Defining a Roadmap Towards Comparative Research in Online Activity Recognition on Mobile Phones

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Abstract: Many context-aware applications based on activity recognition are currently using mobile phones. Most of this work is done in an offline way. However, there is a shift towards an online approach in recent studies, where activity recognition systems are implemented on mobile phones. Unfortunately, most of these studies lack proper reproducibility, resource consumption analysis, validation, position-independence, and personalization. Moreover, they are hard to compare in various aspects due to different experimental setups. In this paper, we present a short overview of the current research on online activity recognition using mobile phones, and highlight their limitations. We discuss these studies in terms of various aspects, such as their experimental setups, position-independence, resource consumption analysis, performance evaluation, and validation. Based on this analysis, we define a roadmap towards a better comparative research on online activity recognition using mobile phones.

1 INTRODUCTION

Activity recognition is being used in various research areas (Incel et al., 2013; Marin-Perianu et al., 2008). Especially, mobile phones have enabled many context-aware applications based on activity recognition, because they are equipped with various onboard sensors, such as an accelerometer, gyroscope, and GPS (Lara and Labrador, 2013). Moreover, they are used by most people in their daily life these days. Research on activity recognition using mobile phones is done mainly in two ways. The first is the *offline approach*, where the data from various mobile phone sensors is collected using data collection tools. This data is analyzed later on using machine learning tools such as WEKA (Hall et al., 2009; Shoaib et al., 2013). The second is the *online approach*, where data collection is done on a mobile phone and data analysis is done online either locally on the mobile phone (Anjum and Ilyas, 2013; Lane et al., 2011) or on a remote server in real time (Gil et al., 2011; Lau et al., 2010).

Most of this research has been done in an offline way (Incel et al., 2013; Shoaib et al., 2014). However, for the practical usability of such activity recognition systems, it is important to evaluate them online on mobile phones, which is a challenging task. In the current research, we see a shift towards an online approach. There are ample surveys which discuss studies using the offline approach (Lara and Labrador, 2013; Incel et al., 2013; Liang et al., 2013). However, studies using the online approach are yet to be surveyed or analyzed. Moreover, to be able to evaluate and analyze online activity recognition methods, research should be aligned in terms of defining test setups, metrics, and platforms. In this work, we fill this gap by presenting a short overview of the current research on online activity recognition on mobile phones, and highlighting its limitations. We discuss various aspects of these studies, such as their experimental setups, position-independence, performance evaluation, resource consumption analysis, and validation. Unfortunately, most of the studies using an online approach lack important aspects, such as reproducibility, proper validation, personalization, classifiers' comparison, and resource consumption analysis. Based on our analysis, we present a roadmap with various recommendations for future studies on online activity recognition. We believe this work will help in a better comparative research in this area.

The rest of the paper is organized as follows. In Section 2, we describe various aspects online activity recognition studies using mobile phones. In Section 3, we present a roadmap for future studies. Finally, we conclude this paper in Section 4.

2 ONLINE ACTIVITY RECOGNITION STUDIES

Online physical activity recognition can be implemented in two main ways on mobile phones. In first case, the main steps in the activity recognition process are performed locally on a mobile device, which is termed as *local recognition*. The main advantage of this approach is that no internet connection is required. For example, this type approach is adapted in (Anjum and Ilyas, 2013; Lane et al., 2011). In the second case, these steps are either fully or partially done on a remote server or in a cloud, which is termed as *remote recognition*. This method may result in less processing burden on the mobile device, however,it will require an internet connection at all times. This type of approach is adapted in (Gil et al., 2011; Lau et al., 2010).

We target only mobile phones as the main entity in the activity recognition process. Therefore, we only consider the studies utilizing strictly local recognition in this paper. Moreover, we also considered the following criteria in selecting these studies:

- They use only mobile phone sensors, where motion sensors are used in a lead role in the recognition process with other on-board sensors in the supporting role. We do not consider video-based activity recognition.

