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A Mobile Sensing and Visualization Platform for Environmental Data

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Abstract

The ubiquity of mobile technology has opened the door to the new era of mobile sensing. Through this new paradigm, physical phenomena can be observed in a distributed way, crowd-sourcing the data measurement tasks to smartphones and/or other popular smart wearables. Mobile sensing and wireless communications can hence be employed to gather data and generate new information and services, benefiting our society. As a proof-of-concept, we have developed a mobile sensing platform able to pervasively collect environmental data. To improve the quality of collected data we have also created an application for pedestrian navigation that works both on smartphones (also using Augmented Reality) and on smartwatches, thus ensuring an appropriate exposition of the mobile device (and its sensors) when collecting data. Furthermore, our navigation app is able to provide users with personalized pedestrian routes that take into account environmental parameters and not only the route length. Finally, we have also devised a web service able to provide graphical visualization and historical evolution of sensed data.

Keywords: Mobile Sensing, Environmental Data, Pedestrian Navigation, AR

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1. Introduction

In recent years the dominant theme in the telecommunications market has been the ability to ubiquitously connect users and devices. Network access has become a commodity thanks to the exponentially growing popularity of mobile devices and the mobile technology has become more and more pervasive, with sensors that can be used to continuously monitor information about the environment, e.g., brightness, noise, GPS position, accessibility, pollution, etc., or the user, e.g., physical activity, stress condition, etc. [1, 2, 3, 4]. All these data can then be exploited to generate new content and services that could help prevent unnecessary exposures to risks.

The expansion of this scenario is changing the contents of the Web itself. Devices such as smartphones, tablets and smartwatches are endowed with a large number of sensors that allow applications to capture distributed information regarding locations visited by the users. Device sensors can be exploited transparently to the user and, also for this reason, it is possible to collect a huge amount of data through them. This new type of Web is based on services generated thanks to the incredible amount of information autonomously gathered by sensors and, for this reason, Tim O'Reilly suggested the name *Web Squared* (or Web^2) [5, 6].

This data collection capability has opened the door to many interesting scenarios (often referred to with the term Big Data [7, 8]), which embody specific technical challenges. In this context we aim at developing a platform able to collect environmental data (e.g., brightness and noise) through the sensors within our smartphones and smartwatches. These data are then processed to determine the level of sun and noise exposure on the streets in different parts of the day and periods of the year.

This information can be used both for health and leisure purposes, as well as for improving city planning. One possibility could be, for instance, to consider light and noise during the process of route calculation. To reach a certain destination, the user will then be allowed to choose among types of path, from the fastest one to the less noisy one, or even those less/more exposed to the sun.

To improve the quality of the acquired data, we must ensure that the user holds the data-collecting device in hand while the application is running; indeed, brightness and noise data collected with the smartphone in one's pocket or purse would not otherwise be truthful representatives of the context. To this end, we have designed an appealing mobile application running while users are wandering around the city. In essence, we have developed a navigation application that works both on smartphones and smartwatches. If the smartphone is used, while walking toward a certain destination, the user has to hold the device in her/his hands, looking at the streets through the camera/screen of the device as the application exploits Augmented Reality (AR) to improve the interaction with the user. Virtual elements (e.g., 3D objects such as directional arrows) are generated and appropriately overlaid on the screen to indicate the path. As it is clear, having the need to look at the smartphone's display to view 3D objects while navigating toward the target, the user is led to hold the device in the best setting for collecting truthful environmental data. When the smartwatch is used to run the navigation app, the device is already exposed to the environment as it is placed on the wrist of the user who is following its indications. As anticipated, the navigation app does not only provide the classic shortest path; rather, it can also suggest alternative routes that take into consideration the preference of the users in terms of environmental parameters.

