A Review and Taxonomy of Activity Recognition on Mobile Phones

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3 authors, including:

Ozlem Durmaz Incel

Galatasaray Üniversitesi

Cem Ersoy

Bogazici University

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A Review and Taxonomy of Activity Recognition on Mobile Phones

Ozlem Durmaz Incel · Mustafa Kose · Cem Ersoy

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Abstract The release of smart phones equipped with a rich set of sensors has enabled human activity recognition on mobile platforms. Monitoring the daily activities and their levels helps in recognizing the health and wellness of the users as an ideal application. Ubiquity of the mobile phones, unobtrusiveness, ease of use, communication channels and playfulness make mobile phones a perfect platform also for inducing behavior change for a healthier and more active lifesytle. In this paper, we provide a review on the activity recognition systems that use integrated sensors in the mobile phones with a special focus on the systems that target personal health and wellbeing applications. Initially, we provide background information about the activity recognition process, such as the sensors used, activities targeted, the steps of activity recognition using machine learning algorithms before listing the challenges of activity recognition on mobile phones. Next, we focus on the classification of existing work on the topic together with a detailed taxonomy. Finally, we investigate the directions for future research.

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Ozlem Durmaz Incel
Department of Computer Engineering
Bogazici University, Bebek 34342 Istanbul/Turkey
E-mail: ozlem.durmaz@boun.edu.tr

Mustafa Kose
Department of Computer Engineering
Bogazici University, Bebek 34342 Istanbul/Turkey
E-mail: mustafa.kose@boun.edu.tr

Cem Ersoy
Department of Computer Engineering
Bogazici University, Bebek 34342 Istanbul/Turkey
E-mail: ersoy@boun.edu.tr

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1 Introduction

Research on human activity recognition that involves the use of different sensing technologies provides a great potential for personal health systems by monitoring the daily activities, hence wellness and health status of their users. Especially the release of smart phones equipped with a rich set of sensors together with their ubiquity is a key enabler for the adoption of personal activity recognition systems on mobile platforms by the masses.

To briefly go over the history of such systems, in the early studies, vision sensing using cameras has been the focus of early research in the activity recognition domain [61]. More recently, inertial sensing, using movement-based sensors that can be attached to the user's body has been investigated [11]. Today, mobile phones can act as an activity recognition platform. In the early versions, GSM signals were used to infer the basic transportation modes of the users, for instance to understand whether a user is in a vehicle or stationary. Also, in the early versions activity recognition systems that use on-body wearable sensors as peripherals that can be connected to a mobile phone were utilized [15]. Currently, smart phones that are integrated with a rich set of sensors, such as accelerometer, gyroscope, GPS, microphone, camera, proximity and light sensors, WiFi, Bluetooth interfaces, provide an ideal platform for personal activity recognition systems.

Not only the inclusion of new sensors and their ubiquity but also unobtrusiveness, zero installation cost, ease of usability make activity recognition on mobile phones more attractive. Compared to using on-body sensors, mobile phones do not disturb or limit the activities of the users, do not require to carry or attach external devices on the body and do not require the installation or calibration of the sensors. Mobile phone-based activity recognition also eliminates the installation of cameras, the limitation of working indoors and violation of privacy compared to vision-based sensing systems. Besides these facts, a survey showed that a mobile phone is considered as essential when leaving home besides a key and a wallet and this reveals that mobile phones naturally fit people's lives without disturbing them [7].

In fact, despite these advantages, activity recognition on mobile phones also faces challenges such as the battery limitation of the phones, limitations in processing and storage compared to more powerful stations, human behavior, such as different use of phones by different people, that need to be investigated for the realization and further adoption of these systems.

From the perspective of personal health and well being systems, the fundamental contribution of activity recognition on smart phones can be monitoring the physical health and wellbeing of the users by screening the physical activities, such as the transportation modes, locomotion and sports activities, through inertial sensors, mainly through accelerometers. For instance, by monitoring the activity levels, daily energy expenditure and physical wellness can easily be calculated. Alternatively, the mobile phone can be used as a fitness coach, for instance for rehabilitation of patients with diseases, such as Parkinson. The patient can be given a program with a set of activities, their duration and sequence and the phone can detect what the user is currently doing and/or if he is performing the activities correctly with a correct sequence. Moreover, by following the daily activities, the routines and behavior of the users can easily be learnt by the activity recognition systems and in case of a drift from these routines, the users can be warned about these changes. Especially considering the elderly, these drifts may be indicators for certain diseases, such as Alzheimer or dementia, and informing caregivers may be crucial. Together with accelerometers, GPS can also provide very useful information for monitoring the activities including also the location information. For instance, again considering elderly, following their daily trajectories and identifying drifts in these trajectories can reveal important findings about their cognitive wellbeing. Other sensors such as the microphone, providing ambient sound information, camera, Bluetooth interface, providing information on social interactions, WiFi and cellular radios, providing location information, proximity and light sensors, providing ambient information, can enrich the activity recognition for personal health and wellbeing by providing additional context information.

Besides using the sensing functionality, smart phones are also ideal interaction platforms for persuasive applications to motivate healthier behavior because of their ubiquitous presence, communication channels, playfulness together with their perceived role as a personal and trusted technology [4,60] as investigated in [25,27]. Virtual companions [8], games [62], social networks [79] can be used as the means to interact with the users in mobile applications in order to persuade them for changing their sedentary or unhealthy habits and even lifestyle for healthier behavior [20].

In this paper, we review the activity recognition systems that use integrated sensors in the mobile phones with a particular focus on the systems that target personal health and wellbeing applications. Our aim is to provide an extensive survey on the topic and to bring the researchers not working in the field quickly up to date about the state of the art, opportunities, challenges and future topics on activity recognition using mobile phones. To the best of our knowledge, although there exist surveys on activity recognition using wearable sensors [9,46,63], a survey on mobile phone sensing [45] and on the classification algorithms for activity recognition on smart phones [3], there is no extensive survey on activity recognition on mobile phones including a taxonomy of existing work especially focusing on the issues of health and wellbeing.

Our contributions are to present a detailed survey on the topic, provide a taxonomy of existing work and investigate the open issues in this domain. We start with a background information on what types of sensors used, what kind of activities are targeted, application domains of activity recognition on mobile phones and how activity recognition systems are or can be used in the field of personal health and well-being. We focus on the activity recognition process and explain the details of used techniques. We particularly explain the steps of the activity recognition using supervised machine learning algorithms. Then, we elaborate on the performance evaluation of the used techniques explaining the performance metrics utilized and experimentation of proposals. The next topic we focus on is the challenges of activity recognition on mobile phones and the possible solutions proposed in the literature to overcome these challenges. In the second part, we investigate the proposed solutions on activity recognition on mobile phones. We classify the solutions according to the sensors used and offline versus online classification methods together with presenting a taxonomy of existing work from different aspects such as the activities targeted, type of classification techniques used, performance testing. In the last part, we provide a list of open issues and directions for future research.

The remainder of the paper is organized as follows: in Section 2, we provide the background information on activity recognition using mobile phone sensors, such as the types of sensors used, activities detected and application domains. In Section 3, we focus on the process of activity recognition particularly on the steps of machine learning techniques and performance metrics. Section 4 is about the research challenges in the field of activity recognition on mobile phones whereas Section 5 includes the taxonomy of existing work. In Section 6, we discuss the open issues and comment on possible future research directions. Finally in Section 7, conclusions are drawn.

2 Background

In this section, first we provide the background information on the sensors available on mobile phones that are or can be used for activity recognition purposes and next focus on the activities that can be inferred using these sensors.

2.1 Sensors

Although today's mobile phones are powerful devices with their computational capabilities and richer functionality with the integrated sensors, they still act as communication devices from the user's point of view [45]. The next step should be to utilize the potential of using the mobile phones as active assistant devices in supporting users' daily activities and the main enablers to realize this step are the integrated sensors on mobile phones and the computational capabilities of today's mobile phones.

Figure 1 shows an example set of sensors available on current smartphones: the conventional sensors such as the cellular radio, WiFi radio, Bluetooth radio, microphone, cameras and GPS, and newer sensors such as the accelerometer, gyroscope, compass, light and proximity sensors. Probably, in the near future there will be more and more sensors integrated on the mobile phones to support a diverse set of applications. For instance, temperature, humidity and

Fig. 1 Example sensors available on smart phones

gas sensors can easily be integrated to infer more information about the user's context. Sensors providing health information, such as blood pressure or heart beat rate, may not be useful when integrated on the phone itself but they are already used as peripherals that can be connected to a mobile phone. In fact, there are applications that can measure the blood oxygen saturation and heart rate using the cameras available on the smart phones [1]. It is clear that, as the technology, particularly in micro-electromechanical systems (MEMS), improves and the research on mobile phone sensing matures, there will be new applications requiring more and more sensors either embedded on the phones or used as peripherals.

As a fundamental sensor on a mobile phone, the *radio for cellular communication* enabled the first ubiquitous applications for coarse-grained context recognition. By using the connection information between the radio and the cell-tower, it is possible to locate the user, such as the user is at home. Although this does not give a fine-grained activity information, it provides location-based information to give a clue about what the user may be doing. Besides such a location-based service, signal fluctuation information between the radio and the cell tower has been used to predict the user's mode of transportation, such as walking, driving a vehicle or stationary [73].

Besides the radio for cellular communication, *Bluetooth* and *WiFi radios* can also be used as sensors for context and activity recognition. For instance, in the "Reality-Mining Project [22]", interactions between or co-location of Bluetooth radios on the mobile phones were used to infer social interactions between phone users. Moreover, fluctuations in WiFi signals can be used to locate the user, such as in the classroom or attending a meeting, and again to predict the user's mode of transportation [58].

