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Research Article **Open Access**

Gwenaël Guillaume*, Arnaud Can, Gwendall Petit, Nicolas Fortin, Sylvain Palominos, Benoit Gauvreau, Erwan Bocher, and Judicaël Picaut

Noise mapping based on participative measurements

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Abstract: The high temporal and spatial granularities recommended by the European regulation for the purpose of environmental noise mapping leads to consider new alternatives to simulations for reaching such information. While more and more European cities deploy urban environmental observatories, the ceaseless rising number of citizens equipped with both a geographical positioning system and environmental sensors through their smartphones legitimates the design of outsourced systems that promote citizen participatory sensing. In this context, the OnoM@p system aims at offering a framework for capitalizing on crowd noise data recorded by inexperienced individuals by means of an especially designed mobile phone application. The system fully rests upon open source tools and interoperability standards defined by the Open Geospatial Consortium. Moreover, the implementation of the Spatial Data Infrastructure principle enables to break up as services the various business modules for acquiring, analysing and mapping sound levels. The proposed architecture rests on outsourced processes able to filter outlier sensors and untrustworthy data, to cross- reference geolocalised noise measurements with both geographical and statistical data in order to provide higher-level indicators, and to map the collected and processed data based on web services.

Keywords: noise mapping; smartphones; participatory measurement; outsourced processes; citizen sensing

***Corresponding Author: Gwenaël Guillaume:** IRSTV (Institute for Research on Urban Sciences and Techniques) Nantes cedex 3, France; Email: gwenael.guillaume.pro@gmail.com
Arnaud Can, Benoit Gauvreau, Judicaël Picaut: Ifsttar (French Institute of Science and Technology for Transport, Development and Networks)
Gwendall Petit, Nicolas Fortin, Sylvain Palominos: ECN (École Centrale Nantes)
Erwan Bocher: Lab-STICC (Information and Communication Science and Technology Laboratory)

1 Introduction

Noise represents both societal and environmental concerns, in particular for cities, which are subjected to a multitude of noise sources and which count *de facto* numerous exposed people. By the way, the Green Paper on Future Noise Policy published by the European Commission reports that the number of European people exposed to continuous daytime outdoor noise levels caused by transport higher than 65 dB(A), represents between 17 and 22% of the Union's population (*i.e.* close to 80 million people) [1]. An additional 170 million citizens put up with noise levels between 55 and 65 dB(A), which is the level at which people become seriously annoyed during the daytime. According to the same report, road transport noise stands for the dominant noise source and accounts for 90% of the population exposed to noise levels higher than the threshold value of 65 dB(A). However, the

Environmental Protection UK[1] organization underlines that "noise can cause annoyance and fatigue, interfere with communication and sleep, reduce efficiency and damage hearing". The World Health Organisation (WHO) recommends in this respect guideline levels L_{Aeq} of 30 dB(A) indoor and 50 dB(A) outdoor, for undisturbed sleep and daytime sound levels respectively [2].

For facing these issues, the European Commission established the European Noise Directive (END) 2002/49/EC that aims at achieving a common approach in Europe to avoid, to prevent or to reduce the harmful effects of environmental noise exposure for health [3]. The END sets the key priorities for the main agglomerations, as among others making available information to the public concerning their noise exposure and its health effects, and imposes to elaborate noise maps. According to this directive, noise mapping means "the presentation of data on an existing or predicted noise situation in terms of a noise indicator, indicating breaches of any relevant limit value in force, the

1 The Environmental Protection UK is a UK environmental Non-Governmental Organization (NGO). Website: http://www.environmental-protection.org.uk/.

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number of people affected in a certain area, or the number of dwellings exposed to certain values of a noise indicator in a certain area". Such representations are commonly issued from numerical simulations that enable the prevision of noise levels with a fine spatial resolution, but that cannot address the needs regarding the time variability of noise (see section 2.1). This led to achieve noise measurements through the creation of noise observatories (see section 2.2) or by punctual (in time) measurements (see section 2.3) at strategic noise black spots in order to improve the time representativeness. However, such localised measurements cannot deal with the requirements in terms of spatial representativeness. Consequently, new alternatives have to be proposed to respond to this space-time duality. One can mention the assimilation of measurement stations data into operational numerical models [4, 5]. Unfortunately, noise observatories represent a costly infrastructure in terms of both amount of deployed sensors and maintenance. In this context, citizen sensing stands for a great opportunity to get close to these requirements of both temporal and spatial representativenesses. This approach rests upon the assessment of noise levels by voluntary individuals thanks to the microphone embedded in their smartphone. The main advantage of this approach is that all noise sources which compose the sound environment are considered, while traditional methods are restrained to the modelled sources (*i.e.* excluding voices, birds, human activities, wind, fountains, helicopters, etc.). Participatory noise sensing results however in a serious challenge for both the public authorities and research [6]. Firstly, the accuracy and relevance of the collected data stand for both a key point and the main current limitation. Secondly, the information fed back to the user is for now mainly limited to an historic of the noise data measured, which could be usefully enriched by indicators dedicated to the understanding of the noise environment that surrounds the user (*e.g.* Repartition of Noise Exposure (RNE), Sound Exposure Level (SEL), etc.).

The present work is incorporated within the framework of the European ENERGIC-OD project[2] (European Network for Redistributing Geospatial Information to user Communities – Open Data), which aims at addressing the issues of both the interoperability and accessibility to geospatial datasets by deploying a set of Virtual Hubs that include INSPIRE-compliant systems and Copernicus/GMES (Global Monitoring for Environment and Security) services. In this paper, a system is described that consists in enhancing citizens participatory sensing within the context of noise exposure assessment. The originality of the proposed approach stands in the full standard compliant Spatial Data Infrastructure (SDI), named OnoM@p, that embraces a specially developed smartphone application based on android SDK. This application can report back to the contributor useful noise exposure information thanks to especially designed outsourced data treatments. These latter processes control the accuracy of the provided data and give access to a new set of indicators based on both geographical and demographic data. The section 2 presents the pro and cons of the classical noise mapping approaches. The section 3 highlights the possibilities offered by participatory noise sensing alternatives, and reviews the existing dedicated tools. The section 4 describes the conceptual model behind the cloud system architecture developed in the context of the ENERGIC-OD project. The system includes the smartphone application, detailed in section 5, that allows the user to collect and to share noise data. Outsourced data treatments, presented in section 6, gather and process the raw data sent by the smartphones and estimates a set of advanced indicators. Finally, the section 7 concludes on the possible improvements and further developments, as the production of noise maps.

