Collaborative Learning from Mobile Crowd Sensing: a Case Study in Electromagnetic Monitoring

Antonella Longo, Marco Zappatore, Mario A. Bochicchio
Dept. of Innovation Engineering, University of Salento
via Monteroni sn, 73100 – Lecce (Italy)
{antonella.longo, marcosalvatore.zappatore, mario.bochicchio}@unisalento.it

Abstract—Personal mobile devices are nowadays so pervasive that a broad range of novel learning practices and paradigms can profitably exploit them. Mobile Crowd Sensing (MCS) is one of them. In MCS, mobiles act as data sources for monitoring tasks (e.g., traffic planning, air pollution monitoring, emergency management), thanks to their computational capability and their embedded sensors. From a pedagogical perspective, MCS offers continuous learning experiences that increases students’ skills and expertise by engaging them directly into practical activities and on-the-field analyses. However, the wide diffusion of mobiles requires a reliable wireless coverage, to guarantee proper Quality of Service levels, thus potentially increasing the electromagnetic field levels in a given geographical area. Therefore, we propose a complete data warehouse solution that exploits MCS paradigm to pursue three main research purposes. Firstly, motivating students from engineering courses to acquire a better knowledge in wireless communication topics by offering them experimental and collaborative learning approaches. Secondly, performing a preliminary screening of the signals received by mobiles for 3G/4G standards (e.g., UMTS, LTE), since this domain did not benefit from MCS solutions so far. Thirdly, identifying prospective areas where more detailed measuring campaigns must be addressed. A deep analysis of the achievable pedagogical benefits as well as the thorough description of both design and implementation phases is provided. Evaluation results and preliminary users’ feedback complete this research work.

Keywords—Collaborative Learning; Seamless Learning; Mobile Crowd Sensing; Multidimensional Data Analysis; Data Warehouse; Electromagnetic Monitoring

I. INTRODUCTION

Digital technologies and mobile devices (e.g., smart phones, tablets, etc.) have become extremely pervasive. There are nowadays nearly 6 billion mobile devices diffused worldwide and estimations forecast nearly 1.5 billion new units per year up to 2017 [1]. Within such a scenario, teaching and learning activities need to be modulated accordingly. Indeed, they have been used so far in environmental monitoring, traffic and parking control or emergency management (see Section III). Amongst mobile-sensed environmental monitoring applications, however, a very few number of research works have concerned the Electromagnetic (EM) domain. Therefore, we believe that our proposal can fill this gap. Indeed, the actual diffusion of wireless technologies and devices make users request more and more high-speed wireless connections and advanced mobile services. This, in turn, determines an overall increase in Quality of Service (QoS) requirements for wireless communication service providers. Such organizations typically increase the number of cellular base stations to satisfy those requirements but this may cause EM field levels to rise [2]. Consequently, why not to use mobiles even to monitor the EM field levels required for their proper functioning?

For these reasons and in such a complex context, we propose a system capable of measuring, storing and assessing EM field levels sensed by a great number of mobiles thanks to their on-board antennas. This approach allows us to offer a scientific learning environment based on opportunistic Mobile Crowd Sensing (MCS) [3] for both schools and universities to improve collaborative experiential learning amongst peers by engaging them into extensive sensing activities directly on site [4]. Students from engineering faculties will improve their knowledge in sensors, wireless communication standards, radio-propagation and EM safety regulations, which are foundational topics in Communication Engineering courses. They will cooperate, by performing measurements in groups across the same geographical area. This will bring two advantages: on the one hand, they will learn by experience and by discussing with their peers, how to avoid situations capable of hindering measurement quality. On the other hand, by merging together many measurements of the same environment, the average measurement quality will improve.