Finally, sensed data can be consulted on a dedicated Web service developed to this aim, allowing users to generate charts showing geo-referenced data as heatmaps or as chronological evolution. In summary, the main contribution of this paper is the development of a mobile based sensing system able to pervasively collect environmental data. For completeness and to improve its effectiveness, the system also includes (i) a pedestrian navigation app for smartphones and smartwatches (with AR used in the former case) that ensures that the device is in the user's hand when collecting data, (ii) the ability to use crowd-sensed data to provide each user with personalized routes and (iii) a Web service generating a graphical representation of average values and historical trends of sensed data.

Clearly, we consider smartphones and smartwatches to collect brightness/noise data as a proof-of-concept of the fact that different mobile devices could be employed and that heterogeneous environmental data could be collected (e.g., pollen and pollution [9]). The rest of this paper is organized as follows: in Section 2 we summarize the related work while in Section 3 we provide a general overview of the proposed mobile sensing platform and of its architecture. The pedestrian navigation application and the Web visualization of collected data are discussed in Section 4 and in Section 5, respectively. Finally, in Section 6 conclusions are drawn.

2. Related Work

In recent years, the widespread coverage of mobile sensing technology and the ubiquitous connectivity have boosted the data acquisition capabilities regarding our cities and, in general, the environment around us. The pervasiveness of the crowd-sensing paradigm has been greatly improved thanks to the research effort and the increasing popularity of mobile devices [10, 11, 12]. Indeed, a lot of research effort has been devoted studying different aspects, ranging from algorithms and techniques proposed to measure specific environmental properties to system architectures and communication paradigms [13, 14, 15, 16, 17].

In particular, Kanhere in 2011 discussed future directions for research on data acquisition using smartphones in urban environments [18]. Several examples are mentioned in the paper, many of which are now part of our everyday lives, such as, for instance, the use of GPS sensors to generate a real-time map of traffic jams in cities.

Agapie *et al.* describe an application that detect the users' exposure to pollution relying on a mobile app [19]. A microblogging service is discussed in [20]; its functionalities include the use of mobile devices to record related contents and share them in real-time. Similar, PRISM is a framework that supports the participatory data acquisition of environmental data using off-theshelf mobile devices [21]. Beside the mobile app that automatically collects environmental data, this solution also includes orchestration capabilities used to manage and coordinate the mobile nodes collaborating in the data acquisition process. Indeed, other works proposed to use a mobile sensing paradigm as a promising solution rather than fixed monitoring stations [9, 22].

The authors of [23] propose a framework for data acquisition using smartphones and specialized sensors. In particular, they show how low cost sensors could be used to acquire temperature and humidity values and then forward them through Bluetooth connectivity to a smartphone. Through this solution, it is possible to monitor a room or other environments and be promptly alerted in case of specific unhealthy conditions.

Several works have been focused on using distributed sensors to enrich online maps with information useful for people with disabilities. For instance, through GPS, regular routes used by people with a certain disability can be stored to create a database of road segments that can be inferred to be accessible [3]; even traffic lights can be tagged as endowed with audible signals (for blind citizens) [24]. Similar, mPASS is a system that exploits crowd-sensing to obtain a geo-referenced descriptions of the urban environment regarding accessibility. This information is later on exploited to provide citizens with personalized accessible way finding [25, 26].

Another interesting paper related to our work explores the challenges faced when developing Augmented Reality (AR) applications for smartphones [27]. The authors investigate and tackle three main problems: (i) data acquisition, i.e., the management of raw data gathered by sensors, (ii) the implementation of the *magic lens* creating the AR overlay superimposed on the environment and (iii) the Points of Interest (PoIs) fetching from a server.

In this context, the main objective and contribution of our work is to provide a holistic solution including both a mobile device application for pedestrian navigation that, when in use, allows the collection of trustworthy data and a Web service that uses gathered environmental data to provide geographic heatmaps and historical progression of sensed data. Starting from this framework and data, new applications and services could be built from it such as, for instance, an application/service providing the possibility to pedestrians to ask for route options considering their preferences and needs in terms of environmental parameters, going beyond the sole path length.

