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CONTENT

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HIGH LEVEL ACTIVITY RECOGNITION USING ANDROID SMART PHONE SENSORS - REVIEW

Aleksandra Stojanova, Mirjana Kocaleva, Marija Luledjieva and Saso Koceski

Abstract. Mobile phones, especially Android based ones, are an important part of human everyday lives. Today smartphones have incorporated sensors that can be used for recognition of human activities. In recent years, Human Activity Recognition (HAR) through smart phones became a well-known field of research. Activity recognition is used in applications in healthcare, smart environment, country security, and entertainment. In this paper we are giving a survey of applications and implemented systems for high level activity recognition using android smart phone sensors.

1. Introduction

Mobile phones have and are still getting an increasingly more important role and are becoming a part of the life of the world population. Mobile phones have drastically changed communication methods since their introduction on the market. Besides ordinary voice and text communication, even initial mobile phone models, have offered additional functions, serving as watches, alarming devices, etc. As the performances of the mobile phones were increasing, the possibilities for their application were spreading. So, nowadays they are used for a myriad of different applications ranging from education, gaming and entertainment to healthcare. They also have great impact on businesses and are widely used for various business applications. As a consequence, nowadays, people use mobile phones to access the Internet more than personal computers and the market demand for mobile phones is permanently increasing.

The number of mobile phone users is extremely growing. So, following market analysis, in 2015, there were 4.15 billion users. This number grew to 4.3 billion in 2016, 4.43 billion users in 2017, and 4.57 billion in 2018. 4.68 billion users are predicted for 2019 and 4.78 billion for 2020 [1]. In 2018, around 1.56 billion smartphones were sold worldwide. There are 14 million jobs directly related to the mobile phones industry [2]. The mobile phone market has also become very popular because big international software companies produce operating systems. Although many operating systems have been introduced in the past two decades, nowadays mobile phones with Android OS are the most popular ones amongst users. In Q1 of 2018, around 68% of all mobile phones sold to end users were phones with the Android operating system. This is mainly due to the fact that the operating system and its ecosystem are open source, which makes Android OS very popular also in the research community.

The increased penetration of mobile phones in both academia and business community is a result not only of the advancements in design and the decrease in prices but also due to the fact that they are becoming “smart” thanks to the development of Artificial Intelligence (AI). The growing popularity of the Artificial Intelligence (AI) and its application in various fields [3], starting from tourism [4], through medicine [5-7], biology [8], gaming [9], robotics [10-13], and also in education [14], is mainly due to the apparatus, i.e. the models and techniques used to mimic human reasoning, learn and improve during time.

Big smart phone manufacturers such as Apple, Samsung and Huawei have introduced smartphones that have powerful AI chips capable of performing up to 5 trillion operations per second using significantly less power for these tasks. AI smart phone market is expected to grow to 3.8 billion by 2012. The true potential of AI-enabled smart phones is in understanding user behaviors, making predictions and support decisions. This is possible by smart interpretation and fusion of the signals generated by the on-device sensors. Smartphones and tablets have a plethora of integrated hardware sensors including accelerometers, light sensors, touch and pressure sensors, cameras and barometers, GPS, and communication chips such as Wi-Fi, Bluetooth, 3G/4G/5G and more.

AI nowadays is mainly employed to create an accurate and rich user profile and to improve the interaction with the user. The fields that gain increased interest in AI application for mobile users profiling and recognition of high-level user activities are the sectors of Healthcare and well-being and Ambient Assisted Living (AAL).

This paper aims at reviewing the latest research in high level activity recognition using android smart phone sensors. All the manuscripts are subject to a review process before publication.

1. Data collection from mobile phone sensors

According to the National standard GB7665-87, sensors are defined as: "Devices which can feel the information to be measured, and convert the information into usable signal in accordance with some rules. Sensors are usually composed of sensitive components and conversion devices." A sensor is a detection device based on certain rules, which can measure the information and transform the signal into another form to meet the requirements of information transmission, processing, storing, displaying, recording and controlling. It is the primary step for automatic detection and control [15].

