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Accepted version

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4th IEEE International Workshop on Sensors and Smart Cities (SSC 2018), Taormina, Sicily, 2018 June 18

Towards a Smart Campus through Participatory Sensing

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***Abstract*—In recent years, the percentage of the population owning a smartphone has increased significantly. These devices provide users with more and more functions that make them real sensing platforms. Exploiting the capabilities offered by smartphones, users can collect data from the surrounding environment and share them with other entities in the network thanks to existing communication infrastructures, i.e., 3G/4G/5G or WiFi. In this work, we present a system based on participatory sensing paradigm using smartphones to collect and share local data in order to monitor make a campus "smart". In particular, our system infers the activities performed by users (e.g., students) in a campus in order to identify trends and behavioral patterns. This information allows the system to decide in real-time which actions are needed to provide the best possible services to users, according to their needs and preferences. Experimental results underline the benefits that the system might bring in a smart campus.**

I. Introduction

Nowadays, the growth of smartphone usage in everyday life seems unstoppable. The pervasiveness of smartphones has completely changed people's lives, as only few other technologies had been able to do in the past.

Today's smartphones come equipped with a multitude of heterogeneous sensors, such as accelerometer, gyroscope, digital compass, GPS, camera, temperature and humidity sensors, heart rate monitor, and microphone. The combined use of data from all these sensors, by applying a variety of data fusion techniques [1], has allowed the emergence of new applications in a lot of different domains, such as healthcare [2], security, social networks [3], environmental monitoring [4], and traffic analysis for intelligent transport systems [5].

Besides, the impressive mass of smartphones, with computational capabilities comparable to those of many PCs, makes it possible to collect and analyze huge amounts of data without requiring the installation of thousands of expensive fixed sensors. This is even more important in the context of smart cities, as the extensive area of interest makes it impossible to exploit only fixed sensors; conversely, the myriad of information that can be collected from mobile devices becomes absolutely essential, paving the way for new types of applications that would not otherwise be possible.

Unfortunately, in many cases, the use of sensor data alone is not sufficient to achieve the desired results, since the events of interest might be too complex to detect. For this reason, the direct participation of users may be desired or even required, as they can enrich the information collected from smartphones and other mobile devices with totally different and complementary information.

With the emergence of the participatory sensing paradigm [6], it is now possible to use humans *as sensors* [7], exploiting their unique abilities to devise sensing applications that monitor the occurrence of complex events, which are difficult to detect with traditional sensing paradigms.

Given the central role of people in the sensing process, the success of participatory sensing systems largely depends on the reliability of the data sent by users. As humans may exhibit selfish and unreliable behavior [8], especially when they can gain benefits from cheating the system, accurately classifying the reliability of user reports and feedback is paramount.

In this regard, various incentive systems for users have been proposed, using mainly game theory and auction theory techniques. The main idea is to reward users for their participation, hoping to improve it both quantitatively and qualitatively. In addition to the obvious possibility of monetary remuneration through micro-payments, various gamification techniques have also been proposed and successfully implemented. Gamification involves using game mechanics such as leaderboards, levels and scoring systems to encourage users to perform certain activities. The most famous example of participatory sensing app that has successfully chosen this approach is Waze, which uses several gamification elements, such as rankings and scores, to encourage its users to send information about traffic and road accidents.

Moreover, an implicit incentive for user participation is the constant improvement of the services offered, exploiting the information sent by users themselves.

Inferring information about the context and activities carried out by users (Human Activity Recognition, HAR) is the basis of many participatory sensing applications. Simply put, inferring the user's activity is a machine learning problem. The first step is the learning phase, which involves collecting preliminary data, from sensors inside smartphones, correctly labeled according to the categories of interest (e.g., possible user activities). The second step consists in identifying features of interest in the training set, which can uniquely identify each category. Finally, the last step is the choice of an appropriate classification algorithm that is able to achieve a high classification accuracy in the case under examination.