2 Noise assessment background

2.1 Simulation-based noise maps

The European Noise Directive (END) 2002/49/EC recommends the use of the French engineering model NMPB 2008 when considering road traffic noise [3]. The method includes two methodological guides: the first guide book deals with the calculation of sound emissions from road traffic [7]; the second one describes the computation of noise propagation [8]. For railway and aircraft noise, the Netherlands national computation method published in [9] and the Report on Standard Method of Computing Noise Contours around Civil Airports [10, 11] are advised, respectively. Besides, the standard method ISO 9613-2:1996 details how considering industrial noise [12].

The generation of simulation-based noise maps presents some limitations. Firstly, such calculations require high computational capabilities due to the hugeness of the entailed data [13]. Secondly, simulations do not include all noise sources. Thirdly, the numerical methods employed can not account for time fluctuations of the sound levels (*i.e.* sound events), which leads to "frozen" noise maps that badly reflect the real sound environment (*e.g.* traffic dynamic, cultural or festive activities, road

2 Website: http://www.energic-od.eu/.

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works or plannings, etc.). Fourthly, numerical simulations at the environmental scale (*e.g.* at an agglomeration scale) rest on engineering computational models that require huge information concerning the investigated area (*e.g.* the building, the topography, the nature of soils and of the road pavements, the yearly probabilities of occurrence of meteorological conditions, etc.) and noise sources (*e.g.* road, railway and air traffics, noisy industries and activities, etc.). Unfortunately, some of this simulation input is sometimes missing, incomplete or difficult to estimate. In particular, the modelling of the main urban noise source, namely the road traffic, necessitates many information (*e.g.* traffic flow, light/heavy vehicles ratio and respective speeds, etc.) over the entire road network [14–16]. Also, the soil constitution stands for an important input data, which is most of the time not available over the whole surface of the land cover.

2.2 Localised noise measurements

The deployment of experimental facilities stands thus for an interesting alternative strategy for noise monitoring. In particular, in contrast with simulations, measurements enable to capture the time variations of environmental noise levels and provide consequently complementary information to calculation results. Traditionally, noise measurements in urban areas are undertaken with a sound level meter or an equivalent professional device and by appointed officers that gather data in some locations under investigation for successive analysis and storage. However this manual collection approach based on expensive equipments is dedicated to noise collection at a limited number of punctual places, and does not fit with the requirements of the increasing demand for higher granularity of noise measurements in both time and space [17]. Consequently, some authors experienced noise levels assessment based on a wireless sensor network [18, 19]. Additionally, since a few years, urban noise observatories appear in a few French[3] and European[4] agglomerations [20]. Such monitoring setups must achieve several targets for complying with the European practice guide [14], namely completing noise mapping approaches, informing citizens about their noise exposure, as well as capitalizing and sharing knowledge concerning environmental noise [21]. In addition, some works aim at capitalizing on noise monitoring networks by assimilating the collected experimental data for correcting simulated noise maps [4, 5]. The rise of "smart cities" projects shows the interest of urban agglomerations for acquiring environmental monitoring stations[5].

2.3 Mobile noise measurements

A finer spatial granularity can be obtained experimentally through mobile measurements [22]. In-transit measurements consists in recording noise levels along a journey and involve two main devices: an acoustic sensor (a sonometer usually) and a global positioning system (GPS). The synchronization of both devices enables to get geo-localized acoustic data (typically global and third octave bands A-weighted equivalent sound pressure levels $L_{Aeq,f_c,1s}$). The representativeness of the collected data is ensured by performing several measurements at given locations and at various moments of the day, in order to end up with satisfying temporal and spatial representativenesses. In practice, a journey is generally defined and this path is discretised into a set of predefined "theoretical" points with a fixed spatial resolution (*e.g.* one point every 5 m in [23]). The gathered experimental GPS positions are then replaced with the nearest ones among the fixed map "theoretical" locations. Thus, if the samples collected at each point are of at least 10 s duration, a few relevant indicators can be estimated for describing the noise dynamics at short term (statistical indexes, time variations, etc.).

Mobile measurements require a soft transportation mode, namely walking or cycling, in order to prevent from the noise produced by the transportation mode itself. Some experimental aspects of the walking measurements are discussed in [24]. In particular, the impact of the mobile transducer's mounting location (shielding effect) is reported to be in the order of 1.3 dB(A) to 1.5 dB(A) according to the device mounting[6] (around the waist or upon the shoulders). Carrying the sonometer over the shoulders [26] is often the solution retained for avoiding the screen effect of the parked vehicles. Otherwise, cycling transporta-

3 Dunkerque and Calais agglomeration community, Lille metropolis agglomeration community, Île-de-France region, Greater Lyons urban community, Saint-Etienne metropolis, Grenoble agglomeration community, Nice Côte d'Azur agglomeration community, Aix-en-Provence agglomeration community.

4 Dublin (IRL), Rotterdam (NL), Oss (NL), Gdansk (PL), Brussels (B), Turin (I), Madrid (E), Barcelona (E).

5 Some smart sensor network solutions are already developed and deployed, as the ASAsense technology (see http://www.asasense.com/).

6 In [25], it is already shown that A-weighted sound level measurements performed with a microphone on a person's body can be affected of –1 to +5 dB(A) according to its location.

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tion mode allows to cover more quickly a large area but entails reducing the spatial resolution, and requires to avoid or even to filter the mechanical noises of the bicycle itself [27]. Another approach for mobile noise measurements consists in placing a microphone on a pneumatic mast mounted on the roof of a car (the microphone is thus held at 4 m high above the ground) and in collecting data at strategic places when the car is parked [24, 28].