Sensors can be classified in several ways: by conversion method (based on their basic physical or chemical effect), by usage, by type of output signal, by material, or by manufacturing techniques.

By working theory, they can be classified into:

- physical sensors and
- chemical sensors.

By usage, they can be classified into:

- positioning sensors,
- liquid level sensors,
- power sensors,
- speed sensors,
- thermal sensors,
- acceleration sensors,
- radiation sensors,
- vibration sensors,
- humidity sensors,
- magnetic sensors,
- gas sensors,
- vacuum sensors and biosensors.

By output signal, they can be classified into:

- analogue sensors,
- digital sensors,
- switch sensors.

By the manufacturing process they can be classified into:

- integrated sensors,
- thin film sensors,
- thick film sensors,
- ceramic sensors.

As nowadays mobile phones are most important for people’s communication, mobile phone sensors become an interesting research area [16]. Almost all mobile devices have a different type of built-in sensors used for monitoring movements, for healthcare (heartbeat, blood pressure), temperature changes, GPS, camera, microphone etc. Sensors can be defined as devices which can measure the information, and can change the information into a functional signal in line with some rules. Sensors are a set of sensitive elements and devices for transformation. [17].

According to the official Android web site [18], there are two types of sensors:

- hardware-based and
- software-based.

Hardware-based sensors are peripheral devices. They obtain their data directly by computing particular environmental characteristics.

Software-based sensors are not peripheral devices, they are more virtual, and they obtain the data from hardware-based sensors.

According to [19], the most used mobile sensors are given in Table 1.

Table 1. *A set of mobile phone sensors.* [19]

Sensor	Description
Accelerometer	Measures the acceleration force that is applied to the device, including the force of gravity
Ambient temperature sensor	Measures the ambient room temperature
Gravity sensor	Measures the force of the gravity that is applied to the device, in three axes (x; y; z)
Gyroscope	Measures the device's rotation in three axes (x; y; z)
Light sensor	Measures the ambient light level (illumination)
Linear acceleration	Measures the acceleration force that is applied to the device, the force of gravity is excluded
Magnetometer	Measures the ambient geomagnetic field in three axes (x; y; z)
Barometer	Measures the ambient air pressure
Proximity sensor	Measures the proximity of an object relative to the view screen of a device.
Humidity sensor	Measures the humidity of the ambient environment
Gyroscope	Measures the orientation of a device in pitch, roll and yaw.

The categorization of mobile sensors as in Table 2 is given in [20]. In Table 2 any sensor is marked as Embedded (Em) or External (Ex), Proprioceptive (PC) or Exteroceptive (EC) and Active (A) or Passive (P).

Embedded sensors are integral parts of devices and can be accessed using pre-defined interfaces, whereas external sensors are not integral parts of devices, rather they exist in the environment and devices are required to find them and communicate with them using standard wireless protocols and communication channels (Bluetooth).

Proprioceptive sensors determine/measure physical properties related to the internal conditions of devices/systems, whereas exteroceptive sensors obtain information from the environment outside the device.

Passive sensors measure the energy generated in the environment outside the device. Passive sensors do not need power supply or battery and gain their power from the electromagnetic waves radiated by the requesting devices, e.g. RFID. On the other hand, active sensors emit energy into the environment and then measure the reaction generated, e.g. LiDAR.

Table 2. *Classification of sensors frequently used in mobile phones sensing systems. [20]*

General Classification (Category)	Sensor Type	Embedded (Em) or External (Ex)	Proprioceptive (PC) or Exteroceptive (EC)	Active (A) or Passive (P).
Tactile Sensors	Proximity Sensor	Em/Ex	EC	P/A
Acceleration Sensors	Accelerometer Sensor Gyroscope Sensor	Em Em	PC PC	P P
Thermal Sensors	Temperature Sensors	Ex	EC	P/A
Image Sensors	CMOS Camera Sensors	Em	EC	P/A
Light Sensors	Ambient Light Sensor Back-Illuminated Sensor	Em/Ex Em	EC EC	A A
Water Sensors	Moisture Sensor Humidity Sensor	Em Ex	EC EC	P P
Location Sensors	Digital Compass Sensor GPS sensor	Em Em	EC EC	P A
Height Sensors	Altimeter Sensor Barometer Sensor	--- Em	EC EC	P P
Medical Sensors	Heart Rate Monitor Sensor Biosensor	--- ---	EC EC	P P
Acoustic Sensors	Microphone Sensor	Em	EC	P
Radio Sensors	RFID Bluetooth	--- Em	EC EC	A A