Microphone can also be used for activity recognition purposes by collecting audio during a user's daily activities, such as being in a conversation, being in a noisy environment [53]. Similarly, the *camera* can also provide a rich set of context information. One example application, EyePhone [56] uses the camera to detect activities such as tracking the user's eye movements to start the applications on the phone. *GPS* is another powerful sensor for tracking the location of the mobile phone and the speed of movements similar to the cellular and WiFi radios but with a more fine-grained information of location.

3-Axis Accelerometer is the most powerful sensor for activity recognition purposes on mobile phones. Although it was integrated in the mobile phones with the objective of enhancing the user experience by changing the orientation of the display according to the orientation of the phone held by the user, it can be used for activity recognition by inferring the user's movements, such as walking, standing, running, sitting and even falling [78]. In fact, activity recognition using inertial sensors has been an active field of research [9] and recently using accelerometers on the mobile phones is receiving a lot of attention from the research community. In Section 5, we summarize the example studies using accelerometers for activity recognition. Similarly, *gyroscope* and *compass* can be used for activity recognition by measuring the orientation of the mobile phone and enhancing the results inferred with an accelerometer.

Proximity and *light* sensors are also the set of sensors embedded in phones for enhancing the user experience. For instance, when the proximity sensor detects that the user holds the phone close to her face, the keys are disabled or similarly the light sensor adjusts the brightness of the screen. For activity recognition purposes, they can be used together with other sensors to infer information. For instance, the light sensor may provide information about the environment of the user, such as being in a dark environment.

It is also possible to use a combination of sensors to infer more detailed information about the user's activities. We will elaborate on such examples in Section 5.4, but to mention, for instance in [67], both the GPS and accelerometer information is collected to infer user's movements. GPS data can be used to identify if a user is walking or in a vehicle but it is difficult to identify whether a user is running or biking by just looking at the speed. Combined with the accelerometer data, it can provide more fine-grained activity information.

2.2 Activities

In the previous section, we have listed the available sensors on the mobile phones and in this section our aim is to give an overview about the activities that can be recognized using these sensors identified in the state-of-the-art activity recognition systems on mobile phones.

When we look at the early work on mobile phone sensing for activity recognition, they address coarse-grained activities associated with location information, such as staying at home or being at the office. However, these inferences do not tell much about the exact activity performed by the user. For instance, being at the office is not equivalent to working [17] or staying at home does not tell us whether the user is watching TV or having lunch. With newer sensors available on the phones we can go beyond using coarse locations using as substitutes of the activities. For instance, by using the information from an accelerometer, identifying that the user is sitting, from a microphone, mentioning that there is a conversation going on, and from the Bluetooth sensor that the user's office contacts are around, we can provide a more detailed recognition process and conclude that the user is sitting at a meeting in the office.

Besides the work on associating the user's location with an activity, some other early work focused on associating user's movement with an activity. For instance, by using the fluctuations in GSM signals, it is possible to infer whether a user is in a vehicle or stationary with around 80% accuracy [73]. Compared to location-based activity recognition, this provides a finer grained activity recognition but for instance it cannot distinguish the similar activities such that a user is running or cycling. However, using accelerometers besides the fluctuations in wireless signals can provide us a more accurate activity recognition.

Location and motion associated activity recognition are the two dominating types of activity recognition using mobile phones. Besides these, recent applications consider using mobile phones for more complex activities for instance in the field of sports: outdoor bicycling, soccer playing, lying, nordic walking, rowing with the rowing machine, running, sitting, standing, walking using accelerometers in [39] or for daily activities such as shopping, using a computer, sleeping, going to work, going back home, working, lunch, dinner, breakfast in [16]. Some recent applications also consider to use mobile phones for detecting dangerous situations such as falls [19, 78].

In Table 1 we present example types of activities that are inferred in state of the art activity recognition systems on mobile phones classified into six different categories according to their objectives.

2.3 Ideal Application Domains for Activity Recognition: Health, Wellbeing and Lifestyle Change

Activity Recognition using mobile phones have been used or have the potential to be used for various application domains. A detailed list of applications of mobile activity recognition was presented in [48]. They classified the application domains into 3 categories: i) applications for end users, such as fitness tracking, health monitoring, fall detection, ii) applications for third parties, such as targeted advertising, research platforms for data collection, corporate management, iii) applications for crowds and groups, such as activity based social networks, place and event detection. In this section, we summarize particularly the applications for health, wellbeing and lifestyle changes that can benefit from the mobile activity recognition research.

Table 1 Types of Activities Studied in the Literature

Class	**Activity Types**
Locomotion	Walking, running, sitting, standing, still, lying
Mode of Transportation	Biking, traveling with a vehicle, riding a bus, driving
Exercise	Outdoor bicycling, soccer playing, biking on a fitness bike
Health Related Activities	Falls, rehabilitation activities, following routines
Daily Activities	Shopping, using computer, sleeping, going to work, going back home, working, lunch, dinner, breakfast, in a conversation, attending a meeting, using an ATM
Usage of the Phone	Text messaging, making a call, browsing the web, composing an email, using an app

The high correlation between the level of physical activity and the level of wellbeing is one of the key enablers of using mobile phone based activity recognition in *healthcare* applications. Common diseases such as obesity or hypertension are all linked to physical inactivity. In the current practice, the patients are asked to keep a diary about their physical activities throughout the day. The success of the diary approach depends on the user's willingness to keep everything written. However, an automatic activity recognition system based on mobile phone sensing can offer a more reliable and flexible solution. Keeping precise information on the user's activities can potentially improve the treatment of a disease.

Activity recognition on mobile phones can also help to follow the daily habits and routines of users, especially elderly. Deviations from routines can easily be identified in such applications and this can assist the doctors or caregivers diagnose conditions that would not be observed during routine examinations [50].

Similarly, mobile activity recognition can be used for the rehabilitation of diseases. For instance an activity recognition system can detect if a user is correctly doing the exercises recommended by a physician [10]. Another field within the healthcare domain would be to recognize the relationship between a user's physical activity level and mental condition. Especially elderly experiencing dementia risk or Alzheimer show inconsistencies in their daily routines. An automatic activity recognition system, summarizing a user's daily routine would be beneficial to keep the progress of her mental condition and status of the disease.

Wellbeing and *fitness monitoring* are also typical applications targeted in the mobile activity recognition studies. The mobile phone can act as a pedometer in monitoring the step count and can easily track distances traveled and calories burned. Additionally, using persuasive techniques mobile phones can interact with the users to change their behavior and lifestyles in being more active [65, 18].

Ambient assisted living is another application domain within healthcare that can benefit from activity recognition systems. Assistance for people with cognitive disorders or people with chronic conditions can be provided and their daily physical activities and routines can be monitored with a mobile activity recognition system. Mobile-phone based fall-detection is another application domain exploited by the researchers recently [19, 78]. Particularly in [78], we focused on detecting falls which is considered as a major obstacle to independent living not only for elderly but also patients with neurodegenerative diseases, such as epilepsy. When a fall is detected especially outdoors, the proposed system also supports online location identification using GPS available on the smart phones.

3 Process of Activity Recognition

The activity recognition process can be summarized as determining a target set of activities, collecting sensor readings and assigning sensor readings to the appropriate activities. In other words, it is the process of how to interpret the raw sensor data to classify a set of activities. Many of the activity recognition studies, not necessarily in the field of mobile phone sensing, focus on the use of statistical machine learning techniques[1] to infer information about the user activities from raw data. The learning phase can be supervised or unsupervised. Supervised techniques rely on labeled, i.e. associated with a specific class or activity, example observations to build classifiers whereas unsupervised techniques do not rely on labeled data. Since an activity recognition system returns a label of an activity, such as running, walking, usually they follow supervised approaches or semi-supervised approaches where a part of the training data can be unlabeled. However, in the literature only [49] focuses on using semi-supervised learning approaches for activity recognition on mobile phones whereas other studies utilize supervised learning techniques.

Supervised learning methods are composed of two main phases: training and classification, i.e., testing. In the training phase, machine learning approaches utilize a given set of examples or observations, called the "training set", to discover patterns from the sensor readings. These examples or observations should be associated with a specific class of activity or in other words should be "labeled" to learn from these instances. Labeling the data in the training phase is usually a tedious and complex process. Either the user should label each activity performed, such as keeping a diary or using an automatic voice recognition system to record each activity performed, or the activities of the user should be recorded with a video camera and the activities are automatically labeled by the system.

[1] Although activity recognition can be performed using rule-based inference or using unsupervised techniques, it can be very challenging to discriminate activities in this context [46].

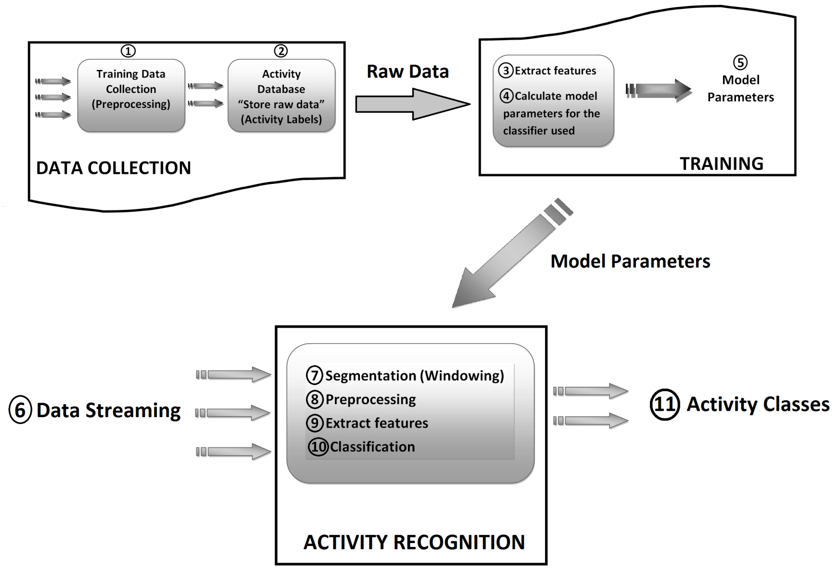

Fig. 2 Typical steps of activity recognition

After the collection of labeled data, usually the preprocessing (noise removal and representation of raw data) and feature extraction (abstractions of raw data to represent main characteristics) steps are followed. The details of preprocessing and feature extraction are explained in Section 3.1. After these steps, training models are built and training parameters are calculated according to the used machine learning technique.