In this paper, we propose a participatory sensing system within the context of a smart campus. The system collects data from sensors in smartphones, smart watches and other wearable devices of users, and merges them to infer the activity performed at that time, such as walking, running, biking, car driving, etc. User activity, combined with contextual information such as time and GPS position, allows the smart campus intelligent system to analyze the flow of people currently on campus, and to identify trends and behavioral patterns on many factors of primary interest.

This information may be used to modify and improve the quality of services offered to students, such as shuttles or security services. In addition, the system also seeks to positively change user behavior by encouraging them to use sustainable modes of transport (e.g., bikes or public transport instead of private cars), with incentives exploiting state-of-the-art gamification techniques.

The remainder of the paper is organized as follows: related work is outlined in Section II. Section III introduces our proposed scenario of a participatory sensing application in a smart campus, and the system architecture is described in Section IV. The experimental results are shown and discussed in Section V. Conclusions follow in Section VI.

II. Related work

Over time, many new research challenges have emerged in the promising field of participatory sensing [9]. In this section, we discuss several emerging application domains in which this paradigm is adopted to offer advanced services to users, making everyday life easier. Data sent by participants must be protected by appropriate encryption techniques, and the highest possible level of privacy must always be guaranteed, especially when the data collected is sensitive, such as health and location information [10]. This is not always easy, because system functionality and privacy generally conflict, and trade-offs are often necessary.

A common scenario addressed by participatory sensing is the personal health care, in which a smart device embedded sensors, collecting data in continuous way, can monitor stress-level, hearth beat, etc. An example of such application is presented in [11]. There, authors describe a system called UbiFit Garden in which smart devices are used to capture and share the levels of physical activities in order to encourage users to perform more exercise during the day.

Other common scenarios concern the use of participatory sensing in smart environments, so as to use information coming from heterogeneous sensors to offer users a variety of services [12]. To achieve such high level goals, these systems need a precise understanding of the state of the surrounding environment. Traditionally, this requires the deployment of costly sensing and tracking infrastructure. Participatory sensing overcomes this limitation by enabling crowd data collection via mobile devices, e.g., smartphones, smartwatches and tablets.

Haze Watch [13] is a system that measures the concentration of elements dangerous to humans in the air, i.e., carbon monoxide, ozone, sulphur dioxide and nitrogen dioxide. The system is based on mobile phones that, interfaced with geo-referenced sensors capable of measuring air quality, enable traditional weather stations to collect information about unpredictable events (e.g., accidental pollution).

Another typical scenario for a smart environment involves using mobile devices to monitor road and traffic conditions. In [14], the authors describe a system called Nericell using accelerometer, microphone and positioning mechanism (GPS or GSM radio) to know both if a road is trafficked or not and localize problems concerning the road conditions, for example potholes. Thanks to the participatory sensing paradigm, the application is able to provide users with a real-time service that is continuously updated.

Other works in literature use the participatory sensing paradigm in application scenarios dealing with Human Activity Recognition (HAR). For example in [15], the authors describe a system based on a client-server architecture that, using embedded sensors in smartphones, is able to discriminate four different activities, i.e., still, walking, running and vehicle. In addition, the system is able to automatically update its classification models through participatory sensing as clients send both sensory data and feedback on recognized activity to the server. MoST [16], [17] is a framework that allows to discriminate between three different activities (i.e., walking, running and standing still), and also provides programmers with an Android library that implements some algorithms of classification and geofencing.

In [18], the authors propose a framework based on the XMPP protocol that uses the participatory sensing paradigm to provide a variety of services to the end customer. The article describes three application scenarios for a smart environment in which the system can be exploited. Among these, the scenario of a smart campus is of interest, since the data collected by students are exploited to improve the services offered by the campus, like suggesting a practical order of activities to be carried out. However, the work described in [18] relies primarily on data originating from social networks.