Individual mobile phones collect raw sensor data from the sensors embedded in the phone. Then information is extracted from the sensor data by applying machine learning and data mining techniques. These operations occur either directly on the phone, in the mobile cloud, or with some partitioning between the phone and the cloud.

A variety of data mining and statistical tools can be used to obtain information from the data collected by mobile phones and calculate summary statistics. Most of the smartphones on the market are open and programmable by third-party developers, and they offer software development kits (SDKs), APIs, and software tools. It is easy to cross-compile code and leverage existing software such as established machine learning libraries (e.g., Weka) [21].

Chunmei et al. in their paper [17] present some applications of sensors in mobile phones such as image and fingerprint sensor, business card recognition, facial recognition, optical sensor and accelerometer sensor.

The paper [22] presents an experiment made on Google Nexus 4 phone. The sensors chosen for examination are accelerometer, gyroscope, magnetometer and GPS. The sensors' accuracy, precision, maximum sampling frequency, sampling period jitter, and energy consumption are measured. The results of the test show that the accelerometer sensor and the gyroscope sensor are very stable with small deviations between the measured value and the real value. The compass has a bigger deviation. However, the compass is almost not working in the fastest sampling rate. GPS sensor is able to determine its location with a deviation which is no more than 10 meters. Lane et al. [21] believe that sensor-equipped mobile phones will restructure many sectors of our economy, including business, healthcare, social networks, environmental monitoring, and transportation. Mobile phone sensing systems, according to this article, will provide both micro- and macroscopic views of cities, communities, and individuals, and help improve how society functions as a whole. In this paper they survey the existing mobile phone sensing algorithms, applications, and systems. Also, other sensor smartphone applications for acquisition and processing the obtained data are given in [23-26].

2. High level activity recognition

Activity recognition (AR) means recognizing the actions of one or more entities using a series of observations on entities' actions and environmental conditions [27-28]. Activity recognition is an important and challenging research area with application in healthcare, smart environment, security and entertainment [29]. Human Activity Recognition (HAR) is a research field that promises a lot due to its contributions in human-centered areas of studying with the aim of improving people's quality of life. These areas of studying are: ambient intelligence, pervasive computing, assistive technologies, health care and smart homes. [30-31]. Activity recognition systems in these areas provide useful information about people's actions and their behavior [32]. For example, patients with diabetes, obesity, or heart disease are often required to follow a well defined exercise routine as part of their treatment. Therefore, recognizing activities such as walking, running, or cycling becomes quite useful for providing feedback about the patient's behavior to the caregiver [33].

Because we live in an era of intelligent environments, the automated detection of Activity has become a point of high interest. Intelligent environments generally exploit information gathered from users and their environments in order to produce an appropriate action [34]. In recent years, the activity recognition process is made by using only sensors from smart phones. 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 a variety of sensors in them [35]. Nowadays, the simplest and most common usage of activity recognition on phones is represented by fitness applications, especially running tracking. Recently, given the whole uncertainty surrounding the security and privacy of user data, steps have been taken towards using activity recognition for user authentication. [36]. When a track of sensor signals is given, the activity recognition system figures out a type of activity for the whole sequence [37].

The input of HAR models is the reading of the raw sensor data and the output is the prediction of the user's motion activities [38]. The Human Activity Recognition process consists of four main stages:

- Data Acquisition,
- Pre-Processing,
- Feature Extraction, and
- Classification.