In the testing or classification phase, unlabeled raw data is classified according to the training model computed. In the following sections, we summarize the main steps in the activity recognition process for the classification phase utilizing machine learning approaches and discuss the metrics used to evaluate the performance of a classification technique.

3.1 Activity Classification Steps

As discussed in [9,63], after the sensor data is collected, the main steps of activity recognition include: i) preprocessing of sensor data, ii) segmentation, iii) feature extraction, iv) optionally dimension reduction and v) classification. Figure 2 shows the typical steps of activity recognition.

The *preprocessing* step contains noise removal and representation of raw data. Initial samples received from any type of sensor are called raw data. Because of the nature of sensors, gathered raw data has a potential noise which prevents us to detect the usual behavior of activity patterns. Because

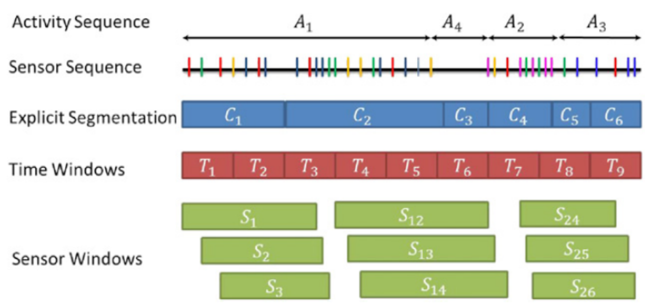

Fig. 3 Different segmentation approaches [42]

of this reason, a preprocessing stage should be applied to the raw data before using it in the activity recognition process. There are different methods for noise removal such as non-linear, low-pass or high-pass, Laplacian and Gaussian filters. The preprocessing step usually takes place both in training and classification, i.e. activity recognition, phases, as shown in Figure 2.

The *segmentation* phase is usually applied to continuous stream of sensor data to divide the signal into smaller time segments since retrieving useful information from a continuous stream of data is a difficult problem. For this purpose, different segmentation methods can be applied to time-series data which enhance the signal behavior and enable us to gather useful information from continuous stream of data. Sliding windows can be considered as one of the segmentation methods. Some examples of stream processing are illustrated in Figure 3. Explicit segmentation can be used at two level approaches such as splitting and merging. By this way, the streaming data is divided into chunks before the classification starts. The drawback of this approach is to decide the appropriate size for each chunk which increases the complexity. Additionally, one always needs to wait for future data to make decisions on the previously splitted data. On the other hand, dividing the whole sequence to equal time windows further decreases the computational complexity. Because of this reason, it is presented as a suitable approach in activity recognition studies dealing with continuous streaming data sampled with constant rates. However, one has to deal with finding the optimal time intervals for targeted activities in this approach which directly affects the system performance. The last approach presented in the figure is to divide the streaming data based on the count of the sensor events. Other approaches like top-down, iterative end point fits, bottom-up and/or any combination of them can be used for this purpose. According to the previous studies, sliding window and bottom-up approaches are the ones which have lower complexity whereas combination of them called SWAB [37] has slightly higher complexity but its performance is as good as the bottom-up algorithm.

The *feature extraction* phase includes the generation of abstractions that accurately characterize the sensor data. In other words, large input sensor data is reduced to a smaller set of features, called the feature vector, that represents the original data in the best way. Examples of features can be mean, variance in the time domain and spectral energy, spectral entropy in the frequency domain (if the signal is continuous, i.e., has frequency components such as voice), or wavelet coefficients in the time-frequency domain. There are also examples of heuristic features such as inter-axis correlation, signal vector magnitude and signal magnitude area which are widely used [33]. Feature extraction step is also performed both in training and activity recognition step as illustrated in Figure 2.

Dimensionality reduction phase can be applied to remove the irrelevant features to decrease the computational effort and memory requirements in the classification process. The aim of dimensionality reduction is to reduce the computational complexity and increase the performance of the activity recognition process. After the previous steps, collected data can be used directly in the classification step. But some part of data may not even contribute to the results of the classification process. It may just create a burden on the complexity of the process and just slows down training and classification processes, hence the dimensionality reduction is applied to overcome these issues. For this purpose, different methods are proposed in the literature which can be grouped as feature selection methods and feature transform methods. Feature selection methods separate most discriminative features whereas feature transform methods combine two or more features which are not effective individually, but meaningful when they are combined.

Finally, the *classification* phase includes mapping the sensor data (i.e. the extracted feature set) to a set of activities. The classification technique may involve a simple thresholding scheme or a machine learning scheme based on pattern recognition or neural networks. As we will elaborate in Section 5.4, common pattern recognition algorithms include decision tables, decision trees, hidden markov models (HMM), Gaussian mixture models and support vector machines. The reader can refer to [63] for the details and comparisons of classification models used in activity recognition research.

To wrap up, although the classification phase and algorithms give the final decision about recognizing an activity, each phase is equally important. Representing raw-data without loosing the useful information in the preprocessing phase [9], efficient segmentation of continuous signals, extracting the best features that characterize raw signals are all the key steps in delivering activity recognition results with a high performance.

3.2 Performance Parameters

Figure 4 presents the possible workload and system parameters typically used in the performance evaluation of activity recognition on mobile phones. In this figure, activities and different users can be grouped as workload parameters

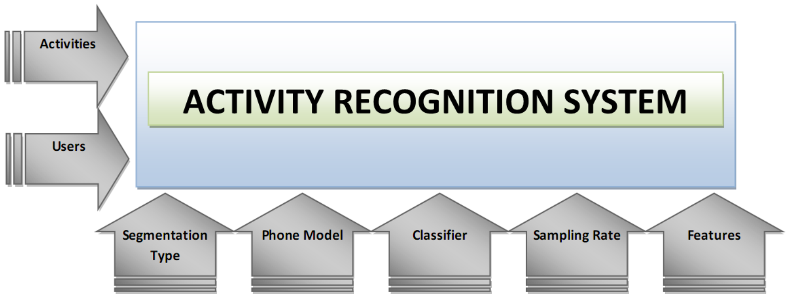

Fig. 4 Workload and System Parameters

whereas sampling rate, phone models, classifiers, features, segmentation type (window size) can be defined as system parameters.

– *Activity:* It is the target action being performed during tests to be recognized. Selected activity sets are also important in terms of the accuracy of the system.
– *Users:* People may perform different activities differently, or can perform multiple tasks at the same time which can affect the activity recognition performance negatively.
– *Phone Model:* Device model is highly important in terms of embedded sensors and computational capabilities. Sensor hardware changes according to the model and its manufacturer which may directly affect the performance as different sensors may have different accuracy and noise characteristics. Additionally, computational power of the device should be sufficient to handle the selected system parameters and test cases appropriately.
– *Classifier:* Classification is the key step in the activity recognition process. Type of selected classifiers play an important role on the system performance.
– *Features:* Features are the signatures of the activities which have an important impact to identify the activities and affects the results directly.
– *Sampling Rate:* It is the rate at which the data is gathered. It affects the capability of the accelerometer to capture the necessary information for target activities.
– *Segmentation type (Window size):* It is the duration in which only data is collected without performing any classification. Each human activity has a pattern except the stationary activities. Because of this reason, collected data during a window plays an important role to identify activities.

3.3 Performance Measures

In the testing (classification) phase of an activity recognition system, the output classes should be compared with the ground truth, i.e., what the user was actually doing in order to evaluate the success of a classification scheme. In most of the studies, cross validation is employed using a large part of the collected data for training where the ground truth is available from the labels associated with the raw data. In some studies, training and test data may be splitted.

Although different studies may use different performance measures, the research community working on activity recognition is adopting similar performance measures: Accuracy, Precision, Recall, Confusion Matrices, F-measure.

Accuracy is the overall correctness of a classification model and is calculated as the sum of correct classifications divided by the total number of classifications. *Precision* is the measure of accuracy and is calculated as:

$$Precision = TP/TP + FP \tag{1}$$

where TP and FP are the numbers of true positive predictions and false positive predictions of a given class. *Recall*, also called *sensitivity*, is a measure of the performance of a prediction model to select instances of a certain class and is calculated as

$$Recall = TP/TP + FN \tag{2}$$

where FN is the number of false negative predictions (the number of positive instances that were classified as negative) of a given class.

F-measure is the weighted harmonic mean of precision and recall and is computed as in Equation 3.

$$F - Measure = \frac{2 * precision * recall}{precision + recall} \tag{3}$$

Classification results can be presented using a *confusion matrix*. An example is shown in Table 2 and it shows how the predictions are made by the model. The rows of a matrix stand for the known class of the data and the columns correspond to the predictions made by the model. The value of each cell in the matrix is the number of predictions made with the model corresponding to the column for the activity given in the corresponding row. Therefore, the diagonal values represent the number of correct classification made for each class.