3. The Mobile Sensing Platform

In this work we propose a system that collects environmental data from sensors within smartphones and smartwatches in order to provide new Web services such as heatmaps and chronological evolutions of specific urban parameters. This information can then be used to aid end-users in choosing their route based on preferred criteria. Clearly, many other purposes can be considered as well, including efficient planning of smart city development etc. To be more specific, we adopt as a reference context a scenario consisting of a person walking toward a specific location at a certain time. It is well known that routes proposed by popular services such as Google Maps (as well as others) are generally based on the shortest/fastest path. However, some user may prefer less polluted and noisy streets, or in summer more shadowy ones, over the shortest ones. In general, any user would appreciate the possibility to indicate a weighted combination of possible criteria and be presented with a ranked list of alternative routes with the corresponding properties.

To fulfill our goals, we need an effective way to collect the data that are going to be considered as trustworthy characteristics of the environment, possibly in a completely autonomous way or with very limited human intervention. Gathered data should also be of good quality; i.e., the sensors (and the mobile device carrying them) should be fully exposed to the measured phenomena. For instance, we cannot measure brightness or noise of a certain location through a smartphone while it is kept in a pocket or in a purse. To this aim, we have designed a pedestrian navigation app intended for mobile devices (both smartphones and smartwatches); environmental data are collected only when this app is in use, thus ensuring that the device is exposed since the user is probably watching it

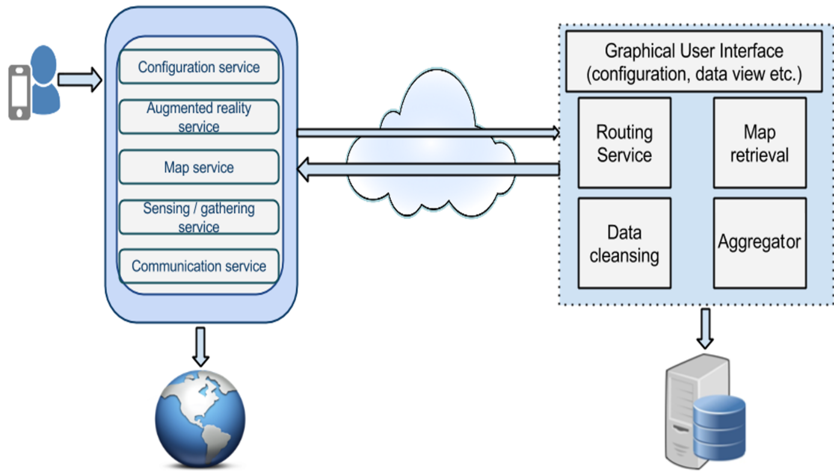

Figure 1: Architectural overview.

right in front of her/his face. Once having collected the data, we also need to be able to exploit them in a useful way. To this aim, we offer both the possibility to provide personalized routes to users and a Web service to citizens and municipalities with a Google Maps based service that enriches maps with historical values about sensed data.

In the following sections we provide a detailed description about the functioning of our mobile sensing platform; yet, for the sake of clarity, we anticipate in Figure 1 its main architectural components. In particular, on the leftmost side of the picture we have the mobile device, which is endowed with sensing as well as communication capabilities and is connected through the server via Internet. The mobile app offers the user the possibility to configure its functional parameters, gather and then visualize/manage the maps. The smartphone version also includes AR features used to overlay directional arrows and PoIs on the screen, whereas the smartwatch version does not for obvious lack of capability. On the rightmost side of the picture we have main components of our (AmazonWS) server. Basically, the server collects data from clients and creates a database with all roads and the corresponding light/noise data recorded during different hours/days.