The main advantages of mobile measurements for the purpose of refining the spatial resolution of noise maps are discussed in [22]. Compared to fixed stations coupled with classical interpolation methods (*e.g.* Inverse Distance Weighting (IDW) or Kriging), the mean errors are considerably lowered. Indeed, the high spatial variations of noise levels and the predominant contribution of the local sources make delicate the assessment of the noise level in a street by means of measurements in neighbouring streets. Mobile measurements allow to get around this problem as the whole network is crossed.

On the other hand, the temporal sampling stands for one of the main difficulties concerning mobile measurements because particular events occurring during the short measurement time (*e.g.* roadwork, traffic jam, siren, etc.) can be unrepresentative of the site. This variability can be minimized by averaging the data piled during the same minute at locations at less than 50 m from the nearest pre-fixed point and, then, applying a spatial Gaussian filter [22]. Another main limitation of mobile measurements concerns the geolocalization of the collected data due to the GPS data deviation occurring sometimes in built-up area (*e.g.* satellite signal lost). According to [29], such errors can be overpassed by filtering the incoherent GPS points too far from the fixed discretised path through an automatic process based on a Differential Global Positioning System (DGPS). However, some errors remain inevitably; for example, if the GPS point falls on the fixed discretised path but at a wrong location. These errors can be much more damaging than the errors on the noise levels themselves, as they can allocate high noise levels to quiet streets, and reciprocally. The use of geographical data, and therefore of a spatial data infrastructure, enables to control the contextual validity of GPS positions and to discriminate more efficiently erroneous coordinates (*e.g.* GPS positions that match with a building location).

3 New crowd sensing alternatives

3.1 Participatory sensing: challenges and opportunities

The emergence of embedded sensor technologies in the everyday life of citizens could revolutionize the involvement of the population in social, economical or else environmental concerns through the self-assessment of their neighborhood environment quality. The participatory sensing concept rests on user-centric monitoring and environmental sensing by means of smartphones [30]. This notion recently arose as a low-cost alternative to large-scale and costly infrastructures sensing based on sensor networks [31]. Thus, numerous approaches rely on citizen-centric surveys [32, 33]. Each citizen can easily contribute to data collection. Opportunities to volunteer to take part in scientific research arise in many disciplines such as health research [34] or environmental monitoring [35].

Participatory sensing places individuals back to their environment and neighborhood community through cloud services that collect and analyze systematic data. The smartphones functionalities provide a convenient way for collecting user feedback in addition to raw data collected by the integrated sensors. Crowdsourcing stands for a great mechanism that directly and naturally engages citizens, in addition to providing huge volume of data and valuable feedback over a wide territory coverage area. Numerous crowdsourcing-based applications were designed for the purpose of grasping problems and gathering data [36–38].

In particular, environmental conditions can be monitored via devoted smartphones applications. The aBluSen application was thus designed as a Bluetooth-based temperature and humidity acquisition system [39]. Air quality monitoring by means of smartphones was also investigated. Thus, the GasMobile architecture relies on both an Android application and a hardware system which consists in a low-cost ozone sensor directly connected to the smartphone through USB host mode [40].

Focusing on acoustics studies, citizen sciences stand for an interesting complement to simulation-based mapping and fixed monitoring stations. Indeed, a large amount of crowdsourced data is required for the purpose of assessing environmental noise (see section 2.1). Furthermore, dedicated processes have to be defined in order to clean up the gathered data, to release relevant noise indicators, as well as to store and to map quality data.

In our knowledge, the first use of mobile phones for the purpose of acoustic data collection relies in reality in

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three Bluetooth-enabled devices: a mobile phone, a GPS receiver and a sensor datalogger [41]. Since this first work, recent researches aim at extending the mobile measurements principle to participatory or collaborative measurements with smartphones. Indeed, these complex devices are able to both capture the ambient sound levels and geolocalize the data. Such works rely on the constantly increasing number of citizens equipped (see section 1), which allows to consider that the high number of measurements performed with heterogeneous equipments can compensate the lower quality (*e.g.* precision, directivity, etc.) of the smartphones microphones in comparison with professional devices. In addition, very large areas and time scales would be covered.

The use of smartphones for the purpose of acoustic measurements gives rise nonetheless to several metrological questions. For example, the microphones contained in smartphones present a directivity chosen in order to maximize the sound field with a normal incidence[7] and can lead to considerable errors at oblique incidence. In addition, studies pointed out the high variations observed according to both the device and noise measurement application [42]. However, the best couples smartphone/software tested in laboratory give an error in the order of 1 dB. The authors also highlight that most of the microphones embedded in the current smartphones are MEMS microphones able to capture sound pressure levels from 30 to at least 120 dB. Besides, according to [43], an automatic calibration process can be applied if identical smartphones and applications are used by all the participants. Nonetheless, other authors reported a variation of the calibration offset even with identical mobile phones and application [44].

3.2 Existing tools devoted to noise harnessing

Numerous smartphone applications are available for the purpose of acoustic data acquisitions [45]. According to the application, a few particular features are available.

One of the most advanced project to date is **NoiseTube**[8] which is a system composed of a mobile phone multiplatform (*i.e.* iOS, Android, Java ME and Windows 8) application and a web portal. The application allows to initialize noise measurements, to upload the collected data to the server and then to visualize on a map thanks to Google Earth [46, 47]. Some contextual information (mainly semantic information) can be provided by the user by means of a tagging component [48, 49]. A calibration process, detailed in [50], is implemented according to both the sound pressure level and frequency. NoiseTube additionally provides users with a noise exposure dosimeter that informs them of their daily "dose" of noise pollution. In addition, NoiseTube can record and collect both perceptive and acoustic data since the volunteer can also respond to a perceptive questionnaire [43, 51]. The latter publication concerning this application, renamed NoiseTubePrime due to new features, mentions the outsourcing of encrypted user data to existing commercial cloud infrastructures in the context of privacy- preserving participatory sensing [52]. Thus, high availability, scalability, ease of deployment and privacy are ensured. NoiseTube contributed mainly to two research projects: the Cart_ASUR project[9] (2012–2016) and the I-SCOPE ("Interoperable Smart City services through an Open Platform for urban Ecosystems") project[10] 2012-2015). Similar features are proposed by the **WideNoise**[11] application (renamed as WideNoisePlus), available for Android and iPhone [53–56], that enables to measure noise levels and to send them to a server for mapping the measurements. Additionally, WideNoise offers users to post measurements on facebook or twitter to raise awareness. The WideNoise application, was developed within the framework of the 7th Framework programme EveryAware (Enhance environmental Awareness through social information technologies) project[12] (2011–2014). Alternatively, **NoiseSpy**, described as a "low cost data logger for monitoring environmental noise" [57], allows to assess personal exposure level. However, the purpose of the study reported in [57] was mainly to demonstrate that mobile phone sensing can be done at a city level and that generated noise map could be provided while still maintaining the user anonymity. The NoiseSpy application is part of the MobSens project that also embraces three other mobile phone applications dedicated to health, social and air pollution sensing [58]. The **NoizCrowd** application, developed within the framework of the BioMPE ("Bio-inspired Monitoring of Pervasive Environments") project[13] (2010–2013) [59], produces noise data in RDF (Resource Descrip-