Table 2 Confusion matrix showing TP, TT and TI for each class [36]

Inferred / **Ground Truth**	**1**	**2**	**3**	
1	TP_1	ϵ_{12}	ϵ_{13}	TT_1
2	ϵ_{21}	TP_2	ϵ_{23}	TT_2
3	ϵ_{31}	ϵ_{32}	TP_3	TT_3
	TI_1	TI_2	TI_3	Total

In the confusion matrix, the rows show the ground truth labels as provided by a human annotator, while the columns show the labels inferred by the model. Diagonal of the matrix shows true positives (TP). Sum of each row provides us the total ground truth of each label (TT). Lastly, sum of each column gives us the total of inferred labels (TI).

Accuracy and precision are the mostly adopted performance measures in the literature, as outlined in Table 3. In [34], the efficiency of performance measures for activity recognition is discussed. Since we usually deal with unbalanced data sets, such that some classes may appear much more frequent than other classes, it is argued in [34] that, since the conventional use of precision and recall assumes a two-class problem (i.e. a positive class and a negative class), instead of using the precision and recall values for all activities as a metric, the average precision and recall over all activities should be computed as follows:

$$Precision = \frac{1}{N} \sum_{i=1}^{N} \frac{TP_i}{TI_i} \tag{4}$$

where N is the number of classes. Similarly, recall can be computed as given in Equation 5;

$$Recall = \frac{1}{N} \sum_{i=1}^{N} \frac{TP_i}{TT_i} \tag{5}$$

4 Challenges of Activity Recognition with Mobile Phones

In this section we first investigate the specific challenges that are only linked with activity recognition on the mobile phone environment, then the challenges related to persuasion and lifesytle change and briefly mention the general challenges of activity recognition since more detailed challenges have been discussed thoroughly in previous work [9].

4.1 Continuous sensing

Continuous sensing, i.e, continuous sampling of the sensors on the mobile device, is a fundamental requirement for activity recognition applications but it is also a fundamental challenge considering the battery limitation of the mobile devices. For instance in [74], it was shown that, a fully charged Nokia N95 device can support telephone conversations more than 10 hours whereas it can function only around 6 hours while the GPS is turned on without taking into consideration whether it is taking samples or not. While supporting continuous sensing applications, the user experience should not be disrupted, such that the user should be able to use the phone for making calls, sending

Fig. 5 Offline/Online Training and Classification

SMS'es, taking pictures, or browsing on the web. In this regard, energy efficient sensing mechanisms are required where the sensors can be duty-cycled for energy efficiency or turned off when not required to take samples. Studies that tackle the continuous sensing problem propose different approaches [74, 64, 76]. For instance in [74], Wang *et al.* propose two techniques for reducing the battery consumption. The first one is to turn off unused sensors automatically according to user states. For this purpose, an XML-style state descriptor is taken as input and used by the sensor assignment functional block. Accordingly, selected sensors are sampled during a specific state whereas differently selected sensors are tracking any possible user state transitions. The second technique simply uses sensor duty cycling instead of continuously sampling the sensors. Although duty cycling the sensors increases the recognition latency, using these techniques, they show that the battery lifetime can be improved by over 75% compared to an existing application, Cenceme [54].

4.2 Running classifiers on mobile phones

As mentioned, algorithms used in the classification of activities originate from statistical machine learning techniques. However, a trendy algorithm [14] in machine learning research may not exhibit a superior performance in the field of activity recognition, especially on the mobile phone platform with limited resources, considering the limited processing power and the battery. Moreover, when we look at the literature on activity recognition using inertial sensors, we observe that most of the studies first collect sensory data and apply classification algorithms offline on the collected data, using a large part of the collected data for training. It is clear that larger the amount of overlap between the training data and the testing data, better recognition results will be achieved (unless the overfitting problem occurs). Offline processing certainly exploits this advantage.

Offline processing can be used for applications where online recognition is not necessary. For instance, if we are interested in following the daily routine of a person, such as in [77], the sensors can collect the data during a day; the data can be uploaded to a server at the end of the day and can be processed offline for classification purposes. However, for applications such as a fitness coach where the user is given a program with a set of activities, their duration and sequence, we might be interested in what the user is currently doing and/or if he is performing the activities with a correct sequence [77]. Therefore, online recognition of activities becomes important, especially for real-world personal fitness and wellbeing applications running on smart phones to provide the context of the users. Figure 5 presents a comparison of offline/online training and classification.

Although smartphones continuously evolve in terms of computation, memory and storage capabilities, they are still resource limited devices and running a resource-intensive classifier may not be possible, such as when classifying audio data [45]. However, early examples of activity recognition applications on mobile phones show that classifiers such as decision trees, the minimum distance classifier, KNN classifiers can run on mobile phones while providing good accuracy rates [41,67]. Considering the resource intensive classifiers, one approach adopted in the literature is to rely on backend servers with uploading sensed data to a server and benefit from their computational resources and download the results of the inferences. However, with this sort of computation, it is not possible to support real-time applications.

4.3 Phone Context Problem

One of the problems associated with mobile phone sensing is the *phone context problem* as identified in [45]. The phone context problem occurs when the phone is carried at an inappropriate position relative to the event being sensed. For instance, if the application wants to take a sample from a light sensor when the phone is located in the pocket or in the bag, the phone context problem is encountered. Especially with accelerometer-based activity recognition, the location where the phone is carried, such as in the pocket or in the bag, impacts the classification performance [45]. In most of the studies using inertial sensors, i.e. the accelerometer, the phone was restricted to be carried in a particular location by the users as we elaborate in Section 5. Recently, in two studies the phone context problem has been investigated [55,59]. In [55], authors develop a system for automatic phone context discovery. In their 3-level inference system, the first level is responsible for inference from the data collected by individual sensors. However, the result of this inference may not be conclusive since individual sensor readings may not identify the context correctly, for instance the conclusion of being in a dark environment made by the camera sensor may not be correct if the camera is covered by the user's hand. In the second step, multi-sensor inference is performed, such that the outputs of individual sensor inferences are combined. Finally in the third level, temporal smoothing and a Hidden Markov Model (HMM) is applied for a final decision. The system is tested with using only the microphone sensor and for the "in the pocket" and "out of the packet" cases and revealed a performance with around 80% accuracy in detecting the position of the phone. In a very recent study [59], Park *et al.* investigated the phone context problem, which was defined as device pose classification in the paper, using kernel-based estimation methods. Instead of using the built-in sensors available on a smart phone, they used Nokia SensorBox (connected via Bluetooth to the phone) including a consumer-grade accelerometer, gyroscope, magnetometer, thermometer, and barometer. However, only the accelerometer was utilized in the experiments. They use SVM and decision tree classifiers utilizing features of Discrete Fourier Transform (DFT) of the horizontal and vertical components of the acceleration signal as well as tilt features derived from the gravity vector and could achieve more than 98% accuracy for offline classification of poses bag, ear, hand and pocket. The authors also evaluated the system performance with online recognition tests for the walking activity, and overall the classifier predicted true device pose quite well.

Although the phone context problem has been attempted to be solved by very recent studies [55, 59], there still remains open issues such as the phone context identification in real-time including different poses and for different activities.

4.4 Training Burden

Another challenge is about running the training phase of the classifiers. Even though a proposed system does online classification, the training phase can be handled with offline processing. Usually, proper training models are being created offline so that these static models can be used in an online classification phase [70]. The offline training phase is not an easy task and it is essential for an activity recognition system since such systems require large, well-defined and proper training sets to create appropriate models. These training sets are collected over a long period of time (couple of days, weeks or even years depending on the related work) with dedicated and a sufficient number of test subjects as presented in [38]. Additionally, collected data sets can be too large to be processed online on other devices like smart phones because of their limited capabilities. Considering these challenges, research on human activity recognition systems explore the ways for online training.

In order to develop a real-world application where the user installs the application and does not require to deal with the burden of the training phase, such that the application can be pretrained or trained quickly without the requirement of a long training phase, and which is ready-to-use, the research question is "Can we recognize the activities with only a limited set of training data and even without any training data in a user-independent way?". This question has been partially addressed in [53] aiming user independent or limited training of proposed systems. A system called Darwin has been proposed to decrease the training burden on users, and improve the user experience on smart phone based on model pooling which is simply sharing and exploitation of classification models which are already built by other phones and by other users. Using model pooling, there is no need to generate training models from scratch. In [40], we also evaluated the performance of classifiers with using training data from other users where the user's own training data was excluded. The results were found to be promising and giving an insight such that the training data coming from two distinct subjects with the same physical features and using the same phone model can be used for each other which is an important hint to be able to create user independent training data sets, as also mentioned in [53].

Another challenge about the training phase is labeling the activities which also appears as a burden on the users. As mentioned, the user may be asked to keep a diary or using an automatic voice recognition system a video recording system the activities can be automatically labeled by the system. In this sense, person independent classification systems are expected to overcome this challenge as discussed in the previous paragraph.

4.5 Persuading Users

Especially in persuasive applications for a behavior or lifestyle change, the success of the application depends on the willingness of the user to engage. Persuasion techniques such as self-monitoring, social influence, fun interaction are often used in the design of such applications [71]. Virtual companions [8], games [62], social networks [79] are commonly used to interact with the users in mobile applications. However, understanding which types of methods and metaphors are the most effective for various applications and people is still under investigation. As also mentioned in [45], metaphors to motivate users to use the application for persuasive computing should be investigated in more detail, possibly by inter-disciplinary research teams including psychologists.