- They are able to recognize different physical activities.

We found 29 publications based on these selection criteria (Anjum and Ilyas, 2013; Berchtold et al., 2010; Das et al., 2012; Das et al., 2010; Frank et al., 2011; Gomes et al., 2012; Guiry et al., 2012; Khan et al., 2013; Khan et al., 2014; Kim et al., 2013; Kose, Mustafa et al., 2012; Lane et al., 2011; Lara and Labrador, 2012; Liang et al., 2012; Lu et al., 2010; Martin et al., 2013; Miluzzo et al., 2008; Ouchi and Doi, 2012; Reddy et al., 2010; Ryder et al., 2009; Schindhelm, 2012; Siirtola and Roning, 2013; Siirtola, 2012; Stewart et al., 2012; Thiemjarus et al., 2013; Vo et al., 2013; Wang et al., 2009; Yan et al., 2012; Zhao et al., 2013). In terms of time line, they range from 2008 to 2014. We analyze these studies in various aspects which are listed as follows: training and classification, experimental setups, position-independence, resource consumption analysis, performance evaluation, and validation.

2.1 Training and Classification

Classification is the core part of the activity recognition process. A classification step typically involves

two steps: training and testing (classifying new activities based on the training). In the analyzed 29 studies, various classifiers are implemented. They are presented in Figure 1 in relation to how many studies implemented each of the mentioned classifiers in the figure. Based on this figure, decision tree, support vector machines, naive bayes, and KNN are the most commonly implemented classifiers. Decision tree is implemented in 11 studies because it is a light-weight classifier, which make it suitable for running on mobile phones.

These classifiers can be trained in two ways: online or offline. Most of these studies have trained their classifiers offline, which makes them static, and they cannot be trained in real-time for new activities. Moreover, these classifiers cannot be dynamically personalized for individual users. This causes a lack of personalization in such solutions. We found that only 17% of all the studies have the capability to train their classifiers online on the mobile phones as shown in Figure 2. Online training is an important feature, as it gives the users the flexibility to train the systems as per their needs in real time, which will lead to better personalization in such solutions. However, 83% of the studies are still missing the online training capability. There is only one study (Berchtold et al., 2010) in this category that uses online training, but it does so on a remote server and not locally on the mobile phone.
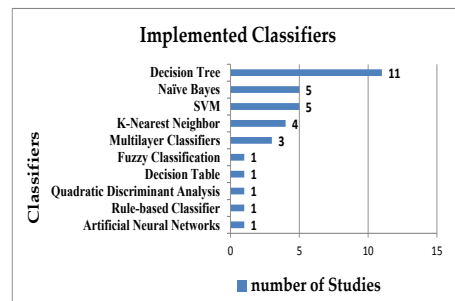

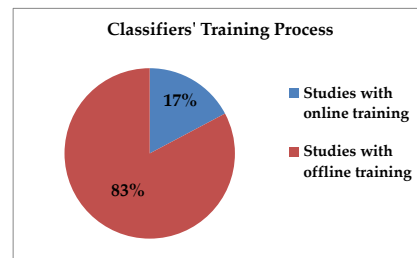Figure 1: Number of studies vs implemented classifiers.

Figure 2: Offline vs Online training process.

2.2 Experimental Setup

There are four common operating system platforms used for developing activity recognition solutions in the analyzed studies. These are: Android, iOS, Symbian, and Debian Linux. Most of these studies use Android. Initially, Symbian was used in a few studies, but recently the focus is more on Android because it is the popular operating system among users these days. For example, we found Symbian in almost all studies in between 2008 and 2010, but from 2011 and onwards, Android gained popularity. The distribution of these platforms among all 29 studies is given in Figure 3.