In addition, different monitoring tasks will be offered in a second stage of development, depending on the educational level of students: for instance, specific survey campaigns across schools and institutions will be available to motivate and engage learners in participating [5].
The proposed solution also plays a significant role as a large-scale, low-cost, preliminary EM monitoring platform. Indeed, traditional methodologies require expensive equipment, highly professional personnel, time-consuming deployments and complex measurement procedures. The MCS approach, instead, by involving a great number of users in each survey, offers a massive sensor usage, it is more flexible and less expensive, thus achieving a distribution level that cannot be reached by traditional methodologies. There are, however, some limitations, due to inhomogeneous sensor availability, varying data quality, time randomness in users’ mobility, uneven sensing coverage and spatial-temporal correlation amongst measurements. These aspects require proper data processing methodologies. Consequently, measurements achieved by MCS are less accurate than standard ones but ideal to perform large-scale surveys. By doing so, prospective geographical areas where EM field levels may exceed regulatory thresholds can be located. In those areas, traditional monitoring campaigns (e.g., based on large-band and narrow-band measurements) will be performed to get detailed insights and to exploit monitoring resources efficiently.

In order to accomplish our research purpose, a great quantity of heterogeneous data has to be collected from mobile devices and then managed to provide users with the required spatiotemporal information. Therefore, a complete Data management solution is presented in this paper. The proposed application encompasses the aggregation and multidimensional analysis of EM field levels as well as of geolocation data coming from Android devices [6].

The paper has the following structure: Section II emphasizes the pedagogical benefits provided by the proposed approach. Section III outlines the theoretical background about MCS and overviews some of the most interesting related works in that research area. Section IV describes the proposed platform. Section V summarizes achieved results and users’ feedback. Section VI draws conclusions and sketches future works.

II. ADOPTED LEARNING PARADIGMS

The proposed approach exploits the MCS methodology to assess EM field levels starting from measures taken by mobile phones. Whilst the following Sections will deal in detail with MCS theoretical background, data management description, platform analysis and result discussion, we devoted this Section to highlight how our research work can profitably capitalize on the adoption of multiple learning paradigms. Indeed, some of the most recent pedagogical trends can be ensued by providing students from engineering faculties (and not only) with mobile applications capable of gathering monitoring data. These aspects acquire even much more relevance as new ways to engage learners, if we consider that both schools and universities are now suffering from declining number of students in their scientific coursework and educational offerings [4].

The first relevant pedagogical outcome is represented by the MCS approach itself. The idea upon which learners deploy a software application on their mobiles to monitor surrounding phenomena opens a great range of didactic possibilities. Students can be more effectively motivated to improve their knowledge about scientific phenomena and processes by involving them in data gathering and interpretation. In this sense, the MCS activity can be seen as a continuous learning experience that increases students’ skills and expertise [7]. As a direct consequence, the more students become aware of the scientific concepts they are dealing with, the more data collection and sensing practices may improve.

Collaborative learning represents another significant model considered in our approach. According to pedagogical trends consolidated in the recent decades, it provides students with the opportunity to become critical thinkers by promoting interactions, by taking responsibility for their own learning, by exploiting positive interdependence and interpersonal skills, by avoiding competition in favor of cooperation [8]. These aspects find applications in every education levels, especially in engineering courses, since prospective engineers must learn to interoperate, to accept alternative point of views and to develop constructive criticism when interacting with their peers [9]. In addition, new technologies, which are employed significantly in engineering courses, can further increase collaboration [10]. Actual engineering students are much more accustomed to employ technological advancements rather than their predecessors, since they belong to the ones born between ‘80s and 2000, the so called “Net Generation” [11] or “Digital Natives’ Generation” [12]. This category of learners exhibits specific features that can be exploited profitably in collaborative education: fast operational speed, predilection to experiential learning, inclination to visual communication, propensity to cooperation and teamwork, tendency to inductive discovery, quick response behavior and desire to receive quick responses in return [13]. Since these students are so technology immersed and natively multi-taskers, we believe that our solution provides them with two appealing perspectives. On the one hand, they are directly involved into crowd sensing activities and on the other hand they are offered with an experiential way to cooperatively learn the fundamental aspects of radiopropagation and electromagnetics.