7 The common use of a smartphone consists of a source (*i.e.* the mouth) located face to face and very near from the microphone.
8 NoiseTube Website: http://www.noisetube.net/.

9 Cart_ASUR ("Mapping of the urban soundscape quality: acceptability of maps") project website: http://noisetube.net/cartasur/.
10 I-SCOPE project website: http://www.iscopeproject.net/.
11 WideNoise website: http://www.widetag.com/widenoise/.
12 EveryAware project website: http://www.everyaware.eu/.
13 BioMPE project website: http://diuf.unifr.ch/pai/biompe/.

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Table 1: Compliance of the main smartphones applications with criteria: (✓) compliant, (✗) evoked with possible future improvement and (—) unmentioned or clearly missing.

Applications	Calibration	Personal exposure	Community exposure	Standards/interoperability	Open source	Risk assessment	Energy awareness	Unobtrusiveness	Context awareness
NoiseTube	✓	✓	✓	✓	✓	✓	—	—	—
WideNoise	—	✓	✓	✓	✓	—	—	—	—
NoiseSPY	✓	✓	✓	✓	—	—	✗	✓	✓
NoizCrowd	✓	✓	✓	✓	—	—	✗	—	—
NoiseWatch	✓	✓	✓	✓	—	—	—	—	—
Ear-Phone	✓	—	✓	—	—	—	✓	✓	✗
SoundOfTheCity	—	✓	✓	—	—	✓	✗	✓	✓
NoiseMap	✓	✓	✓	✓	—	—	—	—	—
Laermometer	—	✓	✓	✓	—	—	—	—	—
NoiseDroid	—	✓	✓	—	✓	—	—	—	—
2Loud?	✓	✓	✓	—	—	✗	—	—	✓

tion Framework) format that enables to link the generated data with other datasets in the Linked Open Data cloud[14] [60]. In addition, interpolation and noise propagation models are involved in order to generate missing data, and the Google Map application is used to display extra information at noise measurements locations. Otherwise, the **NoiseWatch** application[15] is integrated into a three-level assessment structure whose topics are modelling, measuring and citizen rating [61]. The application, implemented by the European Environment Agency (EEA), adds a new layer to the Eye on Earth[16] online project that collects and shares environmental data as information concerning water, air, climate change, biodiversity and land use. **SoundOfTheCity**[17] rests on a continuous, context-aware and unobtrusive participatory sensing approach for measuring noise levels and for monitoring the community exposure under the context of a healthy city [62]. By default, one-second noise measurements are performed every 30 s. The anonymised measured data are sent to a central server that aggregates and generates noise maps. This Android application allows additionally city dwellers to upload sound samples, to annotate the classification of the recorded sound by cause and to provide each user with information on their personal noise exposure. **NoiseMap**[18] is an application built on similar principles as NoiseTube, but with the main distinguishing feature of allowing users to check the collected data, to made them private and to support real-time representation of user submitted data [63]. Numerous other applications were designed for the purpose of assessing noise levels (Laermometer [64], UbiSound [65], NoiseMeter1 [66], 2Loud?[19] [45, 67], etc.). More recently, a team of the French Institute for Research in Computer Science and Automation (Inria) designed and deployed the application SoundCity[20]. The **NoiseBattle** and **NoiseQuest** prototypes address the issue of motivating citizens to collect noise data through gamification techniques [68, 69]. Both gamified mobile applications use the open source application **NoiseDroid**[21] to collect data but in a different way : in NoiseBattle, the "player" conquers areas of the city which is divided into cells, areas being won by providing more noise samples than other participants; NoiseQuest consists in a single player approach for which the correctness of the measurements are prioritized.

Besides, a few works aim at comparing smartphones and/or applications in terms of functionalities, accuracy, context awareness, unobtrusiveness (*i.e.*) and energy awareness [42, 70, 71]. A list of relevant criteria inspired from [62] are pointed in Table 1 for the major smartphone applications. Note that a few features are not necessarily addressed in a similar way (*e.g.* the calibration approaches proposed by the various applications vary, with different levels of accuracy and practicability).

3.3 Scientific and technological bottlenecks

One main limitation of smartphone-based measurements is that mobile phones agents would mainly measure their daily sound exposure while the Directive 2002/49/EC fixed at least two indicators that are much less covered [3]. The control of the sensor faithfulness also constitutes a critical

14 Linked Data website: http://linkeddata.org/.
15 NoiseWatch website: http://discomap.eea.europa.eu/map/ NoiseWatch/.
16 Eye On Earth website: http://www.eyeonearth.org/.
17 SoundOfTheCity website: http://citysound.itm.uni-luebeck.de/.
18 NoiseMap application website: https://www.tk.informatik.tu-darmstadt.de/de/research/smart-urban-networks/noisemap/.
19 2Loud? website: http://www.2loud.net.au/.
20 SoundCity website: http://www.inria.fr/en/centre/paris-rocquencourt/news/launch-of-soundcity-mobile-application.
21 NoiseDroid website: https://wiki.52north.org/bin/view/SensorWeb/OpenNoiseMap.

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issue that may be partly addressed by following the procedure detailed in section 6.1.