In contrast, our system merges data from heterogeneous sensors such as accelerometer, gyroscope, as well as context information to accurately infer user activity on campus and surrounding areas. This allows our system to reason on much finer-grained data and consequently to offer better services tailored to users' preferences.

III. Application scenario

In order to demonstrate the feasibility and capabilities of the proposed system, the smart campus of the University of Palermo has been chosen as case study. A university campus is a great place to test participatory sensing applications, since there are thousands of students who perform various daily activities within it, such as attending classes, having lunch, using sports facilities, studying in the library, etc.

Populated by young *digital natives*, who are accustomed to using a wide range of technological devices on a daily basis, the smart campus of the University of Palermo is well representative of a small-sized smart city, as it enrolls

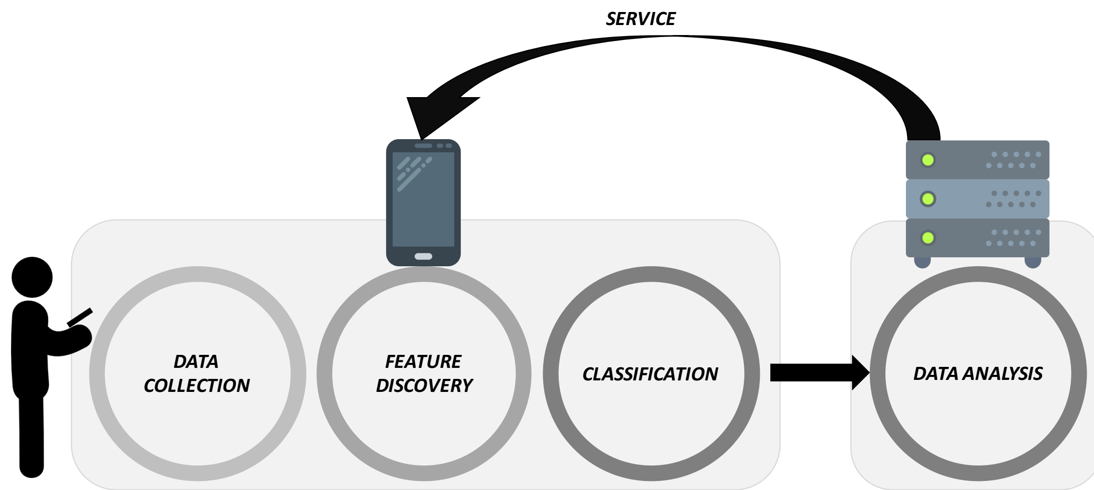

Fig. 1. Proposed system architecture.

more than 40,000 students. In this scenario, advanced services to support users are needed. For instance, students may be interested in real-time information about the campus' internal transport system, as well as in knowing whether the university cafeteria is crowded or whether seats are available in a student lounge or in the library.

A participatory sensing application can leverage information gathered from user devices to provide a constantly updated report of the services offered on campus, enriched with information about the most crowded study sites or the real-time location of shuttle buses. This will allow students to make informed decisions about the timing and methods of their campus movements, as well as better planning their extracurricular activities.

The large number of students and employees of the university, who move daily from one part of the city to another, from and to the campus, has clear consequences on the viability of the entire area surrounding it.

By analyzing the continuous data stream sent by participants, it will be possible to identify patterns in the overall behavior of the student population, accurately understand their habits and exploit this valuable information to constantly improve the services offered.

For example, the system may suggest that administrators change the times or frequency of the campus shuttle buses to suit the expected influx of students during a certain peak time. All this could be done in real-time and on the basis of collected data grouped by day of the week, period of year and time of day. In addition, if the system discovers that some isolated areas of the campus are frequented by people jogging, the patrols of the campus' internal security system may be modified accordingly to ensure their safety. Also, if on certain days of the week some sports facilities are typically left unused after a certain time, the opening and closing times can be optimized.