Alongside collaborative learning, our approach meets two further emerging pedagogical forms: seamless learning [14] and geo-learning [15]. The former one creates a seamless flow of learning experiences deriving from both education contexts and everyday life. It allows students widening the usage of their personal technologies to learn across times and locations. Indeed, our solution enables users to extend sensing capabilities of their devices (since monitoring EM field levels typically is not a default sensing feature) and to perform monitoring activities seamlessly during daily experiences. Similarly, geo-learning refers to knowledge acquisition in and about locations, both indoor and outdoor. It exploits position-based technologies to enrich learning activities with location-aware features. By doing so, different layers of information can be added to physical places. Our approach adheres to such aspects by allowing learners to examine visually field level distributions directly on Google map layers, thus interconnecting places with the preliminary estimations of their EM field levels.

The proposed solution copes efficiently with the pedagogical aspects enlisted above. Indeed, engineering students can 1) easily improve their knowledge on EM
III. MOBILE CROWD SENSING

Constantly increasing human mobility and pervasive wireless devices nowadays enable a new paradigm in collecting data and developing large-scale applications, known as Mobile Crowd Sensing (MCS) [3]. If compared to traditional Wireless Sensor Networks (WSNs), MCS offers many advantages in terms of coverage area, number of deployable sensing nodes, communication connectivity and users’ engagement [4].

From a technological point of view, personal communication devices are used instead of ad hoc sensor nodes [3], thus sensing networks can be enlarged by simply adding new users to the system. Moreover, these devices typically embed multiple sensors (e.g., accelerometers, microphones, gyroscopes, etc.), are equipped with multiple communication modules (e.g., UMTS, LTE, WiFi, Bluetooth) and offer significant computational capabilities (e.g., 64-bit dual-core Cortex CPUs). Consequently, they become capable of behaving as effective and extremely powerful sensing nodes. The availability of numerous communication options generates two different transmission paradigms in MCS [16], depending on whether users send data by using 3G/4G mobile networks (infrastructure-based transmission) or by using short-range data communications standards such as WiFi or Bluetooth (opportunistic transmission). 3G/4G mobile networks (also known as Third Gen./Fourth Gen. mobile networks) comprise the most widely diffused standards, such as GPRS (General Packet Radio Service), EDGE (Enhance Data rates for GSM Evolution), UMTS (Universal Mobile Telecommunication System) and LTE (Long Term Evolution) [14].

From a user point of view, MCS applications enable people to choose when monitoring a specific phenomenon (participatory sensing) or they can automatically collect data in background and subsequently send them to data centers without requiring any users’ participation (opportunistic sensing) [17]. In addition, whilst the most largely diffused MCS applications deal with single-user monitoring activities (personal sensing) such as fitness or healthcare-related practices, another sensing approach is taking place [3] in the recent years. It refers to large-scale phenomena whose effective monitoring is achievable only by involving a great number of users (community sensing).

The brief sketch on MCS provided so far highlights how variegated this research area actually is. A considerable quantity of applications has been recently developed by exploiting users’ mobility and the advanced capabilities of their devices. Such applications now span across a wide range of use cases: traffic monitoring and parking availabilities in urban environments [3]; road safety control [18]; air pollution evaluation [19], [20], [21]; emergency management, such as flood alerting systems [22], or earthquake immediate sensing as in the iShake project [23] or in [24]; noise mapping [25]; large-scale events (e.g., music festivals) planning [26].