Besides, the GPS sensors embedded in smartphones present a typical precision of about 20 m to 50 m and a maximum precision equal to 10 m. The geolocalization stands for a major concern as GPS does not work indoors and is energy-consuming. In addition, a location fix requires a long period of time (on the order of 30 s, *i.e.* around 12 m). Another main source of geolocalization errors is due to buildings that reflect/scatter and occlude satellite signals, leading to a reduced positioning precision in urban environments. However, this issue can be partly alleviated by automatically selecting the best-suited alternative location provider (GPS, cell towers, wifi). In addition, collaborative positioning based on the communication between smartphones improves the positioning accuracy [72].

Participants themselves stand for a key point of collaborative measurements. In [50], the technical officers were preselected and raised awareness among the acoustic measurement. The participants follow then a measurement protocol defined by the research team. However, the contributors to collaborative actions should be volunteers who agree with frequently recording their sound environment with their mobile device, which leads to an "unlimited" number of measurement participants[22]. Consequently, the volume of the data collection can be substantial. The constraints are also reduced for the operator as neither appointment nor particular location are demanded. The freedom granted to the participants carries consequences on many aspects of the data acquisition. The acquisition can be triggered at a time when the smartphone is buried in a pocket, held in the palm in appropriate measurement configuration or, on the contrary, turned to the inside of the hand for instance, or else worn by the user in communication situation. To avoid these uncertainties, some authors designed a set of modules based on signal processing for the purpose of going back to measurement configuration information [44]. Firstly, a *call detection module* returns the state of the phone (in communication or not). If the phone is busy, the module checks the phone status at regular time intervals until the phone is ready to measure the environmental noise. Secondly, a *speech detection module* based on spectral analysis enables to classify speech from ambient noise and thus to avoid the situation for which the smartphone carrier is not calling but still speaking with somebody, or quite simply the case of a passersby conversation. Thus the median amplitude of the spectrogram is calculated for frequencies lower than 4 kHz in order to detect whether a conversation is in progress. Thirdly, the authors implemented a *context discovery module* which checks how the smartphone is carried. For this issue, the 3-axis accelerometer included in the smartphone is exploited. In addition, mobile phones use infrared-based proximity sensors to detect the presence of a human ear for the purposes of both reducing the display power consumption (by turning off the LCD backlight) and disabling the touch screen (in order to avoid inadvertent touches by the cheek). These inner sensors can so be employed to know how the mobile phone is worn (*i.e.* in the hand, in a pocket, etc.). However, according to [44], the proximity sensor is suitable to determine the hand sensing context, but is not adapted for the bag and pocket sensing contexts. A threshold is thus applied on the proximity sensor data, which are only used in hand sensing context. Finally, the context classification is performed by using a k-nearest neighbour (kNN) algorithm and the best classification accuracy obtained rises to 84%. Finally, the collected samples heterogeneity stands for the final bias of the methodology. Indeed, since measurements are achieved completely freely, some regions of the city, and some time periods, are covered with a very high statistical representativeness, while others only gather a few (or none) measurements.

The amount of collected data from such heterogeneous sources (applications, sensors, individuals, environmental quantities), the data management requirements in terms of analysis, research and processing, and the exploiting of the gathered and generated data, place the information system issues at the heart of participatory sensing projects. The geographic information community defined standards for collecting (sensor standards), storing (Relational DataBase Management System, RDBMS), processing (spatial languages) and sharing geodata (view and discovery services). The European INSPIRE Directive incidentally established an infrastructure for spatial information in Europe to support Community environmental policies [73]. The Open Geospatial Consortium[23] (OGC) defined standards (*e.g.* WPS, WMS, SFS, etc. See section 4.3) in order to formalise sensors data. Such standards promote the merging of different scientific skills within the context of territory observatories.

The tripartite organization of crowdsourced-based projects based on the combination of the citizens personal observations and harnessing, the policymakers collection of data, and the scientific researches and develop-

22 Everyone downloading the noise measurement application on its smartphone naturally become a participant and a contributor.

23 Website: http://www.opengeospatial.org/.

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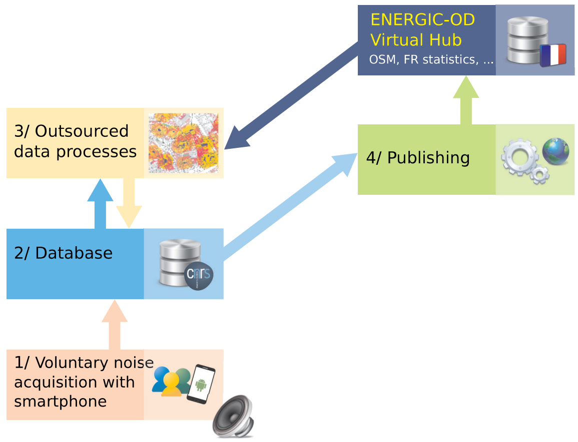

Figure 1: Conceptual model of the OnoM@p system.

ment of dedicated tools, stands for a promising capitalization framework. Environmental noise data can be recorded by the citizens who have sometimes the opportunity to brand their noise data with some associated perceptive feedbacks. These information are a valuable resource for both the scientists and public authorities since they provide a low-cost alternative solution to simulations or fixed sensors network monitoring while keeping the citizen at the heart of both the research and action plans.

4 System architecture: OnoM@p

4.1 Project position

The proposed system is under development within the framework of the ENERGIC-OD project that aims at deploying a set of Virtual Hubs (VH) based on a broker approach to offer to both end-users (through geoportals) and machines (web services, applications), unique and mutually consistent access points to heterogeneous data sources, including INSPIRE-compliant systems and Copernicus/GMES services. In this context, the main originality of our framework's concept compared to approaches detailed in section 3.2 rests upon the proposed system prototype, named OnoM@p (Open noise Map). This system relies upon a smartphone application dedicated to both novice and experts volunteers who are concerned about their own noise exposure and who agree to anonymously upload their geolocalised noise measurements along walking journeys or at specific locations. The OnoM@p infrastructure aims at capitalising on interoperable standards in terms of data formats, transfer protocols, as well as web view and discovery services, for many purposes. First, the data harvested by voluntary citizens are enhanced by means of dedicated automated processes able to control the data faithfulness (see section 6.1), to intersect the upgraded data with both geographical and population data to furnish value-added datasets (see section 6.2) and to redistribute the data to both the scientific community and urban collectivities for then valuating the data through their reuse for other goals and the development of new related-services[24].