Meanwhile, the system seeks to positively change the habits of users by encouraging the adoption of more sustainable means of transport, such as walking, running and biking instead of using private cars. To do this, the system suggests that students use alternative means of transport when the data collected indicate that there will be an excessive peak in vehicle traffic, for example.

Users could also be encouraged to use sustainable means of transport by introducing a leaderboard and various score thresholds that allow them to earn levels and trophies, according to gamification techniques successfully used by many commercial applications of participatory sensing, such as Waze or Ingress.

IV. Proposed System

In this paper, we propose a system adopting the participatory sensing paradigm. We describe a client-server architecture in which the client aims to collect sensory data, extract feature vectors and share such information with the server that will analyze them to infer user current physical activity and offer several services to students. In particular, the system is divided in four main modules.

The first aims to collect the raw data from on-board sensors of client devices. In particular, 3D values provided by the accelerometer (X_A, Y_A, Z_A) and by the gyroscope (X_G, Y_G, Z_G) are considered. Data collection has been implemented using the MoST open-source library and runs on users' smartphones. Differently from other works proposed in literature [19], our system does not take into account the gravity acceleration, allowing the user for holding the smartphone in the pocket pants without worrying about its orientation.

The second module aims to process raw data to extract feature vectors that will be used as input to the classifier. The entire feature discovery process consists of collecting accelerometer and gyroscope values within fixed-length time windows, and extracting a compact feature vector fv containing *maximum*, *minimum*, *mean*, *standard deviation*, and *root mean square* values over the three accelerometer and

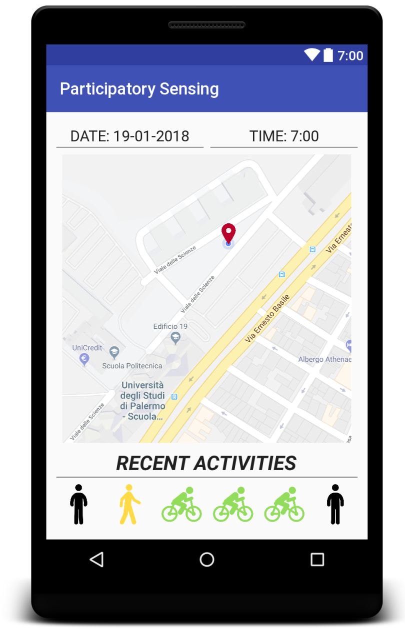

Fig. 2. The Android app used for collecting sensory data and recognizing user activities.

gyroscope axes. According to this representation, each feature vector fv contains 30 elements, i.e., 15 values of acceleration and 15 values of angular velocity.

One of most important aspects of this phase is to choose the proper length for the acquisition window. On one hand, long time windows could provide a better description of the performed activity but could negatively influence the system performances in terms of CPU load and execution time. On the other hand, short windows may improve the performance of the whole system but might not provide sufficient information to correctly classify an activity. Consequently, we have chosen a sampling window of 3 seconds, as discussed in our previous work [15].

The entire classification process is performed on the client and is based on K-nearest neighbours algorithm (K-NN), which classifies a new element according to the similarity with its K neighbors, where K is a small positive integer. Thus, given a training set of labeled feature vectors, an unknown feature fv_{unk} is assigned to a particular class C if the number of K instances closest to fv_{unk} is greater than the other classes. A key factor in a successful implementation of the algorithm is the choice of K; thus, K is generally an odd value to avoid the system ending up in a stalemate.

Finally, locally collected data are shared with the server that will analyze them to identify patterns in user behavior so as to improve the services that the campus provides.

V. Experimental Evaluation

In order to evaluate the effectiveness of our system, we carried out an extensive experimental evaluation.

The experiments were carried out using different smartphone models, equipped with accelerometer and gyroscope.