However, at our knowledge, very few MCS applications allow to assess EM field levels on a large scale with respect to 3G/4G wireless communication standards. Indeed, the majority of those approaches only refers to Wi-Fi indoor coverage analysis and hybrid device localization techniques (e.g., Wi-Fi fingerprinting [27] and pedestrian dead reckoning [28]) such as the Pazl system [29]. Other solutions aim at localizing deployed outdoor Wi-Fi Access Points (APs) within urban areas. The authors in [30], for instance, performed measurements by travelling on public transports in Edinburgh and achieved quite detailed maps of Wi-Fi spectrum usage both in 2.4GHz and 5GHz unlicensed bands. Other solutions are specifically tailored for wireless network operators rather than users, as in the case of [31], where a MCS approach is used to evaluate wireless traffic data and to deploy outdoor femto-cells effectively (i.e., by deploying new base stations to increase signal coverage). As for applications more oriented to normal users, some of them, such as [32], allow sniffing Wi-Fi signal levels for monitoring contexts but they exhibit limited capabilities at the moment. Other available tools allow quantifying mobile signal strength for single devices only [33].

This scenario depicts how the EM monitoring scientific domain actually suffers from a clear lack of MCS approaches with both educational [7] and monitoring purposes. Indeed, the examples cited above only deals with EM field level assessment for Quality of Service (QoS) reasons, since they are used typically to determine coverage quality in a given location or to find the best serving APs. On the contrary, environmental pollution monitoring [19] and emergency management ( [22],[24]) already exploited the benefits that derive from applying MCS methodologies rather than traditional monitoring solutions, such as: better situational awareness, more effective risk assessment, more immediate response request and delivery.

At the end of this Section, before describing how we tackled the aspects mentioned so far in order to fill such a gap, it is important to point out a specific issue in MCS monitoring scenarios. Indeed, one of the most relevant concerns about MCS is related to data quality and data source reliability when users have to provide actively measurements from their own devices, thus generating possible risks of information omission or exaggeration [3]. In order to limit such issues, we revolved to the opportunistic MCS paradigm by automatizing this task in the mobile application installed on their devices, thus freeing users from the burden of sending measurements personally.

IV. THE PROPOSED PLATFORM

A. Architecture and Implementation

The proposed system has been named EDM (that stands for Electromagnetic Device-mediated Monitoring). It collects mobile signal strengths received from the 3G/4G antennas of any Android client device where an ad hoc developed client application is installed. Measurement are then sent to a dedicated server when a data connection is available (opportunistic transmission). Data are gathered from all the available devices and then processed, geo-referenced and visualized. The system has been designed as a 3-tier architecture with a Server Farm (Fig. 1).
The number of physical tiers derives from workload estimations performed in a worst-case scenario. We supposed to deploy the system both in universities and in schools and we hypothesized a working EDM instance on 75% of the available devices (if each student owns a smartphone). By considering 4000 institutions, each having 1000 students (amongst which 750 use EDM), we ended up with an amount of $3 \times 10^6$ prospective users for the system. Starting from this quantity, data volume estimations have been performed as well. We considered a measurement message sent by each device every 10[s], thus obtaining an overall upper bound of $25.92 \times 10^9$ estimated messages per day. It is worth to mention that the selected data sending rate (i.e., one message each 10[s]) specifically derives from our main measurement purpose: since our system aims at providing a preliminary screening of EM field levels, it is not necessary to collect measurements with higher rates.

On each client device, an Android application detects mobile position and acceleration as well as signal strength, then stores them into a local SQLite relational database (DB) and send them to the server whenever a data connection can be established.

On the server side (Fig. 1), a server farm is needed in order to improve reliability and mainly to handle the estimated workload. Indeed, if a single device send a measurement every 10[s], it will send 8640 measurements in just a day. There are two replicated servers to capture data from mobiles and interpreting them. There are also available a Web Server, a Script Engine and an Application Server allowing clients to access the Web Application that has been developed in order to offer multidimensional analysis of data. Cassandra, a NoSQL DBMS, manages data storage aspects. Pentaho Data Integration Community Edition, a leading open source Extract-Transform-Load (ETL) application, is in charge of cleaning up data and loading them into the data warehouse from a separated computation node (see Section IV.D).

Security is guaranteed by a firewall.