4.2 General overview

The Spatial Data Infrastructure (SDI) can be represented as a five- component system such as depicted in Figure 1 that summarizes the conceptual model behind the proposed framework. With the dedicated smartphone application installed on their smartphone (see section 5), each individual can estimate its own noise exposure and, by uploading its geo-localised measurements, contribute to a community noise data collection. The output database is interconnected with OGC standards through services for broadcasting and consulting the database (see section 4.3). Thus more advanced noise-related indicators as statistical and spatial indicators are evaluated (see section 6) by combining the collected noise data with OpenStreetMap and statistical data (*e.g.* demographic data) through the Energic-OD Virtual Hub. Finally, the gathered data are published though Web Services. Such an initiative is thus valuable at once for the citizen (*i.e.* at the individual scale), for the collectivities and for the environmental science community (*i.e.* at the collective scale). For scientists, this project stands for an opportunity to gather a large amount of noise data over a wide area and to study the feasibility of improving the representativeness of simulation-based noise maps by integrating crowdsourced data information. Such a database can be also useful for many other purposes, in particular concerning the data qualification. Such information is also interesting for local collectivities and main agglomerations that can lean upon this collective effort to grasp information regarding the local noise concerns and to better inform the population about its noise exposure.

24 An example of service would be an accessibility help service to quiet places.

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4.3 Tools, frameworks and standards

The smartphone application is implemented through the Android Software Development Kit (SDK). The sound signal processing is developed entirely in Java programming language and integrated into the Android implementation (see section 5). The standards entailed for both the sending of the data by the user and the return of enhanced information toward the smartphone are detailed in Figure 2. The data uploaded by the volunteers from the application feed the database which is managed by the open source spatial database H2GIS[25] that completely complies with the OGC for Structured Query Language (SQL) standards and built on the Java DataBase Connectivity (JDBC) compliant H2 database. H2GIS is harnessed for both building the noise measurements database directly issued from the users contributions, and computing additional noise indicators by compiling the noise data with both statistical and geographical data. The Geographic Information System (GIS) is also employed to filter or alert to potentially poorly localised data based on the geographical database. The data collected along a journey (*i.e.* a track) and shared by the volunteers with the application are forwarded to the database in zipped files that contains 3 files: a GeoJSON file that stores all track coordinates, a txt file[26] that contains the noise indicators computed along the track and another txt file that concatenates some metadata concerning the smartphone, the calibration method, etc. This compressed file is transferred to the server by means of a Web Processing Service (WPS) handled by the open source software GeoServer[27] which is used to share information, to manage the database and to render thematic maps. The zipped files received on the server are thus unzipped and the extracted files are integrated into the database by a relational database management system (RDBMS) SQL script. The cross-calibration process and the estimation of the advanced noise indicators (see section 6) is also handled by GeoServer and implemented through Simple Features Specification (SFS) for SQL. Besides, the resulting data gathered in the database are made available as Web Map Service (WMS) layers that are displayed on the smartphone in a custom map browser thanks to the open-source JavaScript library Leaflet[28] based on HTLM5 canvas.

25 H2GIS website: http://www.h2gis.org/.

26 GeoJSON is an open encoding format of simple geospatial datasets using standard JavaScript Object Notation (JSON).

27 Geoserver website: http://geoserver.org/.

28 Leaflet website: http://leafletjs.com/.

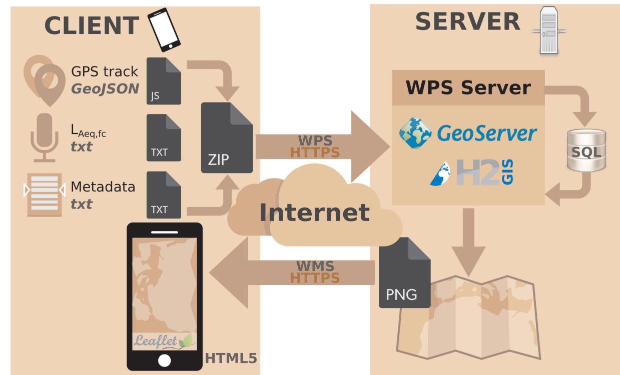

Figure 2: Standard formats and protocols involved in the communication of the smartphone application and the OnoM@p framework.

5 Smartphone application

5.1 Smartphone's microphone calibration

A calibration step must be achieved beforehand any measurement. Two calibrations are conceived within the OnoM@p system, which can be used separately or combined: an *a priori* standard individual calibration described hereafter and an *a posteriori* cross-calibration detailed in section 6.1.

A high dispersion can be observed in measurements if different devices and noise measurement applications are used. This dispersion can theoretically be reduced thanks to an individual calibration process. Such calibration was proposed in [43], restraining however measurements to the case when identical smartphones and applications are used by all the participants. The objective of the *a priori* individual calibration included in the OnoM@p system is to determine the offset values to apply to the raw data furnished by each smartphone per frequency bands. This individual calibration should be theoretically carried out in lab by comparing the smartphone's outputs with reference results delivered by an accurate and reliable microphone, what would debase both the relevancy and operability of the proposed outsourced system expected to be a self-sufficient tool. This solution is nonetheless proposed by the application for individuals equipped with a reference microphone by confronting either A-weighted global sound levels $L_{Aglobal}$ or preferentially A-weighted third octave band sound level spectra L_{A,f_c}.

Incidentally, an alternative practical solution is proposed here that consists in standardising the smartphone's microphone at the vicinity of a public terminal (*e.g.* a fixed noise monitoring station in a street or a sonometer in a concert hall during a musical event) that

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records simultaneously with the mobile device the background noise and relays the results to the server that update the data linked to the user profile in the database with the calibration offset values.