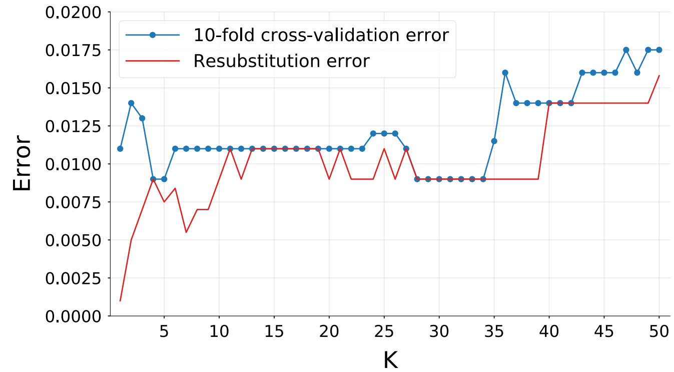

Fig. 3. Error rate obtained with 10-fold cross validation and resubstitution with K ranging from 1 to 50.

The application can be installed on any Android device with Ice Cream Sandwitch OS or later. In particular, we tested the system in several smartphones, such as Samsung Galaxy Note, Samsung S4, Samsung S5 Neo, and Samsung S7. Figure 2 shows a screenshot of the Android app used to collect the sensory data needed to classify the activities carried out by participants. In particular, the app interface provides the user with a history of the most recent activities recognized by the system, as well as context information such as date, time and GPS position.

Assessing the accuracy of the classification algorithm is fundamental to understand the performance of the entire system. Considering the smart campus application scenario, we identified five main activities that our system needs to recognize, namely *standing still*, *walking*, *running*, *being in a vehicle* and *biking*.

The first set of experiments presented here aims to identify the K value to be used for the implementation of the K-NN algorithm. To assess the system performances while considering different values of K, we examined the *Re-Substitution* and *Cross Validation* error rates.

Figure 3 shows the results of the experiments, with K ranging from 1 to 50. Considering that the classification algorithm is executed on devices with limited computational and energy resources, we have not considered higher values of K, since the computational complexity of the K-NN algorithm increases as K grows. Figure 3 shows that a value of K equal to 7 allows the system to achieve an accuracy that is appropriate for our application. Obviously, this is a trade-off between accuracy and computational resources. Such trade-off can be evaluated differently depending on the particular application scenario, giving for example higher priority to energy saving or application responsiveness.

Having identified the K value, we proceeded to analyze the performance of the classification module in terms of accuracy, precision and recall.

To underline the importance of merging data coming from heterogeneous sensors, we performed different tests by using only acceleration values and data obtained from both accelerometer and gyroscope.

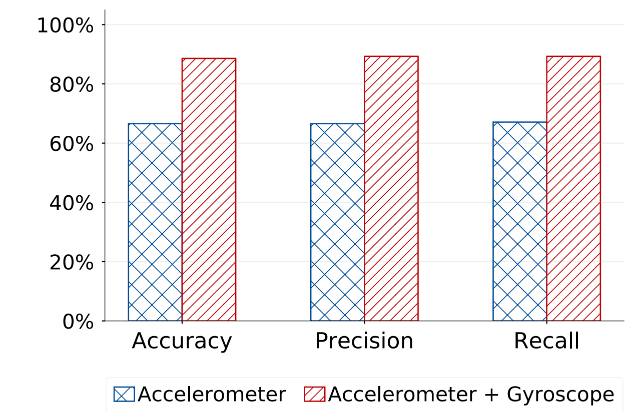

Fig. 4. Accuracy, precision, and recall obtained by exploiting only accelerometer data, or both accelerometer and gyroscope data.

Figure 4 shows accuracy, precision, and recall obtained by both systems. As expected, results confirm that gyroscope data are extremely important.

In fact, exploiting only accelerometer data yielded an accuracy of 66.6%, compared to 88.6% obtained by fusing data from both sensors. Therefore, the experimental evidence concludes that it is extremely advantageous to exploit data coming from the gyroscope, in addition to those of the accelerometer.