B. Data Modeling

In order to analyze profitably incoming data, a multidimensional OLAP (On Line Analytical Processing) DB has been considered, whose DFM (Dimensional Fact Model) [37] is based on the Detection fact schematized in Fig. 2. The main fact relates to the sensed signal strength and to acceleration value, which is exploited to infer whether a user is stationary or is moving (since stationary measurements must be treated differently from measurements taken when moving along a path). Fact dimensions refer to the most relevant features that characterize a measurement: geographical localization, temporal localization, generating device and serving wireless communication network.

C. Measurement Codification

A specific, byte-oriented protocol specifies rules for sending and interpreting data, according to a given set of patterns. Messages exchanged between clients and server convey measurements and are not required to have a fixed length, in order to allow further extensions to the message structure in the future (without modifying the platform).

Table I shows the adopted message codification schema. The message header gathers general information such as the unique mobile identification code (i.e., IMEI, International Mobile station Equipment Identity), its vendor and model, its OS version and the current timestamp. The rest of the message wraps collected data. Those data are divided into three classes depending on which kind of sensor provided the measurement: the GPS, the 3GPP (3rd Generation Partnership Protocol) antenna (which is the antenna adopted for 3G/4G communications) and the accelerometer. It is important to highlight how message header parameters are not used to provide neither clients nor system administrators any possibility to track users via their devices. Indeed, the IMEI id, which may rise some privacy concerns, is simply used as a
univocal indexing key to classify measurements. It allows to discriminate amongst potentially troublesome situations: in order to determine, for instance, whether consecutive measurements from very similar locations come from different data sources (and then are amenable to be interpolated) or not (and then they can be averaged).

Measurements are double indexed via the key-pair: (Measurement-ID; Type-ID). The first index is the incremental number of measurements sent within the same message; the second index identifies measurement types (which are detailed in Table II). EM measurements provide two types of information. Firstly, the network upon which relies the current wireless connection of the device (e.g., GPRS, EDGE, UMTS, LTE, etc.). Secondly, the received signal strength expressed in dBm or ASU (i.e., Arbitrary Strength Unit, which is an integer value proportional to the received signal strength).

<table>
<thead>
<tr>
<th>TABLE I. MESSAGE SCHEMA AND CORRESPONDING SAMPLE CONTENT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Message Section</td>
</tr>
<tr>
<td>Header</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Measurements</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE II. INFORMATION AND SENSOR MAPPING IN MEASUREMENT MESSAGE SECTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measurement</td>
</tr>
<tr>
<td>Section ID</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

D. Data Processing

A specific ETL (Extraction, Transformation and Loading) processing pipeline has been designed to clean up and enrich data coming from sensing devices in order to make them suitable to be visualized within the final Web application. The usage of an ETL approach in this context is needed for several reasons. At first, semantic correctness of measurements is checked against predefined patterns (see Section IV.C) in order to remove possible wrong data (extraction and cleaning phase). Then, useful information is extracted from raw data (transformation phase) before storing them within the DW (load phase). By scheduling this data processing pipeline, it is possible to maintain the DW updated and to make data visualization as dynamic as possible within the Web application.

In order to understand how the ETL pipeline modifies collected data, the performed transformations are enlisted below. They refer to the dimensions depicted in Fig. 2.

- **Device position**: devices are localized via latitude and longitude coordinates. Starting from such data, additional, more user-friendly information are extracted during this step: state, region, province, city and geographical zone are obtained by using specific geocoding API requests to Google Maps [38]. No user localization capabilities are provided with the system, in order to preserve user anonymity.
- **Device typology**: since the proposed system exploits the APIs offered by the Android OS [6], this step verifies compatibility issues between vendors, devices and corresponding OS versions. This is mandatory since some vendors disabled on some device models the access to specific subsections of Android APIs, thus impeding the access to signal strength information.
- **Measurement date**: this step simply modifies the acquired timestamp for each measurement.
- **Network Type**: this phase monitors the wireless network type currently used by the device, comparing them to the ones available in the adopted version of Android APIs. New network types are stored into the DW if not already present.