5.2 Audio stream process

The audio stream furnished by the smartphone's microphone is picked up with a sampling frequency F_s = 44.1 kHz and handled as successive one-second samples for extracting A-weighted third octave band levels $L_{Aeq,f_c,1s}$. The process is made up with three steps. First, an A-weighting filter is applied to the one-second time signal $s_{1s}(t)$ based on a Transposed-Direct-Form II structure (also called "canonical" form). The A-weighted sample $s_{A,1s}(t)$ is then band- pass filtered per third octave bands by means of cascaded series of second-order "biquadratric" (or "biquad") filters sections, this cascaded structure being less sensitive to coefficient quantization and roundoff errors [74]. This second step results in N_f samples $s_{A,f_c,1s}(t)$ that correspond to the A-weighted time signals with spectral components comprised within the frequency range of each nominal frequency f_c. Finally, the A-weighted equivalent sound levels $L_{Aeq,f_c,1s}$ are computed for each third octave band of nominal frequency f_c from the output A-weighted third octave band signals $s_{A,f_c,1s}(t)$ as:

$$L_{Aeq,f_c,1s} = 10\log_{10}\left(\frac{1}{N_t}\frac{\sum_{n_t=1}^{N_t} s^2_{A,f_c,1s}[n_t]}{p^2_{ref}}\right), \qquad (1)$$

with N_t the number of samples within the one-second signal and $p_{ref} = 20^{-6}$ µPa the reference sound pressure. The A-weighted global sound level $L_{Aglobal,1s}$ is evaluated from the third octave band sound levels $L_{A,f_c,1s}$ as:

$$L_{Aglobal,1s} = 10\log_{10}\left(\frac{1}{N_t}\sum_{n_f=1}^{N_f} 10^{\left(0.1\times L_{A,f_c,1s}\right)}\right). \qquad (2)$$

5.3 Smartphone application prototyping

The application is dedicated to Android devices. The interface is made up of several activities detailed hereinafter.

During the measurement (*i.e.* along a track), the application computes each second the equivalent A-weighted sound levels for each of the N_f = 20 third octave bands comprised between the nominal frequencies 125 Hz and 10 kHz (see section 5.2). A third octave bands spectrum is displayed and refreshed at each computation. The minimum, the mean and the maximum global A- weighted sound levels L_{Amin}, L_{Amean} and L_{Amax} are also given and are calculated from:

$$L_{Amin} = \left\{\min\left(L_{Aglobal,n_{1s}}\right) | n_{1s} \in [1, N_{1s}]\right\}, \qquad (3a)$$

$$L_{Amean} = 10\log_{10}\left(\frac{1}{N_{1s}}\sum_{n_{1s}=1}^{N_{1s}} 10^{\left(0.1\times L_{Aglobal,n_{1s}}\right)}\right), \qquad (3b)$$

$$\text{and} \quad L_{Amax} = \left\{\max\left(L_{Aglobal,n_{1s}}\right) | n_{1s} \in [1, N_{1s}]\right\}, \qquad (3c)$$

where $L_{Aglobal,n_{1s}}$ corresponds to the N_{1s} values $L_{Aglobal,1s}$ registered since the beginning of the measurement.

The results correspond to both acoustical and statistical indicators computed for the whole duration of the measurement. The percentile levels[29] L_{A10}, L_{A50} and L_{A90} stand for the sound levels exceeded for 10%, 50% and 90% of the measurement period respectively. Moreover, the average A-weighted sound levels per third octave bands L_{A,f_c} are printed and the global sound level $L_{Aglobal}$ is displayed through both a numeric value and a coloured circular gauge. The Repartition of Noise Exposure (RNE) is also shown in the form of a pie chart that represents a classification of sound levels within five levels ranges, as follows: < 45 dB(A), 45–55 dB(A), 55–65 dB(A), 65–75 dB(A) and > 75 dB(A).

An history screen gathers all performed measurements and proposes three possible actions: to remove selected measurements from the smartphone, to show selected measurements on a map or to show the results in numeric values.

A calibration screen enables the user to calibrate its measurement device. The calibration consists in confronting the result(s) given by the application with the one(s) either *a priori*-known or delivered by a sonometer, for a reference noise excitation. The application proposes two calibration procedures as detailed in section 5.1. Calibration data (*i.e.* correction values and used calibration method) are stored and linked to the user profile.

A help screen gives the user an advice concerning the acoustic measurement in order to improve the measurements quality and consequently the reliability of uploaded data. Thus the user is kept apprised of some practical notions regarding environmental noise measurement, *e.g.* the importance of orienting the microphone in the main

29 L_{A10} represents the peak noise, L_{A50} the mean value of the noise levels and L_{A90} the mean value of the background noise.

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direction of the major sound sources and at a minimum distance of his body, etc. Besides, a full documentation of the application and some presentation videos will also be provided on the OnoM@p website.

In writing the paper, the smartphone application is largely operational, but a few of its sections still need improvements or further developments. For instance, the data transmission from the smartphone to the server database has to be pursued and the implementation of the third octave band filtering explained in section 5.2 must be optimised.

In addition, the graphical user interface will propose two modes of use: a novice mode and an expert mode. The second mode, dedicated to experienced users, shall propose additional functionalities and include specific features (*e.g.* the sound spectrum, some additional noise exposure indicators, calibration options, etc.) and upgraded information (*e.g.* acoustical time series, etc.)

5.4 Database structure

The database is populated with the three files contained in each zip file send by a smartphone. Six tables are used to collect all data in the database:

- appli_track contains the data referring to noise indicators along the GPS tracks;
- appli_user aggregates information about the contributors;
- appli_point is made up with measurement points data with supplementary information concerning the device state;
- appli_calibrate gathers the calibration values for the GPS tracks for each nominal frequency;
- appli_freq gives the sound levels per nominal frequencies for each measurement point;
- freq lists the nominal frequencies.

6 Outsourced data treatment

The collected raw noise data on the server are stored and processed in order to describe and to evaluate the sound environments, based on two steps. The first step concerns the cross-calibration of the raw noise data for the purpose of both detecting the outliers and improving the accuracy of the geo-referenced noise measurements (section 6.1). The second step consists in calculating advanced indicators by combining the cross-calibrated noise data with geographical and statistical data (section 6.2).