4.6 Human Behavior

People can perform multiple tasks at the same time which can affect the activity recognition process negatively. Additionally, various continuous sequences of performing tasks and their periodic variations may result in incorrect classifications. Because of these reasons, accuracy and reliability of sensor data play an important role in the activity recognition.

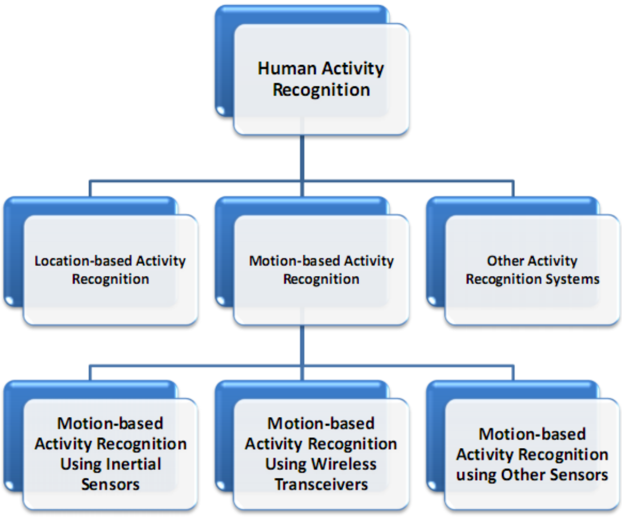

Fig. 6 Types of activity recognition systems on mobile phones

5 State of the Art on Activity Recognition on Mobile Phones

As we mentioned in Section 2.2, location and motion associated activity recognition are the two dominating types of activity recognition using mobile phones. In this section, we first review the studies that focus on location-associated activity recognition, next focus on the studies based on motion-based activity recognition. Finally, we review the studies that consider different types of activity recognition, other than motion and location. Figure 6 shows the types of activity recognition on mobile phones classified according to their objectives.

5.1 Location-driven Activity Recognition

Before the release of smart phones equipped with a rich set of sensors, early examples of activity recognition on mobile phones focused on the use of location information to detect the user activities. Location-driven activity recognition aims to recognize activities associated to certain places [17]. In the Reality Mining project [22], three activities "home, work, elsewhere" were targeted using cell tower and Bluetooth data. An HMM model, conditioned on the hour of the day and day of the week, was built and the associated activities were recognized with 95% accuracy. Similarly in [28] semantic content associated with locations were used to infer user activities, such as shopping, restaurants, recreation, government offices, schools, entertainment. Location data was collected with GPS.

The main drawback of using only location-driven activity recognition is the inaccurate inferences. For instance being at home does not mean eating or sleeping. Moreover, activities inferred with places are usually not of interest for personal health or wellness systems. However, if location information is used with other sensory data, for instance using the microphone or accelerometer, it can help to improve the activity recognition results.

5.2 Motion-based Activity Recognition

Motion-based activity recognition systems mostly utilize inertial sensors, radio sensors (cellular, Wi-Fi) or other sensors such as GPS for motion recognition. In this section we first review the systems that utilize transceiver interfaces on the phones and next summarize the systems that utilize inertial sensors, and finally look at the studied that utilize the combination of these sensors or use other types of sensors such as GPS.

5.2.1 Motion-based Activity Recognition using Transceiver Interfaces

In [73], activities of walking, driving and staying at the same place (dwelling) were identified using only the GSM traces. Additionally, a GSM-based step counter was also proposed. The principle behind the mobility mode inference is that, radio signals observed from stationary sources are fixed in time but variable in space. By observing a series of GSM signals from a set of stable towers, and calculating the Euclidean distance between consecutive GSM measurements, mode of transportation is inferred since stationary, slow and fast walking and driving show different distance values. A boosted logistic regression technique was used for the classification of activities. By measuring the walking periods and assuming an appropriate step rate, user's daily step count was also calculated. The performance of the system was evaluated with 3 users for one month using the Audiovox SMT 5600 mobile platform. The overall accuracy for the transport mode recognition was calculated as 85% and the step counter reasonably estimated the number of steps calculated by commercial pedometers. Although a specific application was not targeted in the paper, elderly care and monitoring elderly's wellness through mobile phones were mentioned as suitable applications regarding the personal health and wellbeing systems.

Shakra [6] is an application for tracking and sharing daily activity levels with mobile phones. Shakra also utilizes GSM signal traces to detect the activities of walking, driving and stationary. The system targets to track the daily exercise activities of people and users are supported to share and compare their activity levels with others for motivating fitness and moderate activity. For the classification, both an artificial neural network and an HMM were used. The application was evaluated with three groups of users with different activity levels, ranging between inactive and highly active, to find out whether the application increased the awareness of the users for their activity levels and persuaded them to be more active. Overall, the HMM performed slightly better than the artificial neural network classification revealing an accuracy of 82%. All of the users were reported to be responding positively about the system to increase their activity levels. However, as authors mention, it is not possible to claim that the users would remain motivated about the system and they mention that this study shows that Shakra is usable and if further developed it can act as an effective health promotion tool.

In [43], WiFi signals were used to infer whether the user is moving or stationary. Whereas in [58] a hybrid approach utilizing both WiFi and GSM signals were used to infer the transportation mode.

5.2.2 Motion-based Activity Recognition using only Inertial Sensors

Accelerometers on the mobile phones were initially included to enhance user experience by automatically changing the orientation of the display according to the orientation of the mobile phone held by the user. However, as widely adopted by the activity recognition research in other areas, i.e. activity recognition using body-worn sensors, accelerometers embedded in the mobile phones also have the potential to recognize the user's motion and activities.

In [70], a classification algorithm is aimed to run on the iPhone platform. For this purpose three iPhone applications are developed called as iLog, iModel, iClassify respectively. iLog is used for data collection for different activities in real time. iModel is a desktop tool for learning and testing models. Data saved by iLog can be imported into iModel which is a Java application built on the Weka machine learning toolkit [2]. By using iModel, labeled data can be used to test an existing model or to learn a new model. Lastly, iClassify can be used to classify walking, jogging, bicycling on a stationary bike, and sitting activities in real time in iPhone applications. In terms of methodology and execution times of classification steps, this study differs from the two previous studies. There is an offline data processing step to learn data models and addition to iPhone 3-axis accelerometer sensor, Nike+iPod Sports Kit is used to collect data which imports the collected data periodically to iPhone via Bluetooth connection. iClassify can report activity classifications once per second. It performs nearly 97% accuracy in recognizing activities.

ActiServ, a service-based recognition architecture, is presented in [12]. ActiServ uses only the acceleration sensor to detect activities of standing, sitting, lying, walking, climbing stairs, cycling, no movement. It uses classifiers based on fuzzy inference systems utilizing features of variance and mean values of the raw acceleration data. It requires minimal personalization effort by the users, only 1-3 minutes of data collection per activity seems sufficient. The performance of the system is evaluated with 20 users, each user generating 2-3 minutes of data for each of the activity classes, using OpenMoko Neo Freerunner phone based on the Samsung S3C2442B processor. If the training data of the user evaluating the system is used with the phone located in the same position both in the training and evaluation phases, then the performance of the system is reported to be 97.3% in terms of accuracy. If the model is trained when the phone is in different position then the accuracy rates drop to 60%. When the training data of the evaluation user is excluded and the data from other users (actually selected from the best matching users) is used, the accuracy rates are between 86% and 63.6%. Although the data was collected on a mobile phone platform, ActiServ is both trained and tested offline on backend servers. ActiServ does not detail a target application but the activities classified and offline processing can be used for monitoring the daily routine of a person, such as a personal activity diary for a wellness application.

Probably the most common device to promote more active life is the use of pedometers which allow for step counting [5]. Examples of pedometer applications developed for smart phones are available in application stores. Similarly, a step counter service was proposed in [57] whose performance was compared with different step counting products. The service used hill detection and threshold calculation for step identification utilizing the magnitude of acceleration and detects the orientation change to improve the performance of recognition. The performance of the server was evaluated with a single user by conducting walks of 500, 1500 and 2500 meters, and each walk was repeated 3 times. For the ground truth, Nike+ sports kit with an iPod was used. According to the experimental results, the service on the average reveals a mean error of 0.5% compared to the reference Nike+ sports kit. The performance was also compared with step counting products such as Nokia step counter with the phone carried in different positions (pocket, belt clip, hand, backpack) and it exhibited better results.

In [13], instead of periodic activities such as walking, cycling, car driving, transitions between physical activities, particularly between sitting and standing, are targeted. Assessment of the behavior of elderly people and pregnant workers facing inappropriate working conditions under ergonomic aspects are the target stakeholders for this work. Features of mean and variance are used from the raw accelerometer data. A set of kernel functions were utilized and cross correlations with the sampled and projected signals were calculated to detect a matching. A correlation coefficient near one infers a sit-to-stand transition whereas near minus one infers a stand-to-sit transition. The performance of the system was evaluated on SonyEricsson w715 phones with 12 subjects and 70% average recognition rate was achieved. Although the target for the system was the detection of inappropriate working conditions or support the health conditions of elderly, it was not tested under the circumstances of these applications.

A physical activity diary using phones equipped with accelerometers is proposed in [77] with a potential application of mobile healthcare. Sitting, standing, walking, running, driving and bicycling activities are targeted to be identified on Nokia N95 platform. 15 different features (vertical features, horizontal features and cross-correlation features) were extracted from raw acceleration signals and Decision Tree (C4.5), Naive Bayes (NB), kNN and Support vector machine machine learning algorithms are used as the classifiers and it was shown that decision tree achieves the best performance among other classifiers, with around 90% accuracy. In order to create a physical activity diary, the system was used by a subject for several months.