To better understand the reasons for this marked difference, as well as to analyze more deeply the results obtained, in Figure 5 and 6 we present the confusion matrices obtained by the two systems. In particular, each C_{ij} cell represents the number of occurrences in class i that have been classified by the system as belonging to class j. Darker cells correspond to higher values, up to a maximum of 1. Therefore, main diagonal values correspond to true positives, and values outside the diagonal indicate classification errors. Ideally, we would like to get a very dark main diagonal, and lighter values in the other cells, which would indicate a low degree of confusion between activities.

Figure 5 shows that the system exploiting only accelerometer data has difficulty in correctly classifying the activities of *standing still* and *being in a vehicle*. Also, even *running* and *biking* are often confused with each other.

These difficulties can be easily explained by the fact that data come from only one type of sensor, which cannot unambiguously describe the patterns of some activities. In fact, using only the accelerometer it is difficult to distinguish between a person who is simply stationary or stationary in a vehicle. Similarly, the accelerometer data of those running or biking may be similar.

As expected, adding gyroscope data overcomes the problem. The confusion matrix in Figure 6 has a very marked main diagonal, which shows how the system is able to recognize all activities satisfactorily, without confusing them with each other.

Finally, since Android smartphones are devices with limited resources, further studies have been carried out to evaluate the resource consumption of K-NN algorithm in terms of processing time and memory load, as the data collection window changed. Results show that, as the length of the data collection window increases, the memory load obtained using the K-NN algorithm is almost constant, whilst the processing time grows linearly. These results are very encouraging, since memory load is a critical factor that could drastically reduce performances of smart devices, negatively influencing the user experience.

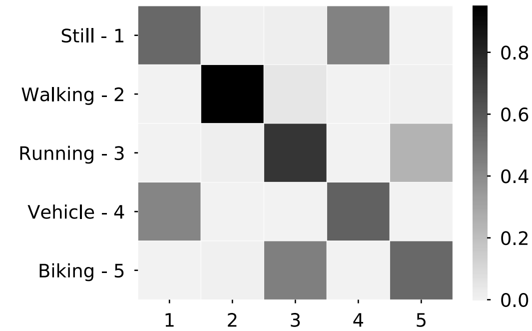

Fig. 5. Confusion matrix obtained by considering only accelerometer sensor data.

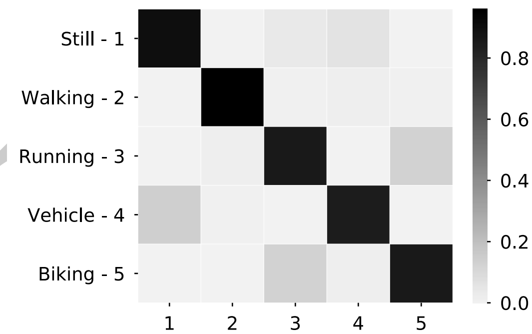

Fig. 6. Confusion matrix obtained by considering both accelerometer and gyroscope sensor data.

VI. Conclusion

In this article, we described a system that exploits the paradigm of participatory sensing aiming to improve services provided to students on the university campus.

The main element of the proposed architecture is the activity classification module. Indeed, if the recognized activity is uncertain or inaccurate the system could provide meaningless services to campus students. The process of recognizing human activities is based on the analysis of sensory data collected from the accelerometer and gyroscope. In particular, the system extracts from fixed length time windows the features of *standing still*, *walking*, *running*, *being in a vehicle* and *biking* activities and sends them as input to K-NN to recognize the activity performed by the user. Experimental results showed the effectiveness of our implementation both in terms of efficiency and accuracy, precision and recall metrics.

As future work, we want to improve the mechanism of sharing local data by users as there may be users who intentionally send incorrect data to create a disservice. To this aim, techniques of reputation management could be investigated and adopted.

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