Mobile Crowd-Sensing: a novel Technological Enabler for Teaching Acoustics

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Abstract. The current advances in technologies and the unstoppable diffusion of mobile portable devices are disclosing novel opportunities in teaching and learning STEM (Science, Technology, Engineering and Math) disciplines both in universities and schools. Embedded computational and sensing capabilities promise to transform mobiles in portable laboratory equipment that can be used even at a professional level. In this paper we propose to leverage the Mobile Crowd-Sensing (MCS) paradigm to gather large datasets of sound measurements in urban contexts thanks to an ad-hoc developed platform and to use both the smartphones and the collected data for improving the quality of current didactic experiences in acoustics, as well as for training students to the usage of professional sound level meters. The proposed platform has been validated through the extensive usage in a real monitoring context in Southern Italy.

1. Introduction

Mobile personal devices are nowadays growing in diffusion day by day, since larger quantities of new and powerful models reach the market every year (ITU, 2014). Consequently, the more the users familiarize with such devices in their everyday life, the higher grows the need of modulating scientific teaching and learning activities accordingly, since learners should not experience any relevant technological mismatch between their educational contexts and their daily activities. Despite this straightforward aim, the majority of learning scenarios still shows significant biases between their technological offer and the typical and more technology-intensive activities that students perform outside schools and universities. This situation affects countries in Western Europe differently, depending on several socio-economic factors. By limiting our analysis to the Italian situation only (Gasperoni & Cammelli, 2012), we can see, on the one hand, that nearly 87% of students from high schools has Internet connectivity at home and nearly 89% of them normally uses smartphones, and, on the other hand, only 74.5% of schools has Internet connectivity. This infrastructural gap can be filled

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easily and without excessive costs by leveraging the current diffusion of mobile devices.

In such a scenario, indeed, mobiles not only can increase connectivity possibilities for students but they can also play a twofold key role. Firstly, they represent a promising solution to engage students in collaborative, large-scale monitoring experiences, thus addressing the need of improving hands-on and laboratorial activities as requested by recent trends in pedagogical studies, especially in STEM (Science, Technology, Engineering and Math) disciplines. Secondly, they allow enlarging the scope of traditional monitoring campaigns significantly, especially in environmental monitoring contexts. These two aspects can be addressed by considering a novel and very promising sensing paradigm, known as Mobile Crowd Sensing (MCS) (Ganti, 2011). According to MCS principles, mobile devices, along with their embedded sensors, represent powerful sensing nodes that can 1) be scattered across huge areas without deploying expensive, traditional Wireless Sensor Networks (WSNs), 2) acquire opportunistically contextual awareness from the surrounding environment, 3) allow users to improve their knowledge about specific scientific phenomena and research challenges.

Therefore, in this paper we present a MCS system capable of introducing students to noise monitoring as well as didactic topics about acoustics thanks to their own smartphones. Users are simply required to install an app in order to start using the system, which mimics the behavior of professional noise monitoring equipment and allows learners to experience the typical problems of performing and interpreting measurements correctly and accurately. At the same time, the system allows its users to access regulations and guidelines about noise monitoring and abatement, in order to make them better aware of regulatory aspects. The proposed system exploits a client-server approach according to which noise measurements are collected (and possibly commented) by smartphone users and then forwarded by a context broker towards a dedicated server farm where raw data filtering and data aggregation steps are performed. Real-time monitoring results (in both frequency and time) and alerts on measurements exceeding regulatory thresholds are presented to users during their measurements.

The paper is organized as it follows: Section 2 overviews learning opportunities disclosed by BYOD and IBL approaches. The proposed platform is briefly described in Section 3. Section 4 presents our didactic experimentation, in terms of learning contexts and objectives, planned coursework, exploitation of the proposed platform. Conclusions are outlined in Section 5.