V. FINDINGS AND RESULTS

A. Evaluation of Developed Applications

Two kind of applications (a mobile one and a Web-based one) have been developed in order to involve learners in this

![Fig. 2. Detection fact schema](image)
experimentation. The mobile application allows students collecting and examining measurements. It renders each device a client for the architectural model defined in Section IV.A. As depicted in Fig. 3, the mobile app shows geographical coordinates, received signal strengths (both in dBM and in ASU units), serving wireless communication network and acceleration values. It is important to specify how the main purpose of this app concerns single-learners. Indeed, they can visually examine the intensity of the signals received by their devices, thus coping with the seamless and geo-learning paradigms described in Section II. This makes students better aware of the measurements they are providing to the system and about the reciprocal effects between their movements and the received signals. Signal intensities are reported on the screen by using a rainbow color scale, which ranges from red values (weak signals) to green values (strong signals), applied to a circle-based representation where each circle radius is proportional to the signal strength measured in ASUs.

The collaborative aspects of the system, as well as its true MCS nature, are much more visible by examining the second application specifically developed in the framework of this research work. It is a Web application capable of visualizing EM field levels on large geographical areas and multi-dimensional analysis over the collected measurements. The geographical representation is offered via additional overlays on Google Maps, showing the Kriging interpolation [39] on measured data. This produces smooth signal intensity maps as color-based surface plots. The multidimensional analysis is provided via specific tabbed panels, as depicted in Fig. 4, where signal intensities for different wireless network types are plotted along a time axis. Other visualization showing different data aggregations are also available. System scalability has also been evaluated by considering data dimensional growth and data warehouse dimensional estimate (which are not reported in this paper since they are deemed as out of the scope in this specific context).

B. Evaluation of Students’ Feedback

The proposed system has been developed and tested amongst students from a Master Engineering degree in Computer Science, at our university.

We gathered two different group of students. The first one only involved learners from a Computer Science course, which actually does not offer an extensive didactic coverage on wireless communication systems. The three students belonging to this group have been put in charge of the platform prototype development, by following a co-working, collaborative approach. This has been done in order to ascertain whether the cooperation amongst the developers may improve their critical thinking and questioning about how to structure correctly the application with respect to a knowledge domain different from their reference expertise. The second group of students involved 15 learners from various engineering courses at our university (computer science and telecommunications) and it has been created in order to test the platform prototype, therefore platform developers from the first group have not been allowed to participate. The main purpose of this second pool of evaluators was to examine how the proposed system may improve learners’ engagement in wireless communications topic, by assessing it through an ad-hoc questionnaire.

As for the first group of students, its participants directly performed the system planning and development phases in a cooperative way. They have been involved collaboratively in the following steps: system requirements elicitation; data model design; system architecture definition; platform implementation; application deployment.

From a pedagogical point of view, it is important to point out again that such students belong to a Computer Science coursework, which does not involve courses on advanced topics in electromagnetism or wireless communications. We deliberately selected them in order to evaluate how the experiential approach may improve their interaction with scientific topics that do not pertain to their traditional didactic curricula. By working as a team, they started from the examination of the problem in order to highlight system requirements. Although they can exploit the guidance of an EM domain expert, they sketched autonomously a working plan to produce a first prototype of the system, whose correctness has been confirmed by the domain expert.

In this phase, we noticed a strong interoperation and overall responsibility improvement amongst the developers’ team members in order to overcome proactively their difficulties in mastering EM topics. This is clearly visible, for instance, in the study of wireless communication standards and radiopropagation aspects that the students correctly performed prior to the usage of Android APIs [6] for the retrieval of 3GPP parameters [40] from the devices. Therefore, the knowledge of purely theoretical contents has been pursued starting from an experiential approach that pushed them towards a critical thinking behavior.