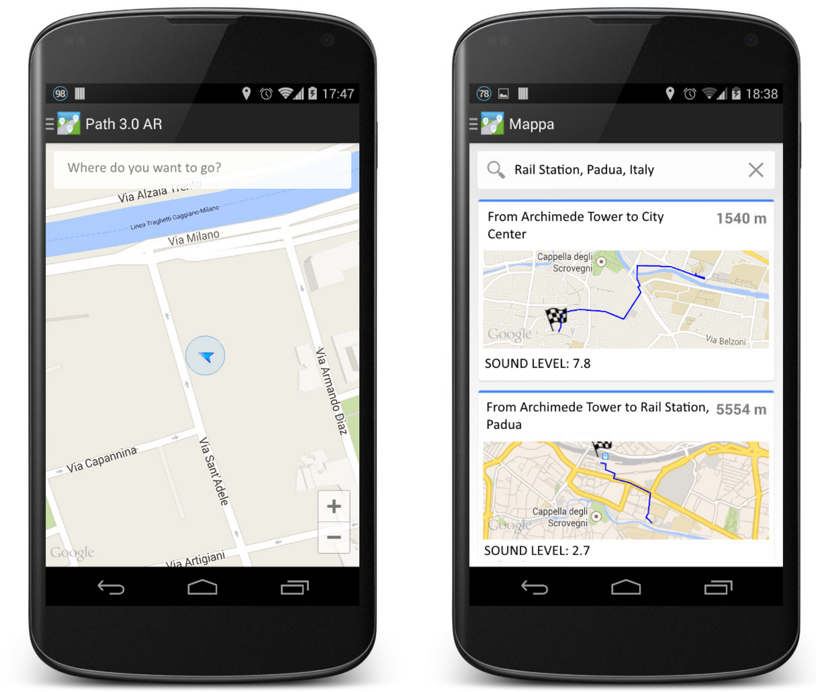

Figure 2: Application screenshots with destination/route search.

3.1. Data Acquisition

The mobile sensing application is a crucial part of our system; from its effectiveness and reliability in data sensing depends the success of our platform. We have developed our software using the Android platform considering its popularity. The application gathers information using the light sensor to measure brightness and the microphone to measure noise. As mentioned, these data would result severely underestimated if collected with the smartphone hidden in a pocket or in a purse. Therefore, we have embedded the data gathering functionality into a pedestrian navigation app that can be run both on smartphones and smartwatches. The smartphone version, in particular, is endowed with an AR navigation system also including the display of PoIs. The aim is to lead users to hold their mobile devices in front of them, perfectly exposed to the phenomena we intend to measure. Clearly, the user is informed by an initial disclaimer about the undergoing data sensing.

The acquired environmental data are cleansed by the mobile application; this means that outliers are eliminated and that each sample is associated to the time/day of collection and to its position on the map considering the actual roads and not just the GPS coordinates, which may have errors. Once cleansed and appropriately normalized and formatted, these data are sent and stored in an anonymous way on a logically centralized server; they can be later on exploited to deliver the intended services.

When running our application, initially a Google Map view is displayed (leftmost screenshot in Figure 2) and the user is asked to enter a destination in the address bar, which is then forwarded to the server. Once received this destination, the server sends back to the user a list of possible routes (rightmost screenshot in Figure 2) including the classic shortest one and alternative routes created specifically considering users' preferences in terms of brightness/noise. By tapping on one of the listed routes, it is possible to open the AR navigation view on the smartphone's display. At any time, the user can modify the preferences in terms of brightness/noise through a dedicated menu.

When the AR application for pedestrian navigation is in use, the user is directed toward the chosen destination through textual and graphical instructions, the latter shown in AR thanks to the Wikitude library. As reported in Figure 3, the user can also choose to superimpose on the screen PoIs related to specific topics (e.g., bars, attractions, events); related information and interaction options (e.g., opening a Web page, dialing a phone number) are displayed when clicking on the PoIs.

Instead, when using the smartwatch as the navigator (and collector of sensed data) the app works in a regular (non AR) way, as shown in Figure 4. The smartwatch is hence in charge of collecting environmental data, which are then transferred to the connected (via Bluetooth) smartphone and forwarded by the latter to the server.

Figure 3: Pedestrian navigation app.

Figure 4: Pedestrian navigation on the smartwatch.