2. Mobile Learning and Mobile Crowd-Sensing

In the last decade, Mobile Learning (ML) has been considered as the natural evolution of e-learning approaches, as asserted by Brasher et al. in (Brasher & Taylor, 2004). Nowadays, handheld-UIs (Kratz, Hemmert, & Rohs, 2010) enhance user engagement and lower the learning curve for unskilled users, thus making mobiles an ideal platform also in educational contexts. In addition, smartphone users can benefit from a wide and heterogeneous variety of embedded sensors, as well as more reliable supporting wireless infrastructures. The proliferation of mobile-based e-learning systems in the recent years is ascertained by recent statistical trends referring to the main online mobile app stores: more than 50% of colleges and universities in United States (Dobbin et al., 2012) already had a similar didactic offering and the trend Europe is expected to be the same. The ML approach is boosted by specific market catalysts: high mobiles penetration rates, national content digitization efforts, growing BYOD (Bring Your Own Devices) policies in schools and advantageous billing conditions from network providers (Adkins, 2013).

Within such an interesting and continuously changing scenario, mobile sensing has acquired more and more relevance, so that now it can be considered as a novel IT paradigm by its own, the so-called Mobile Crowd-Sensing (MCS) (Ganti, 2011), since it merges the pervasivity of large community of users to traditional measuring aspects. MCS allows users (and learners) to experience directly how to perform measurements on physical phenomena and how to behave when specific events have to be monitored, thus demonstrating how ML and MCS are inherently related.

Many MCS solutions addressing a wide range of contexts has been presented in scientific literature so far, such as traffic monitoring and parking availabilities in urban environments (Ganti, 2011); road safety control (Aubry et al., 2014); air pollution evaluation (Leonardi et al., 2014); emergency management (Degrossi et al., 2014); large-scale events planning (Stopczynski et al., 2013). As for noise monitoring, many apps allow users to control sound levels, such as Advanced Decibel Meter (Gates, 2013), Sound Meter Pro (Mobile Essentials, 2015) or Decibel Meter Pro (Performance Audio LLC, 2012). These apps are for personal use only: they reproduce main SLM functionalities and allow users to check how loud their surrounding environment is; however, they do not provide noise measurement aggregation on a geographical/temporal basis. Very few research works address urban noise mapping, such as the “Ear-Phone” project (Rana et al., 2010) where Nokia phones were used to predict sound levels in a given environment, “NoiseSPY” (Kanjo, 2010), which exploited mobiles carried by bicycle couriers to collect noise data in Cambridge, or the “2Loud?” project (Leao, Ong, & Krezel, 2014) that uses iPhones to assess nocturnal noise within buildings near highways in Australia. One of the main limitations in such activities is that users are only involved as data collectors, without actually engaging them in real learning experiences.

Therefore, we aim at providing users with didactic materials along with metering capabilities on their own mobiles and we also aim at contextualizing measurements w.r.t actual noise monitoring regulations.

3. Research Purposes

Starting from the brief overview about ML and MCS presented in Section II, it is possible to understand the potential educational improvements that can be achieved by their proper combination, as suggested in (Heggen, 2012). Such an improvement can be brought to students' learning experience by complementing traditional didactic topics about physical phenomena and processes with the possibility of being directly involved in data gathering and interpretation activities by simply installing an ad-hoc software application on their own mobiles. In this sense, MCS activities can be seen as a continuous learning experience that increase students' skills and expertise (Becker et al., 2013).

For such reasons, our research activity has been focused on improving the learning and teaching quality of noise monitoring and acoustic phenomena. The motivations supporting our choice are manifold. Firstly, students can immediately perceive sound pollution levels, instead of other "invisible" pollutants (e.g., air and electromagnetic fields), thus they can compare their "nuisance perception" against the corresponding instrumental evaluation and unit of measurement. Similarly, noise monitoring activities can be performed even without attaching external sensors to the smartphones, as it is instead required in the case of air or quality monitoring (since mobile devices do not embed dedicated sensors for the analysis of such phenomena), so that students can immediately access to a reliable source of sensor data without needing any additional equipment.

In addition, noise monitoring campaigns require very expensive Sound Level Meters (SLM), whose costs typically ranges from 500 to 3k EUR, thus hindering their usage in schools. Moreover, students cannot even benefit from noise monitoring data in their own communities, since local authorities are reluctant to deploy monitoring stations across cities due to high buying (nearly 5k EUR) or rental (typically 1k EUR per month) and maintenance costs. These stations are deployed mainly near airport landing/takeoff routes and they are available rarely for monitoring residential or industrial areas, congested roads, railways, highways. Consequently, students can fill this knowledge gap thanks to their data collection activities, by becoming themselves the sensor data providers.