In a recent study [59], Park *et al.* focus on the classification of the mobile phone's position relative to the body and estimation of walking speed only using the accelerometer. Phone position classification is used to tackle with the phone context problem as discussed in Section 4. Walking speed estimation is used for health monitoring applications. Regularized kernel methods are used for the classification together with the features of raw acceleration data, such as the discrete Fourier transform, horizontal and vertical components. The system is implemented on the Nokia N900 platform and tested with 14 subjects. The median absolute speed error was reported to be 0.039 m/s, which amounts to 3% of the average walking speed.

In [29] the acceleration sensor was used to detect six different activities, namely sitting, lying, standing, walking, running and jumping. The performance of the system was tested with five subjects with the mobile phone located at different locations to investigate the phone context problem, as discussed in Section 4, with a projection based method. The system is shown to achieve 90% classification accuracy with sixteen different device orientations and three device locations.

Similar to the other studies, in [44], Kwapisz *et al.* concentrated on recognizing the common human activities such as walking, jogging, ascending stairs, descending stairs, sitting, and standing. They used inertial accelerometer sensor of Android based smart phones. This study differs from other studies in terms of the data size collected for the training phase which is performed by twenty-nine different subjects. The classification steps are performed with the help of the Weka toolkit by using a decision tree, logistic regression and multilayer neural networks. They used ten-fold cross validation for all experiments. According to the results, multilayer perceptron achieved the best performance with 91.7% accuracy rate.

As discussed in Section 2.3, activity recognition may target different application domains. In this context, Iso *et al.* presented a gait analyzer based on the three-axis accelerometer mounted on a cell phone for healthcare and presence services in [31]. Their proposed system could determine a set of activities (walking, running, going up/down stairs, and fast-walking) with an overall accuracy of about 80%. Additionally, in [26], Fontecha *et al.* proposed a complete elderly frailty detection system by using accelerometer-enabled smart phones and clinical information records of the subjects. There are many different factors to be evaluated for frailty detection and diagnosis. In this manner, assessment of physical condition through gait and other physical exercises is one of the most important factors. This work presents a mobile system to collect elderly data based on gait and balance tests. They create instances for each subject with the combination of dispersion measures coming from accelerometer data and risk factors from patient records. By comparing different instances, they create an affinity tree which is used for frailty diagnosis.

Differently from other studies, Zhixian *et al.* concentrated on energy efficiency and introduced an activity-sensitive strategy ("A3R" - Adaptive Accelerometer based Activity Recognition) for continuous activity recognition in [76]. They studied the individual's locomotive activities such as standing, slow-walk, sit-relax, sit, normal-walk, escalator-up, escalator-down, elevator-up, elevator-down, downstairs. The proposed system achieved an overall energy saving of 20-25% by adapting the accelerometer sampling frequency and the classification features seperately for each activity in real-time.

A system for monitoring the human physical levels for medical diagnosis on mobile phones was presented in [30]. A simple gait detection algorithm employing an average magnitude difference function was implemented. Walking and resting were the only activities monitored in this study. The activities are detected on the mobile platform and transmitted to a server for logging. The system also provides an interface for a caregiver to visualize and analyze the activity levels. The performance of the application was tested under various settings, such as the impact of the handset location, reliability of the activity detection algorithm, impact of phone activity on the algorithm's reliability, impact of handset type and power characteristics in terms of error percentages which varied between 0.68% and 10.23% varying according to the headset position relative to the user's body and device model.

As we have summarized, most of the algorithms focus on simple activities such as locomotion. In [21], more complex activities are targeted to be monitored, such as cleaning, cooking, medication, sweeping, washing hands, watering plants, besides the simple activities such as, biking, climbing stairs, driving, lying, sitting, standing and walking. The activity recognition system was developed on the Android platform. Fetaures extracted from the raw data include mean, min, max, standard deviation, zero-cross and correlation. Weka machine learning toolkit was used to test six different classifiers: multilayer perceptron, Naive Bayes, Bayesian network, decision table, best-first tree and K-star. Although the classification accuracies for simple activities were found to be above 90% except the Naive Bayes classifier, the best accuracy achieved for complex activities was around 50%. Simple activities could retain their high classification accuracy even when tested together with the complex activities.

Similarly in [75], locomotive micro-activities are used to identify semantic activities such as cooking, working, eating, relaxing cleaning, on a break, meeting. This 2-tier activity recognition approach utilizes both time domain features, such as the mean, variance, two-axis correlation, as well as the frequency domain features, such as the FFT magnitude, FFT energy and FFT entropy using a wide variety of classifiers (Decision tree J48, Naive Bayes, Bayesian network, LibSVM and Adaptive Boost (Adaboost) using J48 as the weak learner). Using lifestyle data with 5 users for 152 days, the proposed approach is reported to achieve an average accuracy of 77.14%. with a 16.37% improvement compared to the 1-tier approach. The same authors investigate the recognition of complex activities using higher order features and SVM-based fusion mechanisms in [66]. The same dataset was used and they reported an average accuracy of 86.17% for the same set of activities.

In [47], Lee *et al.* proposed a real-time activity recognition system on smart phones based on hierarchical hidden markov models by using accelerometer sensor data. In this work, they tried to recognize stand, walk, run and stair up/down actions by using low-level HMMs whereas they provide activity information such as shopping, taking bus, and moving by walk based on previously identified actions. The two step HMM structure proposed in this study is important in terms of reduced computational complexity which is appropriate for limited mobile environment.

As we mentioned in the list of challenges in Section 4, the training phase of the algorithms using machine learning approaches creates a burden on the users. The research community is interested in building classification models where the activity recognition phase can be performed in a user-independent way without the requirement of training data collection by the user [51]. User independent activity recognition on mobile phones has been recently addressed in [72]. In this work, the targeted activities are walking, running, cycling, driving a car and idling (sitting/standing). In the experiments, in both the training and testing phases, the phone was carried in the pocket of the subject's trousers. 21 features in total were extracted from the magnitude of acceleration, including standard deviation, mean, minimum, maximum, five different percentiles (10, 25, 50, 75, and 90), and a sum and square sum of observations above/below certain percentile (5, 10, 25, 75, 90, and 95). In order to recognize activities, first a static decision tree is used to detect whether the user is active or inactive. If he is inactive, then the classes to be recognized are sitting/standing or driving. But if the user is active, then the classes to be recognized are walking, running and cycling. In the second stage, performance of both KNN and QDA (quadratic discriminant analysis). The performance of the classifiers are tested both with offline and online classification and in the offline case QDA revealed 95.4% accuracy, while KNN performed with an accuracy of 94.5%. In the online case, the accuracy achieved with QDA was 95.8% whereas it was 93.9% for KNN. In the online tests, 7 subjects tested the system and training data of three subjects were excluded to make user-independent inferences. Although the reported recognition rates are quite high, authors report two cases where user-independent classification has not performed very well. The walking activity of one of the subjects whose training data was not used, was recognized with 65.6% accuracy when QDA was used and cycling activity of another subject whose training data was not available was recognized with an accuracy of 76.3% using KNN. It is reported that in both cases, cycling and walking were mixed together. Authors also report that walking is one of the most challenging activities to recognize user-independently since different subjects have different personal walking styles.

Although in [72] the classification phase was performed online on the mobile platform, together with feature extraction and segmentation phases, the training phase was performed offline, similar to [54,67]. In [41,40], we focused on online recognition of activities on smart phones together with performing the training phase also on the mobile platform. This work is motivated by the fact that considering the challenge of training burden mentioned in Section 4, research on human activity recognition systems explore the ways for online training [23]. We also focused on the common activities targeted in the literature: sitting, standing, walking, biking and running. We used three different classifiers Naive Bayes, Clustered KNN and Decision Tree using mean, maximum, minimum and standard deviation in the feature set. These classifiers were selected considering the limited processing and storage on smart phones and since these classifiers and features were commonly used in the previous studies, using the same set makes it easier to compare our findings with the similar studies. Performance of the classifiers is tested with ten different subjects on different Android based mobile platforms considering the most effective system parameters like the window size and the sampling rate. According to the results, Clustered KNN method exhibited a much better performance with an accuracy around 92% excluding biking and 73.4% accuracy with biking activity. The Naive Bayes classifier performed with 48% accuracy excluding biking activity and 32% accuracy including biking. On the other hand, its performance is nearly the same as the Decision Tree classifier which performed with 86% accuracy excluding biking and 76% accuracy with biking. Similar to [72], we also evaluated the user independency of the system in the training phase. When we excluded the training data of the users in the classification phase and used only the training data from other users, the average accuracy dropped to 48% with the decision tree algorithm including the biking activity. However, for the users who performed the tests on the same platform the accuracy was not affected although they did not use their own training data. We are currently working on this issue to better evaluate the user independency of activity recognition using these classifiers on the Android based platforms.

5.2.3 Motion-based Activity Recognition using Other Sensors

In [67], Reddy *et al.* proposed a different model for activity recognition. In this study, they designed, implemented and evaluated a transportation mode classification system which runs on a mobile phone by using 3-axis accelerometer and GPS sensors. Simply, they focused on outdoor activities and classified them into following five groups: walking, stationary, biking, running, and motorized transport. In fact, they first considered the use of different sensors, such as Bluetooth, WiFi and GSM cell radio. However, experimental evaluation concluded that the most dominant sensors in the performance improvement are the accelerometer and the GPS sensors. Although the GPS sensor was observed to be the most dominant one, it was not successful in identifying the biking and running activities since they reveal similar speed patterns. To distinguish these activities from each other, they used the acceleration sensor and could achieve a recognition accuracy over 93%.