4. Pedestrian Navigation

A main component of our system is the pedestrian navigation system. To provide correct guidance navigation to the users, our system has to be able to respond to routing queries. Also, this has to be done by exploiting the information collected through the sampling operations and interrogating the cartography service. In order to facilitate the implementation of this component and to optimize its operations we have decided to resort to PGRouting, an open source routing library that provides great support in this regard. This library leverages on the GIS functions of the database, adding the path computation through classic routing algorithms (e.g., Floyd-Warshall, Shortest Path A *, Dijkstra and Traveling Salesman). However, to operate correctly, the library has some prerequisites on the database, in particular:

- The (road) network model must be correct in terms of road intersections and road junctions (ends of adjacent sections).
- The database must contain information on the (road) network topology so that a corresponding graph model can be built for the algorithms.

To tackle the first problem, the library provides a *noding* function. This procedure receives as input the table containing the geographic data and a tolerance value, then re-elaborates the information trying to remove inconsistent situations such as the following ones.

- Unmanaged intersections as case 1 in Figure 5. In some cases the segments in the database may intersect without the presence of a corresponding intersection point. In this situation subsequent routing operations would not be able to exploit the intersection as a turning point. The noding function analyzes the GIS data to identify possible overlaps and creates additional vertices by breaking the segments. The procedure keeps track of the number and order in which the original elements were decomposed.
- Adjacent segments with extremes that do not coincide as shown in case 2 of Figure 5. In this case the function tries to simplify and join in a single

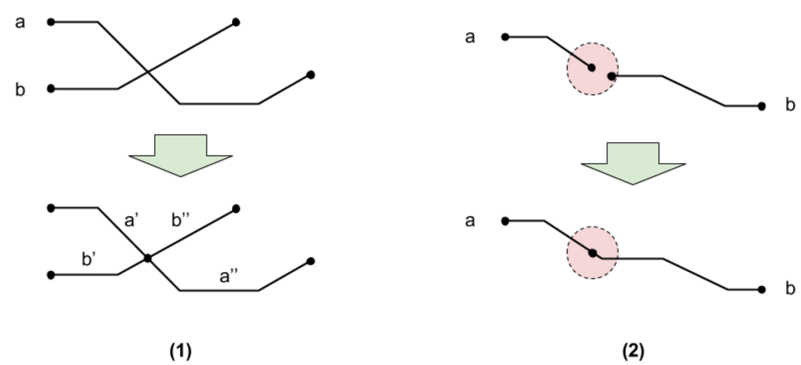

Figure 5: Noding application cases.

vertex the elements that are within a tolerance distance. Without this processing the two segments could not be used by the routing algorithm since they are not communicating.

4.1. Alternative Paths

Our navigation system includes also the possibility to compute the classic shortest path, which is computed using the classic Dijkstra's algorithm. To identify the source and destination nodes, the server performs a search in the database by calculating the vertices closest to the provided coordinates and using the distance as a metric.

However, as previously discussed, our system includes also the ability to compute routes taking advantage of the information received from light and noise samples. In this case, the implementation of the routing algorithm exploits a procedure that is similar to what is done for the shortest path. Yet, the exploited data structure is manipulated so that the additional information related to the labels is used. Two main issues had to be addressed in this context. First we had to introduce the management of the time context considered by the query along with the other data. In fact, while the length of a route is the same in any day or at any hour, its brightness and noise levels differ significantly, thus generating different results. We had hence to introduce a classification of the received samples depending on the moment they were acquired (morning, mid-day, afternoon, evening, night). Second, we had to modify the weight computation logic by introducing the evaluation of the samples in a way that is consistent with the routing objectives. Indeed the weight computation has to consider:

- the samples received for the considered time frame by the considered edges (roads);
- a tolerance threshold in the allowed extension of the path with respect to the shortest one;
- the possible absence of samples regarding the considered edges.

All considered, we have hence decided to use following formula

$$c = l + (\alpha * l(\frac{\sum_{i=1}^{n} v(t)_i}{n} - \beta)) \tag{1}$$

where c is the weight computed for the edge, l is the length of the segment expressed in meters, α is a parameter between 0 and 1 that indicates the ratio between the weight component depending on the length and the one depending on the labels, $v(t)_i$ represent the sample values collected in the time class t normalized between 0 and 1, β is threshold parameter between 0 and 1 used to scale segments without assigned (brightness/noise) data. Default values for α and β are 0.25 and 0.5 respectively.