Another relevant aspect is related to the lack of students' interest in noise regulations, which are seen typically (and wrongly) as marginal, boring and only theoretical. This misleading perception prevents learners from understanding significant aspects such as: health-related noise pollution risks (Goines & Hagler, 2007); medium- and long-term noise monitoring strategies (Lewis, Gershon, & Neitzel, 2013); systematic noise abatement policies (Den Boer & Schroten, 2007).

The issues briefly sketched so far determine a set of requirements about how a MCS-based learning system should be realized. Therefore we adopted them as a guideline in order to design and implement a platform for high schools (and even for introductory scientific university coursework) in order to improve experiential learning amongst peers by engaging them into extensive sensing activities directly on site, as it will be described in details in the next Sections of this paper.

4. The Proposed System

In order to complement our platform sensing capabilities with pedagogical features, we elicited a series of requirements by performing interviews and by profiling voluntary students at our University. The requirements were: 1) collecting and sensing sound levles; 2) annotating measurements with optional user's comments; 3) assisting students in how to perform measurements correctly and how to achieve acceptable accuracies; 4) providing students with learning materials about sound, acoustics and noise regulations. As for regulations, it is important to make students aware of the noise scales and quantifiers required by national and European laws to assess how noise affects life-quality. We adopted both an instantaneous indicator (Sound Pressure Level (SPL) in units of dB(A)) and a time-averaged one (Equivalent Continuous Sound Level $L_{EQ(T)}$), needed since noise sources vary in time and duration (Alton Everest & Pohlmann, 2009).

Our platform manages sound measurements, this requires proper data modeling. We have followed a Data Warehouse (DWH) approach (Golfarelli & Rizzi, 2009) in order to process data in an Extract-Transform-Load (ETL) pipeline. Firstly, measurements are gathered from sensors and then they are cleansed, transformed and stored in order to make them available for final users. Students can both examine in real-time their own measurements and the ones from other students. The core concept in our data modeling (according to the Dimensional Fact Model (DFM) approach (Golfarelli & Rizzi, 2009)) is represented by each noise measurement. We correlated this informational entity with a series of additional elements: noise quantifiers and calculations; measurement timestamp; geographical position; sensor type; users' comments.

As for the platform logical architecture, we have realized an Android-based mobile app to collect measurements compliant with Italian and European noise regulations (DPCM 14/11/1997), (European Union, 2002) and to involve students in didactic activities (e.g., training on a simulated sound level monitor, accessing the noise regulation repository, etc.) and a cloud-based Web app for receiving data from servers and managing them properly (i.e., remote persistent storage, time/space data aggregation, filtering, correlation between measurement and student's comments for achieving psychoacoustic evaluations (Fastl, 2005)). The logical architecture of the proposed platform has a three-layer structure (Fig.1): starting from the bottom, the first layer (data layer) consists of a non-persistent storage solution for mobile-hosted sensor data, a persistent storage component for measurement history (implemented via an instance of MongoDB, the No-SQL documental DBMS) and a persistent relational DB for noise regulations and guidelines. The second layer has context-brokering capabilities (for managing multiple sensors) as well as data integration, filtering and reporting functionalities (thanks to Pentaho CE (Pentaho, 2014), a freeware ETL application). The third layer (data presentation) offers a Web app for accessing data reporting and integration results. Some of the platform components (i.e., data brokering and storage functionalities) have been implemented by revolving to FIWARE, a set of open APIs easing the development of smart applications in multiple vertical sectors, ranging from technology to society.