The proposed classification system does not consider a specific mobile phone orientation which makes it convenient to use. In order to reduce the energy consumption, sensor readings are enabled only if a user goes outside by being triggered through a connected base station change. In this study, they evaluated different classification algorithms, such as Naive Bayes, Chain Hidden Markov Model, Support Vector Machine, Nearest Neighbor, Hidden

Markov Model (HMM), Decision Tree (DT), and compared these classifiers with each other. According to the evaluation, DT followed by HMM provided the best results and because of this reason they decided to use DT and HMM together at the final evaluation instead of others. The classification algorithm com- bines GPS speed data and variance and frequency components of accelerometer signals. Weka machine learning toolkit and generalized HMM library is employed to train the classifier and then the classifier is transported to work on Nokia N95. The final classifier is programmed by using Phyton for Symbian S60. Overall, the system provides nearly 93% accuracy.

Similarly in [69], a system called Ambulation was proposed for monitoring the mobility patterns of using the accelerometer and GPS sensors available on mobile phones. The system targets patients who suffer mobility-affecting chronic diseases, such as Parkinson. Variance, mean, FFT coefficients from raw acceleration data are used as the features together with the decision tree classifier. Using acceleration the system can identify the activities of walking, running and stationary. By also using the GPS sensor, additional activities of biking and driving are also identified. The system also displays the mobility traces of people and through these traces one can easily detect anomalies in the change of mobility behavior.

Differently from other studies, in [52], Martin *et al.* investigated the effects of using different set of sensors on the overall system performance while considering different factors. In this work, they emphasize that priori information on the orientation and the placement of the device relative to user's body may enhance the results of the system in terms of accuracy. For this purpose, they also used proximity, light and magnetometer sensor data addition to the accelerometer sensor data. The system performance is evaluated by using lightweight classification techniques such as Naive Bayes, a decision tree and a decision table. According to the results, a computationally low-cost decision table with best suitable feature set can achieve 88% accuracy rate with all sensors listed previously.

5.3 Activity Recognition Systems Utilizing Other Context Information

In [74], a novel design framework, called EEMSS, for energy efficient mobile sensing is proposed. A hierarchical sensor management strategy is used to recognize user states as well as to detect state transitions. User states may contain a combination of features such as motion (running, walking), location (staying at home or on a freeway) and background condition (loud or quiet) which all together describe user's current context. The state transition system implemented on Nokia N95 can define the following states currently; walking, vehicle, resting, home talking, home entertaining, working, meeting, office loud, place quiet, place speech, place loud. The sensors used for activity recognition are accelerometer, WiFi detector, GPS and microphone. EEMSS is able to detect states with approximately 92.56% accuracy by processing testing data offline and improves the battery lifetime by over 75% compared to an existing application, Cenceme [54].

In [54], authors present design, implementation and evaluation of a social networking application, called Cenceme. Basically, users are able to share their contextual information through social platforms like Facebook and MySpace using this application. Cenceme benefits from offine computational powers of backend servers for training whereas it additionally performs online classification. In this study, authors have focused on sitting, standing, walking and running activities as well as audio info of the environment. For this purpose they used accelerometer, Bluetooth, audio sensors and GPS which are embedded in Nokia N95. Classifiers used in this study can be grouped as audio and activity classifiers. The audio classifier benefits from DFT and its feature vector consists of the mean and the standard deviation of the DFT power. On the other hand, feature vectors in the activity classifier are the mean, the standard deviation and the number of peaks per unit time. Simple 3 level decision tree performs classifications online on the Nokia platform for identifying the activities of walking, running, standing and sitting states. Additionally, backend classification derives contextual information from collected data. The performance of the proposed system is tested with 22 subjects over three weeks on the Nokia N95 platform. The overall system performance in terms of recognizing online activities is not stated clearly. However, they emphasize the misclassification of standing and sitting cases.

5.4 Taxonomy

In this section, we provide a taxonomy of the reviewed examples of activity recognition systems using mobile phones according to different metrics ranging from the types of sensors used, to the number of subjects included in the experiments. Table 3 summarizes the general aspects of the studies that are discussed in this section, ordered by the type of activity recognition followed in the system, i.e. motion-based, location-based. Looking at the dates of publications, most of the studies have been presented quite recently, in the last couple of years. The most commonly used sensor is the acceleration sensor. WiFi, GPS or any other sensors are added to improve the sensing power and accuracy of the results. *Sitting*, *standing*, *walking*, *running*, *driving*, and *bicycling* are the common activities being targeted to be recognized in the applications. There are also other studies which target to recognize contextual information, such as location, environmental audio data, of the users as in [74].

From the perspective of personal health and well being systems, most of the studies target applications such as fitness applications or tracking of daily activities. In earlier studies, the classification algorithms are implemented on Nokia N95 which is one of the first mobile phones with sensing capabilities. In the recent studies, Android phones are commonly utilized. Very diverse set of classifiers (decision tree seems to be the most common one) and features have been used in the papers with different number of test subjects which make it difficult to compare the performance of the studies even those performed with the same set of activities. As we discuss in Section 6, the collection of open datasets is required for benchmarking. Additionally, the number of test subjects in most of the studies is quite limited, even in some of them, less than 10 test subjects were included. This makes it difficult to generalize the findings of these studies. Accuracies differ between approximately 80% to 97% depending on the set of activities used and the processing techniques.

Table 3: *Taxonomy of Activity Recognition Systems on Mobile Phones*

Reference	**Sensors**	**Activities**	**Application**	**Platform**	**Classification**	**Features**	**# of Subjects**	**Performance Result**
Eagle *et al.*, 2006, **[22]**	cell tower and bluetooth	home, work, elsewhere	social interactions between users	MIDP2-enabled mobile phones, Nokia 6600	HMM	static Bluetooth device ID, staying in the same location, charging, missed phone calls, text messages, alarms etc.	100	95% accuracy
Hariharan *et al.*, 2005, **[28]**	GPS	shopping, restaurants, recreation, government offices, schools, entertainment	user patterns	web-connected mobile computer and GPS	Bayesian network model	timing, velocity, frank loss of signal after a slowing of velocity, web-based location resources	-	-
Sohn *et al.*, 2006, **[73]**	GPS, cell tower	walking, driving, dwelling, step counter	elderly care and monitoring elderly's wellness	Audiovox SMT 5600	logistic regression	spearman rank correlation coeff., no. of common cell towers, mean Euclidean distance, variance in Euclidean dist. values, variance in signal strengths	3	85% accuracy
Anderson *et al.*, 2007, **[6]**	GSM signal traces	walking, driving and stationary	tracking and sharing daily activity levels	windows smart-phones, i-mate sp5s	artificial neural network, HMM	means and variances along the two dimensions	2,3,4 (3 groups)	82% accuracy (HMM)
Krumm, 2004, **[43]**	WiFi signals	moving, stationary, location info			HMM	WiFi signal strength features (e.g. variance)	10 walks	87% accuracy
Mun *et al.*, 2008, **[58]**	WiFi and GSM signals	dwelling, walking or driving	transportation studies, urban planning, health monitoring and epidemiology	Nokia N95	decision tree	signal strength variance, duration of dominant WiFi access point, no. of unique cell IDs, residence time in a cell footprint	-	83% accuracy
Saponas, 2008, **[70]**	accelerometer, Nike+iPod Sports Kit	walking, jogging, bicycling, sitting	fitness applications	iPhone	Naive Bayes	extracted from 124 distinct features	8	97% accuracy

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Reference	**Sensors**	**Activities**	**Application**	**Platform**	**Classification**	**Features**	**# of Subjects**	**Performance Result**
Berchtold *et al.*, 2010, **[12]**	accelerometer	standing,sitting, lying,walking, climbing stairs,cycling, stationary		OpenMoko Neo Freerunner	fuzzy inference systems	variance and mean values	20	97.3% accuracy
Mladenov *et al.*, 2009, **[57]**	acceloremeter	step identification	Middleware, creating a layer btw. client app. and raw sensor access	Nokia N95	hill detection and threshold calculation	utilizing the magnitude of acceleration	1	mean error of 0.5% compared to the reference Nike+ sports kit
Bieber *et al.*, 2010, **[13]**	accelerometer	transitions between physical activities	Assessment of inappropriate working conditions under ergonomic aspects	SonyEricsson w715	matching - kernel functions and cross correlations with the signals	mean and variance	12	70% average recognition rate
Yang *et al.*, 2009, **[77]**	accelerometer	sitting, standing, walking, running, driving and bicycling	physical activity diary, healthcare	Nokia N95	Decision tree, Naive Bayes, KNN, SVM	15 different features (vertical, horizontal and cross-correlation features)	12	90% accuracy
Park *et al.*, 2012, **[59]**	accelerometer	estimation of walking speed	health monitoring	Nokia N900	regularized kernel methods	discrete fourier transform, horizontal and vertical components of raw acceleration data	14	0.039 m/s median absolute speed error
Henprasertttae *et al.*, 2011, **[29]**	accelerometer	sitting, lying, standing, walking, running and jumping		accelerometer embedded mobile-phone	rules and threshold based classification, instance-based learning	mean and standard deviation	10	90% accuracy
Kwapisz *et al.*, 2011, **[44]**	accelerometer	walking, jogging, ascending stairs, descending stairs, sitting, standing	customization of the mobile device's behavior based on activity, health care	Android-based cell phones	decision tree, logistic regression, multilayer neural networks	average, std. dev., avg. absolute diff., avg. resultant acceleration, time between peaks, binned distribution	29	91.7% accuracy (MNN)