This allows us to be compliant with the conditions even for borderline cases. In fact, for high values of $v(t)_i$ (close to 1) the weight provided by sample values will be predominant, while the length of the path will dominate in case of low values $v(t)_i$ (close to 0) and will be the only parameter considered in case of absence of data.

As an example, we can see in Figure 6 possible route alternatives proposed by our algorithm when the query is issued at (or refers to) 3pm. We can notice that the suggested routes have similar total lengths, increasing slightly depending on the preference given to brightness or noise. The shortest route, in red, is

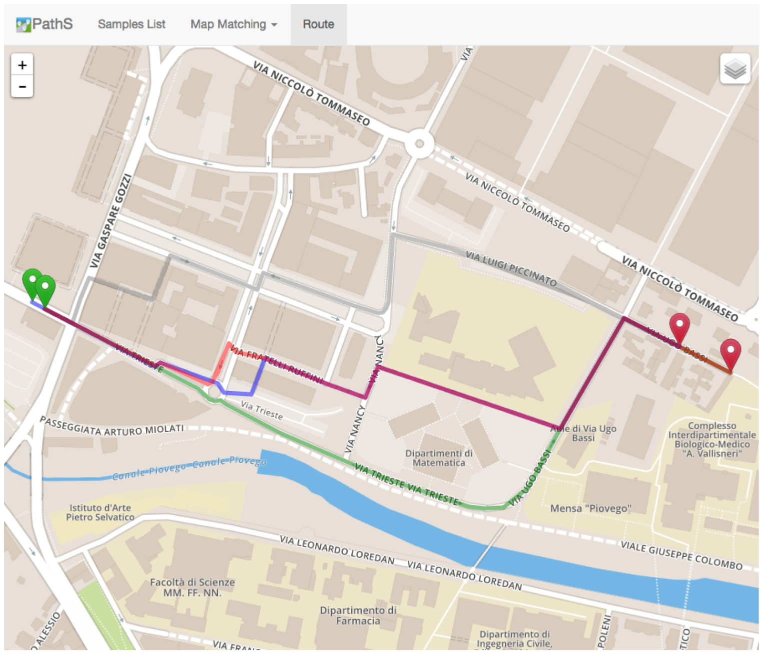

Figure 6: Route alternatives at 3pm.

practically coincident with the one, in blue, provided by external services e.g., Google Maps. Instead, the less bright path, in gray, tries to avoid for as far as possible areas with high brightness values, while the path in green suggests the longest of the fourth paths but avoids sections with higher noise sampling. On the other hand, if we repeat the same query at 7pm results are different as the light exposure in all the streets is lower and similar one to the others (Figure 7); thereby, we do not have anymore among the options the path longer but with less brightness (the one that was depicted in gray in Figure 6).

5. Web Visualization of Data

Gathered data about brightness and noise are transferred as serialized JSON content to the server. The data and their elaborations can then be accessed via a Web page by citizens and municipalities. Currently available data elaborations include the possibility to show recorded parameters regarding specific days,