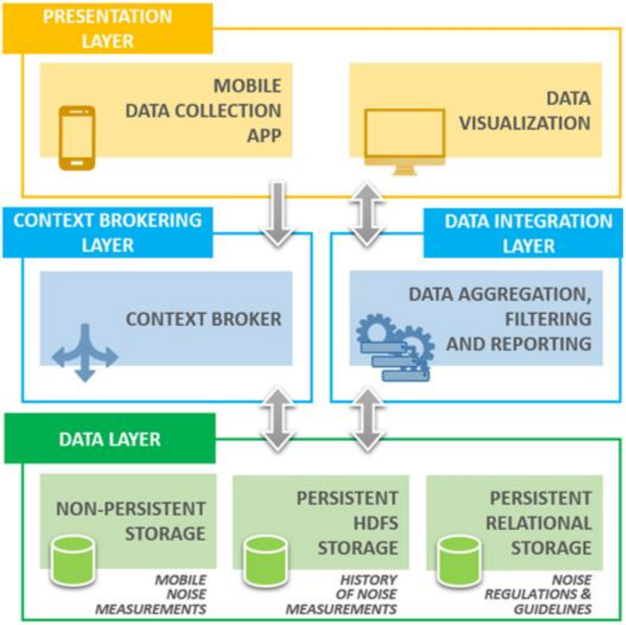

Fig.1 – Platform logical architecture in the large

5. Research Outcomes

In order to engage effectively students in *learning-by-doing* activities, the user interface of our mobile app offers a series of controls and interaction options that can be also found in a professional SLM. Therefore, students can: 1) learn how to use such equipment; 2) understand physical aspects of noise monitoring without the need of an expensive SLM; 3) become aware of the physical quantities and corresponding units of measurement involved in noise monitoring campaigns.

Figure 2.A depicts the app page for the participatory measurements (opportunistic ones can accessed by performing a different selection at the beginning of the app usage session). Both $L_{EQ(T)}$ and *SPL* values are reported and plotted on a XY graph as well as the selected observation time period *T*. Once each measurement ends, users can choose whether enriching their data with comments and personal evaluations about the perceived noise annoyance, by simply accessing a dedicated page. This page mimics a professional SLM.

Specific dialog boxes appear after user's key actions. For instance, once a participatory measurement is concluded, a dialog box on the screen reminds her/him how a measurement should be performed correctly (Fig. 2.B). Other dialog boxes alert users when $L_{EQ(T)}$ thresholds are exceeded. The app also allows users to annotate participatory measurements with comments (e.g., about the emitting source, the measurement context, the perceived loudness, etc.).

The developed mobile app also provides students with detailed descriptions about these quantities (Fig. 2.C) as well as with dedicated app pages where students can examine thresholds as well as Italian and Communitarian regulations (Fig. 2.D) in order to improve the didactic quality of the app.

Preliminary tests have already been performed on both data gathering and management phases. We have also taken into consideration typical users' concerns about privacy issues, which very often arise when mobile devices are used as data sources, by discarding any metadata capable of identifying the device owner. Mobile devices are only indexed thanks to their IMEI (International Mobile Equipment Identity) code, so that their owners can remain unknown to both platform managers and other users.

The accuracy of mobile-gathered measurements is also a matter of concern in the scientific community, due to the inherent technical limitations that mobile-embedded sensors suffer if compared to professional metering equipment and due to the concrete possibility that some measurements are taken in a wrong way. As for the first issue, a series of results in scientific literature demonstrates how mobile-embedded microphones actually reach a satisfactory reliability, quantifiable in a bias ranging between ±1.5dB and ±8dB, as described in (Keene, 2013), (Kardous & Shaw, 2014). As for the second aspect, we implemented, as a step of the ETL process, a univariate algorithm for the outlier detection in order to remove measurements having an excessive sound level amplitude in a given temporal window. We opted for a slightly modified version of the Tukey's method (Hoaglin, Iglewicz, & Tukey, 1986), which is simple and quite effective with datasets following both a normal distribution and a not highly skewed lognormal distribution.

Proper visualization functionalities have been also implemented in the Web app (Fig. 3) that allows users to examine measurement results as heatmaps displayed on a geographical layer in GoogleMaps.

