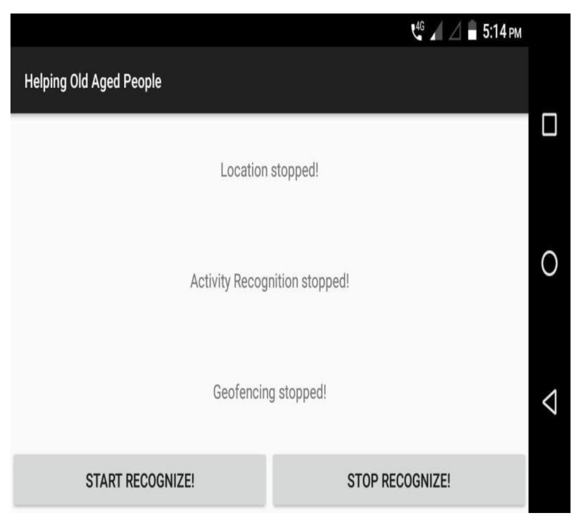

Fig. 2 : System Architecture

The purpose of system implementation can be summarized as follows: making the new system available to a prepaid set of users (the deployment), and positioning on-going support and maintenance of the system within the performing organization (the transition). At a finer level of detail deploying the system consist of executing all steps necessary to educate consumers on the use of new system, placing the newly developed system into production, confirming that all data required at the start of operation is available and accurate, and validating that business functions that interact with the system are functioning properly. Transitioning the system support responsibilities involves changing from a system development to a system support and maintenance mode of operation, with ownership of the new system to the performing organization.

A key difference between system implementation and all other phases of the lifecycle is that all activities up to this point have been performed in safe, protected, and secure environment, where the issues that arise have little or no impact on day to day business operations. Once the system goes live, however, this is no longer the case. Any miscues at this point will almost certainly translate into direct operational and/or financial impact on the performing organization. It is through the careful planning, execution and management of system implementation activities that minimize the likelihood of these occurrences, and determine appropriate contingency plans in the event of a problem.

**LOCATION START/STOP:**

Here, the location object represents a geographic location which consists of latitude, longitude, time stamp and other information such as bearing, altitude and velocity. Android location APIs make it easy to build location –aware




applications. It becomes possible with the help of Google Play

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Services. This location service is used to get the current location, periodic location updates, look up addresses etc.

**ACTIVITY START/STOP:**

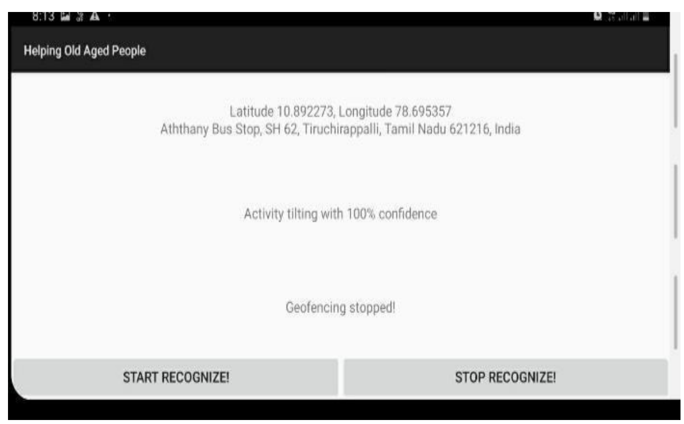
- In this module , the Activity Recognition Client that wakes up your device at a regular interval and then collects the data from the device's sensor and after that this collected data will be used to determine the Activities with the help of some Machine Learning algorithm
- The Activity Recognition Client returns a list of activities that a user might be doing with some confidence percentage.
- This confidence percentage tells you about the surety of the activity.
- For example, the activity which is having more than 75% confidence, then there is a probability that the user might be doing that activity
- **STILL:** When the mobile device will be still i.e. the user is either sitting at some place or the mobile device is having no motion, then the **Activity Recognition Client** will detect the **STILL** activity.
- **ON_FOOT:** When the mobile device is moving at a normal speed i.e. the user carrying the mobile device is either walking or running then the **Activity Recognition Client** will detect the **ON_FOOT** activity.
- **WALKING:** This is a sub-activity of the **ON_FOOT** activity which is detected by the Activity Recognition Client when the user carrying the mobile device is walking.
- **RUNNING:** This is also a sub-activity of **ON_FOOT** activity which is detected by the Activity Recognition Client when the user carrying the mobile device is running.
- **IN_VEHICLE:** This activity detected when the mobile device is in the bus or car or some other kind of vehicle or the user holding the mobile device is present in the vehicle.
- **ON_BICYCLE:** When the device is on the bicycle or the user carrying the mobile is on a bicycle then this activity will be detected.
- **TILTING:** When the mobile device is being lifted and is having some angle with the flat surface then the Activity Recognition Client will detect this activity.
- **UNKNOWN:** The Activity Recognition Client will show this result when the device is unable to detect any activity on the mobile device.