These studies use different sensors for activity recognition, either alone or in various combinations. Usually different sensors are combined for better activity recognition. A large portion of these studies use only the accelerometer. However, in some cases, it is used in combination with other sensors such as GPS, gyroscope, microphone, magnetometer, and pressure sensor. The accelerometer is used alone in 76% of the analyzed studies and its combination with other sensors counts for 24% of the analyzed studies.
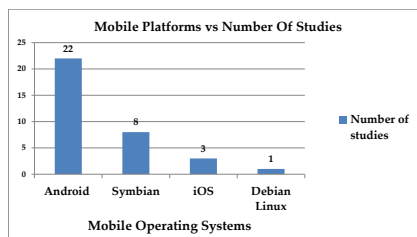

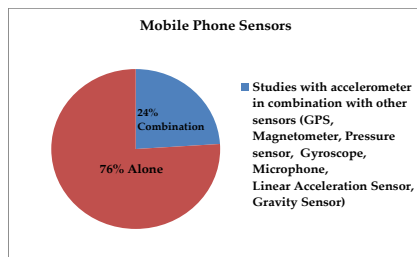Figure 3: Platforms used for activity recognition systems.

Figure 4: Sensors used in activity recognition systems.

2.3 Position-independence

In most of the existing studies, when data is collected for physical activity recognition, the mobile device is kept on a fixed body position. Therefore, the trained classifier will only work well for that specific position and can produce poor results if used with other positions. This is because some sensors like accelerometer and gyroscope are position-sensitive. There are

three ways to counter this problem (Thiemjarus et al., 2013). First way is to use position-insensitive data features. The second solution is to train classifiers for all possible positions and then dynamically detect the position first before classifying an activity. This is called a position-aware classifier. In the third way, various signal transformations are used to minimize the effects of changing positions. Solutions that use a fixed position, such as a pants pocket, may not be practical. Users cannot be forced to always keep the mobile device in a specific position. It is still a challenging problem to have a completely position-independent solution while using position-sensitive sensors like accelerometer and gyroscope. However, there are some studies which have tried to solve this problem to some extent. We highlight these studies in Figure 5. There were some studies where there was no information available about the position. We believe these studies assume a fixed position, because position-independence is an important contribution and should have been mentioned explicitly in these studies if considered. Figure 5 shows that only 34% of the studies considered the position-independence property, therefore future studies should consider this feature for a practical and user-friendly activity recognition system. It is important to note that orientation-independence is also an important aspect for activity recognition but we do not consider it in this study.
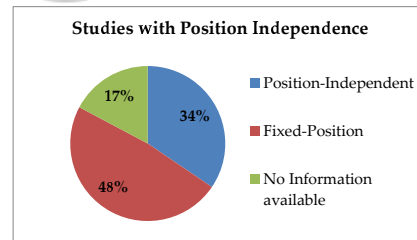

Figure 5: Studies with the position-independence.

2.4 Validation

To validate various aspects of a physical activity recognition system, it should be tested with a reasonable duration and with a reasonable number of users. These aspects can be memory, CPU, and battery usage and its tradeoff with recognition performance, such as accuracy. The reasonable duration of the testing and the number of users can vary in different applications and should be decided by the researchers accordingly. We evaluated all 29 studies in terms of the duration of the testing and the number of users involved. It is clear from Figure 6 that 18 studies are missing the testing duration information, out of which 9 studies have no information on how many users were involved in the testing process. For the
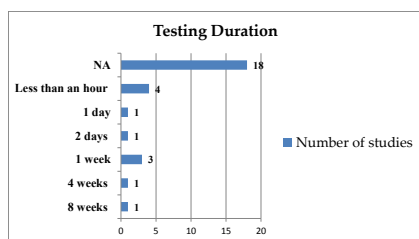
Figure 6: Testing duration for implemented systems.

rest of the studies the number of users ranges from 1 to 21. The lack of proper validation in these could be caused by the fact that many of them are still a work in progress.

2.5 Resource Consumption Analysis

One of the important aspects of evaluating online activity recognition systems is to measure the resource consumption beside the recognition performance, because it enables us to compare different systems in a fair way. We found three resources which were evaluated in general in these studies. These are: memory, CPU and battery usage, and they are measured in MBs (memory), usage percentage (CPU), and number of hours or watt-hour per hour (battery). The battery, memory, and CPU usage is measured in 38%, 21%, and 31% of all the studies, respectively.