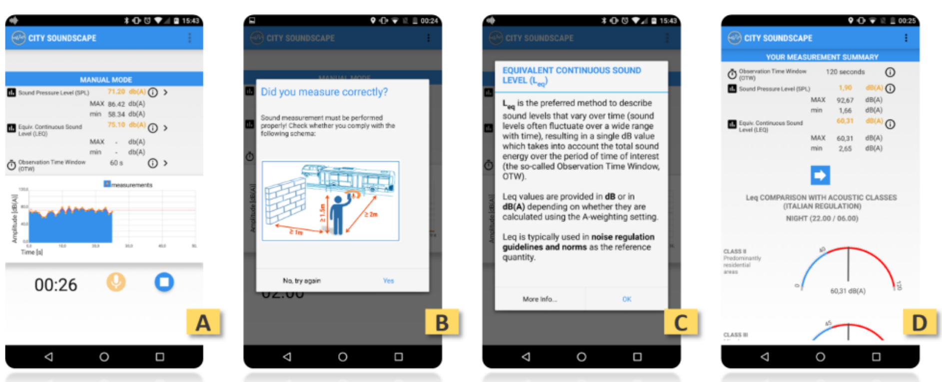

Fig.2 – Mobile app: user interfaces

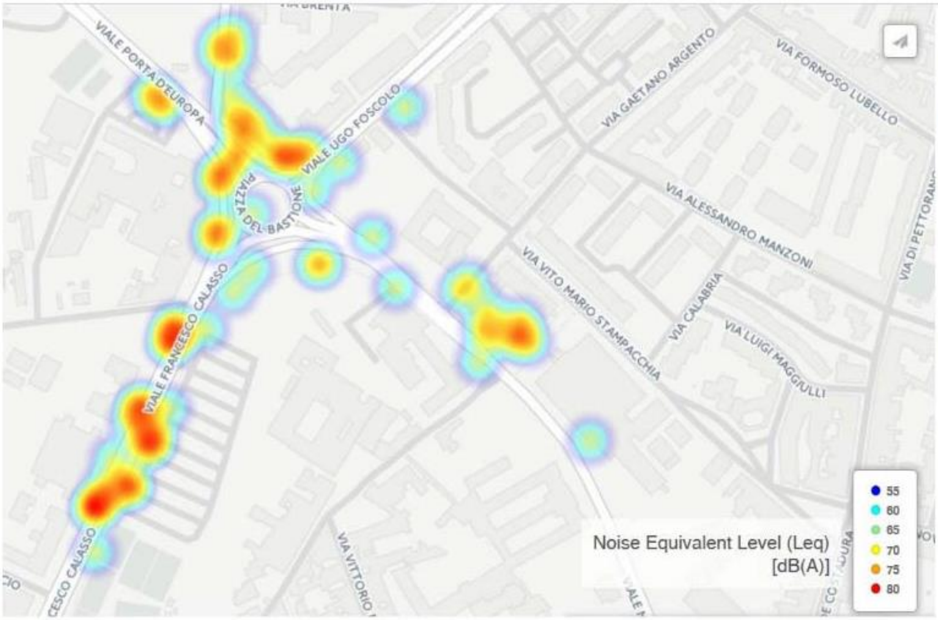

Fig.3 – Web app: geo-referenced heatmaps of noise measurements

6. Conclusions

The platform presented in this paper represents a MCS-based approach tailored to noise monitoring and to learning support in acoustics. The system has data gathering and sending capabilities, sufficient metering accuracy, raw data filtering and aggregation features, ease of usage, clarity of content presentation and availability of adequate learning support material. In order to do that, we leveraged mobile-embedded microphones, along with the geolocalization capability of such devices. We developed a mobile app to collect noise measurements, along with a complete data management system for data aggregation and filtering purposes. The adopted approach allows not only to perform sufficiently accurate and large-scale monitoring campaigns without revolving to expensive professional metering equipment, but it also allows students to effectively exploit the learning-by-experience approach as well as to widen systematically their knowledge about acoustics and noise control regulations. We performed a series of preliminary tests with students from the Engineering Faculty of our University, achieving promising results for both learning outcomes and app usability. At the moment of writing this paper, the deployment of larger test cases, involving a set of high-schools from our administrative region is about to start, thus offering us the possibility to collect noise measurements from urban scenarios thanks to a significant number of students.

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