As for the second group of students, its participants have been engaged in testing the applications developed for the EDM platform (see Subsection V.A). They have performed measurement sessions indoor and outdoor at our Engineering faculty. In this case, students came from both Computer Science and Telecommunication engineering courses. We set up a multiple-choice questionnaire based on the psychometric Likert approach [41]. By using a 5-point Likert scale (i.e., an ordered scale from which the interviewed users have to choose the option that best aligns with their opinion) we aimed at ascertaining users’ feelings with respect to the system and the pedagogical opportunities it may disclose to them. The questionnaire consisted of the following questions:

- **Q1**: Do you think that practical experimentation would improve the quality of the courses you are attending?
- **Q2**: Do you think that adopting mobile devices such as smartphones and tablets is a good way to provide a preliminary monitoring of significant physical phenomena such as environmental pollution?
- **Q3**: Do you feel comfortable in using the provided mobile app?
- **Q4**: Do you feel comfortable in using the provided Web visualization app?
Q5: Do you desire to improve your knowledge in wireless communications topics now that you have used the provided apps?

The achieved results are reported in Table III. As it can be seen, we obtained an overall majority of positive opinions. More specifically, the request for more practical experiences in academic courses (Q1) is cross-disciplinary, since students from both Computer Science and Telecommunication has expressed the same opinion. The second question (Q2) is biased towards a positive approach about MCS, thus demonstrating how the usage of mobile devices is now pervasive for engineering students. Q3 and Q4 show an overall satisfaction for the provided applications (see Subsection V.B) although some users requested for a better visualization map in the Web application that will be consequently improved in its next version. Interviewed users demonstrated a positive attitude also towards Q5.

<table>
<thead>
<tr>
<th>Question</th>
<th>Negative Opinions</th>
<th>Neutral Opinions</th>
<th>Positive Opinions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1</td>
<td>5%</td>
<td>12%</td>
<td>83%</td>
</tr>
<tr>
<td>Q2</td>
<td>17%</td>
<td>22%</td>
<td>61%</td>
</tr>
<tr>
<td>Q3</td>
<td>7%</td>
<td>10%</td>
<td>83%</td>
</tr>
<tr>
<td>Q4</td>
<td>11%</td>
<td>27%</td>
<td>62%</td>
</tr>
<tr>
<td>Q5</td>
<td>12%</td>
<td>31%</td>
<td>57%</td>
</tr>
</tbody>
</table>

In this preliminary stage, the two subsets of students allowed us to verify the correct functions of the application and its pedagogical suitability. A broader set of tests, involving a larger number of students is now in progress in order to ascertain pedagogical benefits of this collaborative, MCS approach on a wider scale. Schools will be engaged in the experimentations as well.

VI. CONCLUSIONS

In this paper, a platform for opportunistic mobile crowd sensing of electromagnetic field levels has been presented, named EDM (Electromagnetic Device-mediated Monitoring). It exploits Android-based personal devices to capture received signal strengths in order to perform extensive measurement campaigns. The proposed solution also acts as a learning environment capable of promoting collaborative learning in both schools and engineering courses. It contributes to explore novel and emerging learning paradigms, such as geo-learning and seamless learning. In addition, it complements the expensive, traditional EM monitoring policies by offering a large-scale, low-cost, flexible and sufficiently accurate way of sensing EM field levels.

A complete data warehouse solution has been described, highlighting system architecture, data modeling aspects and measurement processing methodologies. A mobile application enabling learners to examine the signal intensities sensed by their own devices. Similarly, a Web application has been developed to visualize collaborative measurements and to provide detailed multidimensional analyses. Students from a Master Engineering course in Computer Science tested the entire platform during both its realization and its preliminary test.

By applying such an approach, large surveys can be performed in order to find those geographical areas where EM levels may exceed regulatory standards and where more sophisticated measurement devices can be subsequently carried out. Extensive trials involving a large number of students from both our universities and local schools are about to start. In the same way, advanced techniques to merge measurement data properly are under evaluation.

ACKNOWLEDGEMENT

This work has been partially supported by Engineering Ingegneria Informatica S.p.A. and Essentia S.r.l. We thank Simona Podo, Vincenzo Scialpi and Matteo Zoecco for their valuable support in developing the tool.
REFERENCES