Battery consumption is an important criterion for the feasibility of activity recognition solutions using mobile phones. It is still a challenge to propose energy-efficient solutions which do not drain the mobile phone's battery quickly. Some of these studies (Guiry et al., 2012; Lane et al., 2011; Liang et al., 2012) use the number of hours for which the battery lasts while running the activity recognition application as a resource consumption metric. This can be misleading because of the different battery capacities in various mobile phones as well as how old these batteries are. A relatively better metric can be the watt-hour per hour which shows the amount of watt-hours used by the activity recognition application in specific time duration. This metric has been used in some of the studies (Miluzzo et al., 2008). However, this is also not platform-independent, because the efficiency of the hardware such as CPU and the operating system is also an important factor for the battery life. These factors can vary wildly in various phones. There is a still need for a metric which can be used across multiple platforms like Android, iOS and Symbian. These aspects need further research.

2.6 Performance Evaluation

Most of these studies use classification accuracy as a performance metric for evaluation. Various physical activities were used for evaluating the classification performance of different classifiers. The most commonly used activities are: walking, running, walking upstairs and downstairs, sitting, standing, and biking. We do not present the accuracy values in this paper for comparative analysis, because it is hard to compare them due to different experimental setups. For example, these studies use different sensor combinations, classifiers, data features, sampling rates for data collection, and sets of physical activities.

3 ROADMAP FOR FUTURE STUDIES

There has been significant progress in the shift from the offline towards the online approach. This work is still in its infancy and further research needs to be done to explore this area in detail. Moreover, it is hard to compare various studies because of their different experimental setups and validation methods. We present the following recommendations which need to be taken into account while conducting future studies on online activity recognition.

Reproducibly: For reproducibility, it is necessary that important details should be clearly presented in the paper. For example, some information were missing in some of the reviewed studies such as the sampling rate , the position-independence property, and validation details. There were five studies (Frank et al., 2011; Gomes et al., 2012; Lane et al., 2011; Miluzzo et al., 2008; Wang et al., 2009), where we did not find information about the sampling rate for sensor data collection.

Proper Validation. These systems should be properly validated with a reasonable number of users and for a reasonable amount of time. This reasonable value can be defined in the context of each specific study and is to be explored.

Resource Consumption Analysis. For a fair comparison of various classifiers, a tradeoff between the recognition results and the resources consumed in that process are both important. That is why resources consumption analysis should be considered in future studies. Moreover, there is a need for a platform- and device-independent performance metric to the resources consumed by such systems, especially for battery consumption.

Personalization. To make a step towards personalization, providing online training support should be

considered in the future studies, because it is important for its practical usability. Online training support was missing in 85% of the reviewed studies, which means future studies should concentrate on this aspect besides online testing.

Position-independence. More efforts should be done towards activity recognition systems that are not dependent on a specific body position, thereby giving users more freedom. Moreover, it should be explicitly mentioned if this feature was considered or not for clarity unlike some of the existing studies.

Comparing Classifiers. Most of the existing studies implement one or two classifiers with a specific experimental setup. This makes it hard to compare multiple classifiers because of the different experimental setups and validation methods. There is a need for studies where multiple classifiers are validated in the same experimental environments to have a fair comparison about their performance results and resource consumption. Such type of studies can play a role in defining a benchmark for future online activity recognition research.

4 CONCLUSIONS

We reviewed the current research on online activity recognition using mobile devices which only uses on-board sensors and do local processing. Though there has been a significant amount of progress done in this direction, there is still room for improvements. We discussed various aspects of the existing studies such as experimental setups, resource consumption, and validation. We presented an overview of the current research, and a roadmap for future studies with various recommendations. In future, we intend to explore these aspects further in depth.

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