**GEOFENCING:**

Here geofences were added to receive the information when we enter, exit or dwell in a Geofence. The geofences are defined by a GeofenceModel, and you should use the requestId as a identifier.

To capture the Geofence transitions without the app running, you can hook up a BroadcastReceiver to the intent action stored in the Geofencing GooglePlayServicesProvider.BROADCAST_INTENT_ACTION constant. The intent will come with the geofence, the location and the type of transition within the bundle.

The library has support for direct geocoding (aka getting a Location object based on a String) and reverse geocoding (getting the Street name based on a Location object). There are pretty basic calls in the API for both operations separately.




**STOPPING**

We should invoke the stop method whenever the calling activity/fragment or whatever is going to be destroyed, for cleanup purposes.

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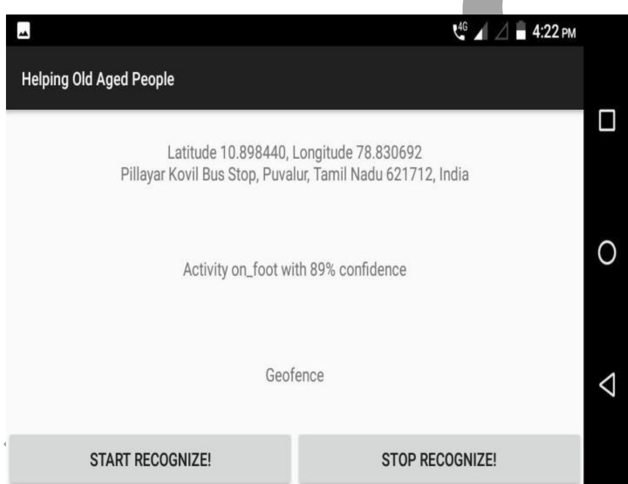
## 4 CONCLUSION

It is developed and implemented as per the requirements, it is found to be bug free as per the testing standards that is implemented. Any specification-untraced errors will be concentrated in the coming versions, which are planned for development in near future. The system developed was successful in depicting the aim. As the system developed was successful in depicting the operation of accelerometer sensor and Network Service Provide, it can automatically integrated with some minor changes in real time application where it communicates with hardware components (mobiles).

## REFERENCES


[1] Akram Bayat , Mara Pomplun , Duc A. Tran "A Study on Human Activity Recognition Using Accelerometer Data from Smartphone's", 2014 ieee international conference on. IEEE,2014

[2] Gheorghe Sebestyen , Ionut Stoica , Anc , a Hangan ,"Human Activity Recognition and Monitoring for Elderly People",2016 ieee



international conference on. IEEE, 2016

[3]A. Jalal, S. Kamal, and D. Kim, "A depth Video-based human detection and activity recognition using multi-features and embedded hidden Markov models for health care monitoring systems," 2017 ieee international conference on. IEEE,2017

[4]A. Jalal ,M. Mahmood, and M. A. Sidduqi , "Robust spatial-temporal features for human interaction recognition via artificial neural network",2018 ieee international conference on. IEEE,2018

[5]A. Jalal , M. Maria A. Hasan , "Multi-features descriptors for human activity tracking and recognition in Indoor-outdoor environments",2019 ieee international conference on. IEEE,2019

[6]Mouazma Batool ,Ahmad Jalal ,Kibum Kim ,"Sensors Technologies for Human Activity Analysis Based on SVM Optimized by PSO Algorithm",2019 ieee international conference on. IEEE,2019

[7]M. Malekzadeh, R. G. Clegg, A. Cavallaro and H. Haddadi, "Mobile sensor data Anonymization", 2017 ieee international conference on. IEEE,2017

[8]MARIO MUNOZ- ORGANERO , (Members ,IEEE) , "Outlier Detection in Wearable Sensor Data for Human Activity Recognition (HAR) Based on DRNNs" 2019, ieee international conference on. IEEE, 2019

[9]F. J. Ordonez and D. Roggen, "Deep convolution and LSTM recurrent neural networks for multimodal wearable activity recognition,"2016 ieee international conference on. IEEE,2016

[10]M. Panwar , S. R. Dyuthi , K. C. Prakash , D. Biswas , A. Acharyya, K. Maharatna , A. Gautam, G. R. Naik, "Cnn based approach for activity recognition using a wrist-worn accelerometer",2017 ieee international conference on. IEEE,2017