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Reference	**Sensors**	**Activities**	**Application**	**Platform**	**Classification**	**Features**	**# of Subjects**	**Performance Result**
Iso *et al.*, 2006, **[31]**	accelerometer	walking, running, going up/down stairs, and fast-walking	health care and presence services	three-axis accelerometer mounted on a cell phone	gait appearance probabilities based on Bayesian theory	wavelet components, periodograms of the best basis and the momentum of the information entropy distribution of the best basis	2	80% accuracy
Fontecha *et al.*, 2012, **[26]**	accelerometer	collecting elderly data based on gait and balance tests	frailty detection and diagnosis	Android based mobile phones	affinity tree	dispersion measures such as arithmetic mean, std. dev., amplitude, variance, absolute mean diff., acc. mean, pearson's coefficient of variation	20	80% precision (HMM)-
Lee *et al.*, 2011, **[47]**	accelerometer	stand, walk, run and stair up/down, shopping, taking bus, moving by walk		Android based smart phones	hierarchical HMM	x, y, z acceleration values	3	
Zhixian et al, 2012, **[76]**	accelerometer	standing, slow-walk, sit-relax, sit, normal-walk, escalator-up, escalator-down, elevator-up, elevator-down, downstairs	energy efficient continuous activity recognition	Android based smart phones	J48 adaptive decision tree classifier in the Weka toolkit	mean , magnitude, variance, covariance, energy based on FFT component, entropy based on FFT histogram	4	energy saving of 20-25%
Hynes *et al.*, 2011, **[30]**	accelerometer	walking, resting	medical diagnosis	Java ME mobile handset	average magnitude difference function based algorithm	average magnitude difference, normalized average magnitude difference	10	10% reduction in power consumption

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Reference	Sensors	Activities	Application	Platform	Classification	Features	# of Subjects	Performance Result
Dernbach *et al.*, 2012, **[21]**	accelerometer	cleaning, cooking, medication, sweeping, washing hands, watering plants, biking, climbing stairs, driving, lying, sitting, standing and walking	technology-driven assistive healthcare	Samsung Captivate	multilayer perceptron, NB, bayesian network, decision table, best-first tree and K-star	mean, min, max, standard deviation, zero-cross and correlation	10	90% accuracy for simple activities, 50% accuracy with complex actvities
Yan *et al.*, 2012, **[75]**	accelerometer	cooking, working, eating, relaxing cleaning, on a break, meeting	web log mining, mobility data mining, social network data mining	Nokia N95	Decision tree, Naive Bayes, Bayesian network, LibSVM, Adaboost	mean, variance, two-axis correlation, FFT magnitude, FFT energy and FFT entropy	5	77.14% accuracy
Siirtola *et al.*, 2012, **[72]**	accelerometer	walking, running, cycling, driving a car and idling (sitting/standing)		Nokia N8, Samsung Galaxy Mini	Decision tree with KNN and QDA	21 features (e.g. magnitude of acceleration, standard deviation, mean, minimum, maximum)	8	95.4% accuracy (offline QDA), 94.5% for KNN
Kose *et al.*, 2012, **[41, 40]**	accelerometer	walking, running, cycling, sitting, standing		Android phones	KNN, NB, Decision tree	min, max, average, variance	10	92% with KNN
Reddy *et al.*, 2010, **[67]**	accelerometer, GPS	walking, stationary, biking, running, and motorized transport	physical activity monitoring, personal impact and exposure monitoring	Nokia N95, iPhone, TMobile G1	Decision tree, KMC, NB, NN, SVM, C-HMM, DT-HMM	magnitude of 3 axis of acc., mean variance, energy, DFT energy coefficient btw 1-10 Hz, speed	16	93% accuracy
Ryder *et al.*, 2009, **[69]**	accelerometer, GPS	walking, running, stationary, biking, driving	healthcare	Android mobile phones, Nokia N95	Decision tree	variance, mean, FFT coefficients	-	-

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Reference	Sensors	Activities	Application	Platform	Classification	Features	# of Subjects	Performance Result
Martin *et al.*, 2012. **[52]**	accelerometer, magnetometer, gyroscope, proximity, light	walking at different paces (slow, normal, rush), running, sitting, standing	wellness and pathology treatment	Google Nexus S	Naive Bayes, Decision Tree, Decision Table	mean, variance, zero crossing rate, 75 percentile, interquartile, correlation btw. sensors, power spectrum, centroid, FFT energy, frequency-domain entropy, signal energy	16	88% accuracy with Decision Table
Wang *et al.*, 2009, **[74]**	accelerometer, WiFi detector, GPS, microphone	walking, vehicle, resting, home talking, home entertaining, working, meeting, office loud, place quiet, place speech, place loud	Customized applications like: Ringtone adjustment placement, Medical Applications, Personal Safety Applications	Nokia N95	Decision tree	3 characteristic features that defines each of state: location, motion, background sound (e.g. FFT, magnitude of acc. data)	10	92.56% accuracy, 75% improvement at the battery lifetime
Miluzzo *et al.*, 2008, **[54]**	accelerometer, bluetooth, audio sensors, GPS	sitting, standing, walking, running, audio info	social networking	Nokia N95	Decision tree	DFT, FFT and its feature vectors for audio; mean, std. dev. and no. of peaks per unit time deviation of DFT power	22	-

6 Open Issues and Future Research Directions

In this paper, we have provided a review of existing activity recognition systems on mobile phones. As can be seen from the date of publications in the list of references, it has become a quite hot topic in the recent years with the release of smart phones equipped with a variety set of sensors. However, there are still significant open issues, such as the recognition of composite activities rather than locomotion activities, which require further research. Moreover, the current performance results can be improved and extended. In this section, we present a list of some possible future research directions:

– ***From Locomotion Activities to Complex Activities:*** Most of the studies infer locomotion activities, such as walking, running. However, the link between these basic activities and more complex activities and the context information of the user is weak. For instance, it is rather straightforward to detect if the user is running but inferring if the user is running away from danger or jogging in a park is different [32]. Although some initial work [21,75] attempted to address this issue, recognition of more complex activities and mapping these activities to the application domains where this activity information can be useful should further be explored.
– ***Fusing Sensor Information for More Accurate Context Recognition:*** The most common sensor used in the presented studies is the acceleration sensor whereas in some of the studies GPS and microphone also accompany the accelerometer. Which sensors should be used together for which types of target applications for better context recognition should be explored. Besides the embedded sensors in the mobile platform, external sensors, such as the ones measuring physiological information attached to the user body, can also be utilized, or the ambient sensors, such as the ones deployed in smart homes for user behavior recognition [35], can be used together with the mobile phone sensors for a complete user behavior recognition.
– ***User Independent Systems:*** The data collection and labeling in the training phase of the supervised machine learning algorithms are challenging tasks and may decrease the adoption of the activity recognition systems. Hence, user independent systems with a high recognition rate should further be explored for the success of these systems. Moreover, the use of unsupervised learning techniques can also be investigated although it is a challenging task.
– ***Group Activity/Behavior Understanding:*** Most of the studies propose to recognize the activities of individuals from the sensing data. In [68], body-worn sensors were used to recognize group activities such people walking together, queuing on a line. Accelerometers on mobile phones can also used for distributed activity recognition. For instance, people running together can be identified using the acceleration and Bluetooth (for proximity detection) sensors available on the phones. This open topic should further be investigated for different application domains utilizing different sensors.

- ***Open Datasets:*** One of the fundamental difficulties in activity recognition research is the challenge of comparing the results of different proposals, since they are usually carried with different number of people, different activities, different mobile platforms. There is an urgent requirement for the collection of open datasets. Although examples of mobile datasets, such as Reality Mining [22] and Nokia-Idiap [38] datasets, exist, they do not utilize the sensors, especially the acceleration sensor, for activity recognition. Small datasets such as the CenceMe [54] also exist but they do not provide ground truth for performance analysis.
- ***Persuasion Methods:*** As we mentioned in Section 4, finding efficient ways for persuading users for a behavior change is important, especially in healthcare and wellness domains. Finding efficient methods and metaphors [24] to motivate the users is still under investigation.
- ***Phone Context Problem:*** The location and the orientation of the phone where it is carried is a fundamental challenge in mobile activity recognition. Although the phone context problem has been attempted to be solved by very recent studies [55, 59], there still remains open issues such as the phone context identification in real-time including different poses and for different activities (In [59], real-time pose recognition was only tested with the walking activity).
- ***Online Classification and Training:*** Most of the presented studies benefit from offline classification methods where the data is collected on the mobile phone but trained and classified offline on a a backend server. In order to develop real-world applications, classification of activities should be performed online on the mobile platform especially for health and wellbeing applications. Performance of the classifiers utilized in the presented papers should also be evaluated with online recognition. Moreover, in an ideal system, the training of the classifiers can continuously be improved as long as the user collects data. For instance, using active learning approaches [49], the user can be queried to label the data to improve the recognition rates.

7 Conclusion

In this paper, we provided a review of the state of the art studies in activity recognition on mobile phones, especially targeting healthcare and wellbeing applications. By providing background information on the types of sensors used, targeted activities, performance metrics and the steps of the activity recognition process, we aimed to present a general snapshot of the problem of activity recognition. We identified the fundamental challenges of activity recognition especially on the mobile platform such as the challenge of continuous sensing and running classifiers on the phones, considering the limited resources available on the phones. Following the challenges identified, we explored the recent studies on the topic and summarized the existing work with a taxonomy. According to this survey and taxonomy, we identified that most of the proposals use offline training and classification, simple activities of locomotion are usually targeted and they are usually user dependent systems. Along these lines, we presented a list of open topics for further research such as fusing information from different sensors for better context recognition, developing user independent systems to eliminate the training burden and compiling open datasets to compare the results of different proposals.

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