The data is acquired using sensors and proceeded towards pre-processing; this preprocessed data is further forwarded for a classification process which shows the accuracy of recognition. Therefore, most of related works focus on analyzing the performance of classification algorithms such as: Decision Trees, Naïve Bayes, Nearest Neighbor algorithms, Support Vector Machines, Hidden Markov Chain, Multi-Layer Perceptron and Random Forrest [37]. The activity recognition process flow is shown in Figure 1.

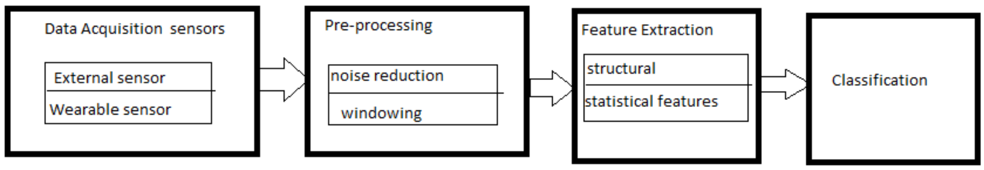

Figure 1. *Activity recognition flow*

The activity of humans, especially in their everyday lives, can be divided in two broad categories:

- Low-level or Simple activities
- High-level or Complex activities.

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

A high-level activity, also known as physical activity or complex activity, is the compilation of a series of multiple actions, or, in other words, it is combination of different simple low-level activities. Some daily living complex activities are cooking, cleaning, watering plants, physical exercise, etc.

Nowadays, the researchers' main interest is detecting high-level or complex human activities.

According to the survey given in [33], human activities are divided into seven groups such as Ambulation, Transportation, Phone usage, Daily activities, Exercise/Fitness, Military and Upper body. In [38] instead of seven, human activities are divided into eight groups. There phone usage was combined into Daily activities category, upper body and military categories are removed, and Household activities, Kitchen activities, Self-care activities, and Transitional activities were added. We are considering this categorization and we made our survey in 5 broader categories of activities: Daily Activities, Transportation, Ambulation, Kitchen and Home Activities, Exercise/fitness or outdoor activities. The categorization of activities is given in Table 3.

Table 3. *Type of activities*

Category	Activities	References
Daily Activities	Ironing, Eating, Drinking, Using a phone, Watching TV, Using a computer, Reading Book/magazine, Listening to music/radio, Taking part in conversations, Getting up from bed, Sleeping, Note-pc, Carrying a box, Getting up. Applying make-up, Brushing hair, Shaving, Toileting, Flushing the toilet, Getting dressed, Brushing teeth, Washing hands, Washing face, Washing clothes, Drying hair, Taking medication	[32][38][36] [39-40] [47] [49]
Transportation	Riding a bus, Cycling, Driving	[28][40-43] [49]
Ambulation	Running, Sitting, Standing, Lying, Ascending stairs, Descending stairs, Riding an escalator, Riding in an elevator, Falling, Stopping, Casual movement, Lying down and getting up, Sitting down and getting up, Walking up and down stairs	[28][36] [40][42] [45] [47]
Kitchen and Home Activities	Filling a kettle, Adding a tea-bag, Adding sugar, Adding milk, Making coffee, Making tea, Making an oatmeal, Frying eggs, Making a drink, Cooking, Checking tools and utensils in the kitchen, Making a sandwich, Cooking pasta, Cooking rice, Feeding fish. Wiping tables, Vacuuming, Taking out the trash, Cleaning a dining table, Washing dishes, Sweeping with a broom, Cleaning up	[28] [32][40] [48-49]
Exercise/fitness or outdoor activities	Walking in treadmill, Running in treadmill, Aerobic dancing, Jumping, Jogging, Playing basketball, Playing football, Rowing, Walking, and Running.	[40-42] [45] [47]

In [39] a smartphone-based living-activity monitoring system for elderly people is presented. There smartphone of an elderly person continuously recognizes indoor-outdoor activities by using only built-in sensors and uploads the activity log to a web server. The activities they perform that the proposed system recognizes are: Brushing teeth, Drying hair, Shaving, Toileting, Washing dishes, Vacuuming, Talking, Walking, Running, and Going outside. The usage of the motion detection or falling is very important in elderly people's lives. For example, if a fall of a person is detected and after that there is no movement or standing up, an emergency phone can be called automatically, or some phone from the healthcare.