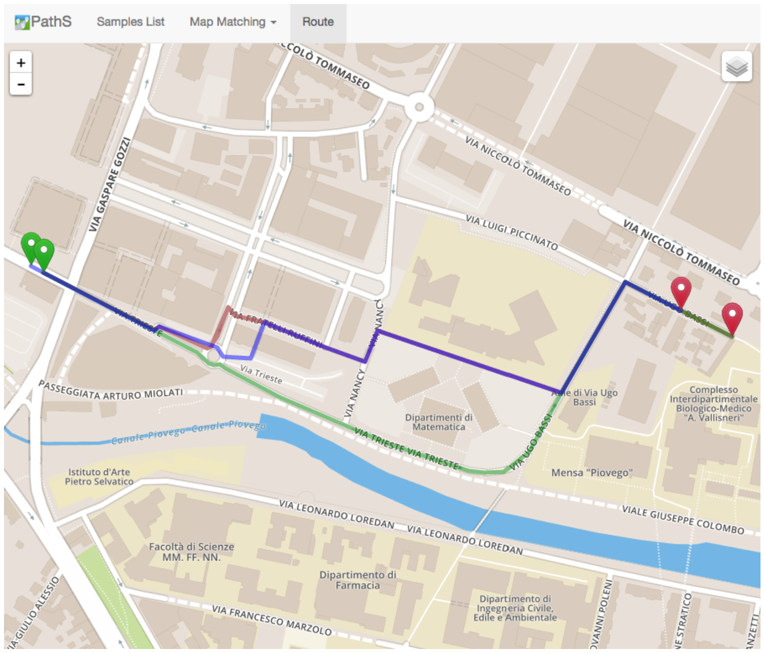

Figure 7: Route alternatives at 7pm.

hours and locations. As an example, Figure 8 shows a visualization example of data gathered in Padua, Italy, during a trial we performed. The figure is basically a heatmap; in this way we can provide an immediate perception of the parameter values through colors. As shown, the user can also choose a specific area in the map (the red circle in the figure) and visualize its related data instead of considering the whole visualized map as the area of interest. The same heatmap-like form is used even to represent the quantity of samples available for the considered area in the considered time frame. Furthermore, by clicking on a point in the map, histograms are shown including detailed information and data evolution over time corresponding to the chosen coordinates. Clearly, the amount of data available depends on the popularity of our application.

Through the control panel shown in Figure 9, heatmaps can be used in two different ways: (i) to report the average value of a specific parameter (or the total number or samples collected) during the considered period (Control Panel

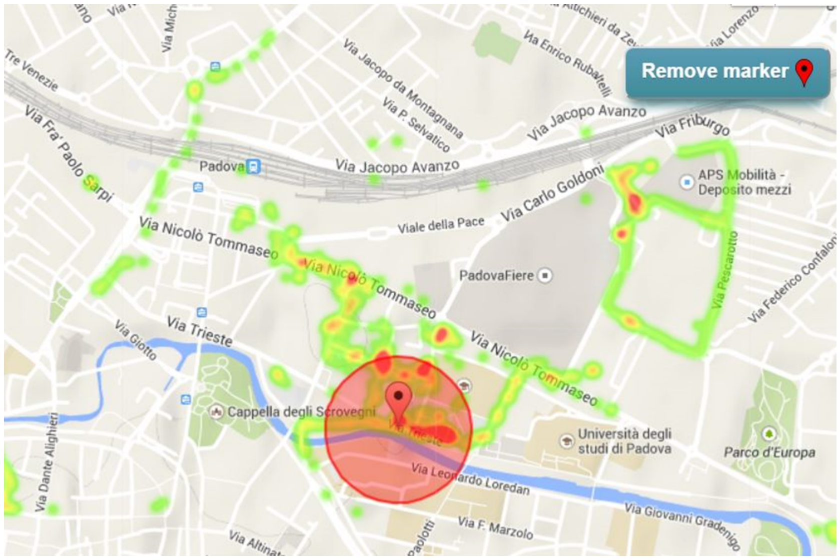

Figure 8: Heatmap visualizing collected data.

- 1 in the figure) or (ii) to show a video-like evolution of these values along the considered period (Control Panel - 2 in the figure).

As already mentioned and as shown in Figure 10, collected data referring to a certain location can be visualized also in the form of an histogram (or of a line) showing the sensed values on the y-axis and the time on the x-axis; in this way, the evolution along time can be provided. In particular, the chart refers to brightness and noise levels acquired through our application in the surroundings of the Department of Mathematics of the University of Padua, in Italy. The depicted values correspond to a large sensing campaign involving about 200 students (mostly freshmen) of the bachelor degree in Computer Science, and their smart devices. These students installed our application on their Android smartphones and have been encouraged to use the app as much as they liked. As a further result, this testing campaign also proved the functioning of our device on a vast plethora of heterogeneous devices. We counted 45 different devices and our application had problems only with four of them due to their obsolescence: a Samsung Galaxy S2 plus (Android v.4.2.2), an Asus Nexus 7