Similar activities and more outdoor activities such as car driving, cycling, shopping, and walking are recognized and distinguished in [40]. There, feed-forward neural network (FF-NN) and recurrent neural network (RNN) are used as a classifier for HAR task.

Other projects also include five indoor and outdoor activities like: walking, limping, jogging, walking upstairs and walking downstairs. Upstairs and downstairs walking are difficult to discriminate. Activity data were trained and tested using 4 passive learning methods: quadratic classifier, k-nearest neighbor algorithm, support vector machine and artificial neural networks. The best classification rate achieved was 84.4%, achieved by SVM (Support Vector Machine) with features selected by SFS (Sequential Forward Selection) [41]. Six activities are considered in [42], where the implemented mobile system on smartphone-cloud platform is presented. For recognizing six human activities (Jogging, Walking, Standing, Climbing Stairs Biking and Sitting), four machine learning methods are used: Decision Tree (J48), Multi-layer Perception (MLP), Random Forest (RF) and Instance-based k-Nearest Neighbor (IBK)). Also, six activities recognition (Walking, Running, Sitting, Standing, Upstairs, Downstairs) using Android platform are considered in [36].

[35] also presents a way of detecting twelve daily physical human activities such as sitting, laying, standing, attaching to table, walking, jogging, running, jumping, pushups, going down the stairs, going up the stairs, and cycling with acceleration and gyroscope sensors data resulted from using android smart mobile phones. In order to obtain precise results, these models were divided into two categories: six of them under support vector machine (SVM) and the other six under the k-nearest neighbor (k-NN).

In [43], complex activities can be decomposed into a number of simpler ones. For this reason, a two-stage continuous hidden Markov model (CHMM) is proposed. This approach is used for activity recognition using accelerometer and gyroscope sensory data from a smartphone. The proposed method consists of first-level CHMMs for coarse classification, which separates stationary and moving activities, and second-level CHMMs for fine classification.

Implementing a new, accurate and robust HAR system for smartphones is given in [28]. This system can recognize a large variety of activities using a single device and provide high recognition accuracy while allowing its users the freedom to keep the device in different pockets or to hold it in hand. In this system, three smartphone sensors (the triaxial accelerometer, the pressure sensor, and the microphone) are used to recognize 15 different activities with the help of a nonlinear discriminatory approach (KDA) and a nonlinear classifier (SVMs).

In [44] a new method is used for recognizing daily human activities based on a Deep Neural Network (DNN), using multimodal signals such as environmental sound and subject acceleration. There it is shown that acceleration features are effective for recognizing daily activities. The deep learning approach is also used in [45], [29] (where 6 activities are recognized - walking, walking upstairs, walking downstairs, sitting, standing and lying) and [46], where 12 different activities can be distinguished.

The TAHAR architecture for the recognition of physical activities is presented in [32]. This architecture combines inertial sensors for body motion capture, a machine learning algorithm for activity prediction and a filter of consecutive predictions for output refinement. With this kind of architecture, 33 different activities can be recognized with good precision.

3. Conclusion

Smartphones as a part of people's everyday lives are becoming more and more sophisticated. This has opened the doors for many interesting data mining applications of smartphones. Human activity recognition presents the building block of this kind of applications. For the purpose of using smartphones for high level activity recognition, different systems are made that use data from sensors as an input, and predict users' activities. This paper presents a comprehensive survey of recently made approaches and implementation of systems for high level activity recognition with android smartphone sensors. First, we introduce the basic concepts of activity recognition (smartphone sensors, types of activities). Then, we review the techniques and algorithms used for recognition of activities. High level activity recognition, based on Android smartphone sensors, leads to many possible future research directions. 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 a combination of sensor types. Also, they may use a combination of sensors for recording complex activities for higher accuracy. Other algorithms for feature selection and classification based on machine learning can be investigated to improve recognition as well.

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