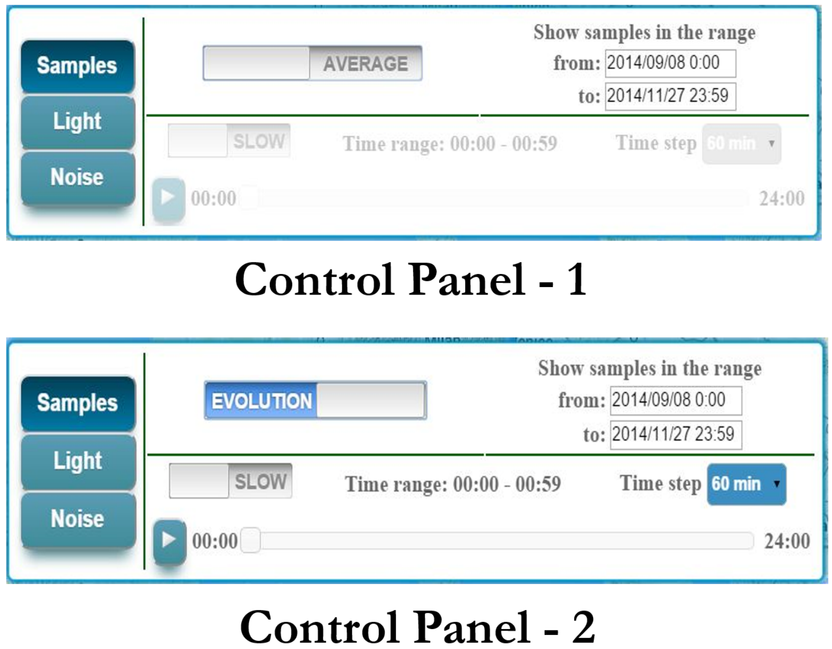

Figure 9: Heatmap's control panel.

(Android v.5.1.1), Samsung Ace 2 (Android v.4.1.2) and a Xiaomi Redmi 1s (Android v.4.1.1).

Regarding the app, through a dedicated menu, the user can configure the sampling frequency and duration (e.g., sound recordings) and the sensing behavior in general. Collected samples, enriched with geographical coordinates and timestamps, can be forwarded to a remote server immediately or, if configured so, when an open, cost-less wireless access point is available. In our case, the raw data corresponding to the charts have been collected on four parallel and independent measurements; the sampling frequency of the light sensor is configured to sample data every 100 m, while the microphone is accessed every 60 s. The bars show the average value between the measurements every 10 minutes of time lapse.

Figure 10: Histogram charts showing brightness and noise values along time.

6. Conclusion and Future Work

We have designed, developed and successfully tested a holistic solution for mobile sensing. Our solution includes a mobile application for pedestrian navigation that is effective in gathering quality environmental data from mobile devices (while also enhancing pedestrian navigation). Coupled with this application, we have developed a server able to appropriately store these data once correctly associated to road segments and the possibility to compute alternative paths for users based on personal preferences in terms of environmental parameters and not just on the path length. Furthermore, to promote awareness and smart planning, we have also created a Web service that provides heatmaps and other charts regarding acquired historical values of environmental parameters (i.e., brightness and noise levels in our case study).

We plan to extend this work in many ways. For instance, by including data gathered from more sensors in order to collect, elaborate and report information also about traffic, pollution and accessibility [28, 29, 30]. Although gathered data have all been in a reasonable range of values, the relation about the quality of the phone and the quality of the data from the sensors has not been carefully investigated yet.

We also plan to exploit multiple ways to promote the use of our system, including social networks and applications. An improved version of Google Maps able to generate custom routes depending on a wider set of users' needs (also considering disabilities) and preferences is already under development. Finally, we plan to investigate the tradeoff between sensing effectiveness and energy consumption in determining the best sampling frequency [31, 32, 33, 34].

Acknowledgments

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