6.1 Cross-calibration

Even if an *a priori* standard individual calibration is achieved (see section 5.4), what is not necessarily the case, both some deviation and some dispersion remain in the noise measurements, which can be associated with the sensor or with the operator. Moreover, the individual calibration is an expensive and time consuming process, which loses in efficiency if the apparatus deviates with time or with atmospheric conditions (*i.e.* air temperature, ambient pressure, hygrometry).

Thus, an *a posteriori* cross-calibration is proposed within the OnoM@p system, which is able to deal with a heterogeneous mobile sensors network with not necessarily previously calibrated devices. The objective of this outsourced cross-calibration is to rely on the mobile sensors network for correcting the errors in the raw data furnished by each individual sensor. This cross- calibration method, which is described in detail in [75], is made of three successive steps: an outlier detection process, an individual sensor correction based on the mobile sensors network and a standardisation procedure involving fixed high-quality noise monitoring stations.

The **outlier detection** stage aims at detecting the sensors that provide inappropriate data, namely a high dispersion in the measurement errors of an individual sensor. This dispersion can have several potential causes: a careless user during the acquisition, a lack of quality of the sensor, etc. Inversely, the sensors that provide high deviations but low dispersions can easily converge towards low errors, with the help of the mobile measurements network, and are thus not pointed as inappropriate. Consequently, a sensor with, for example, a systematic error equal to +10 dB(A) compared to the mobile sensors network should not be flagged as defective, whereas a sensor leading half of the time to an error of −5 dB(A) and the rest of the time to an error of +5 dB(A) compared to the mobile sensors network should be highlighted as defective. The procedure followed to determine if a given smartphone is valid or defective consists in, first, calculating the differences between the sound levels measured by the smartphone with the average of the sound levels issued from the whole sensors network during the same periods of the day (not necessarily the same day) and at close locations (*i.e.* within a maximum radius of 20 m or at least in the same street). Then, the dispersion in these differences is estimated and the investigated sensor is flagged as defective if a given threshold is exceeded. This estimate can however be biased by the high variability of the measured $L_{Aeq,f_c,1s}$ in both time and space. As a result, a large dispersion can be due to a high instability of the couple sensor/operator, but

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also be the consequence of sound events occurring during the measurements. Thus, a balance has to be found between eliminating the apparently untrustworthy sensors, and keeping a sufficiently large number of sensors for assessing sound level variations. These threshold values are discussed in [75].

The second step of the cross-calibration process consists in estimating each smartphone bias **according to the smartphones network**. This bias is evaluated as the average of the differences between the sound levels measured by the smartphone and the average of the sound levels values returned by the mobile sensors network for the same conditions as for the outlier detection stage (*i.e.* same periods of the day and close location). The underlying idea is that, if a smartphone provides accidentally one measure that deviates from the other smartphones, it may be due to the real variation of the noise level; but if it deviates systematically, this deviation can no longer be regarded as random but reveals instead a bias of the apparatus. As a result of this second step, each sensor is associated with an estimated bias, which is stored and serves to correct subsequently the raw data furnished by the corresponding smartphone. However, the correction achieved at this stage makes the assumption that the smartphones network has a zero average bias, what is not necessarily the case.

The last step relies on the estimate of the average bias of the smartphones network through a **comparison with a fixed high- quality sensors network**, if available. This average bias is evaluated by calculating the difference between the noise levels measured by the whole smartphones when they pass in the vicinity of a fixed trustworthy sensor. The bias estimated by means of each fixed sensor is averaged over the fixed sensors network. This assumes however that the sound levels provided by the fixed sensor and the ones given by a perfect mobile sensor passing by in front of it are equal, what cannot occur as the locations of both sensors cannot be rigorously the same. Further studies are required to design transfer functions between the fixed sensor position and the smartphone location for reducing this bias. Note finally that the average bias of the smartphones network remains probably similar from one city to another. Consequently, the estimated bias could be imported from a city equipped with a high-quality sensors network, hence limiting the installation and monitoring costs.

The cross-calibrated data make up a set of geo-referenced $L_{Aeq,f_c,1s}$ values that can be considered as reliable and are stocked in the database. These data are then used to estimate the basic and advanced indicators presented hereafter.

In writing the paper, this protocol was experienced with a Matlab® algorithm and has to be transposed into SQL programming language.

6.2 Indicators calculation

6.2.1 Basic indicators

The common indicators are calculated by aggregating the cross-calibrated data gathered within a buffer area whose radius (equal to at least 20 m) depends on the amount of collected data. The estimated basic noise indicators are the day-evening-night equivalent sound level L_{den} and the Daily Average Noise Patterns (DANP), which are the average $L_{Aeq,1h}$ value per 1 h-period of the day, evaluated as in [76]. The L_{den} value (Eq. (4b)) is deduced from the DANP values (Eq. (4a)), by introducing the following evening and night penalties:

$$\mathrm{DANP}_{[h_i;h_{i+1}]} = 10\log_{10}\left(\frac{1}{N_i}\sum_{n_i}^{N_i} 10^{\left(0.1\times L_{Aglobal,n_i}\right)}\right), \quad (4a)$$

$$L_{den} = 10\log_{10}\left(\frac{12}{24}\times 10^{\left(0.1\times L_{day}\right)} + \frac{4}{24}\times 10^{\left(0.1\times\left(L_{evening}+5\right)\right)} + \frac{8}{24}\times 10^{\left(0.1\times\left(L_{night}+10\right)\right)}\right), \quad (4b)$$

where $[h_i; h_{i+1}]$ as subscript in the DANP indicator refers to the time slot of the day (*e.g.* [17h;18h]) and N_i is the number of $L_{Aglobal}$ values reported in the buffer area during this period.

In writing the paper, the publishing of the noise map with GeoServer remains under development.

6.2.2 Advanced indicators

Beyond these basic energetic indicators, advanced indicators can be calculated to improve the description of sound environments, which must be selected among the large variety of sound indicators proposed in the literature [77]. This high diversity stands for the specificity of the urban noise pollution characterized by both high spatial and temporal variations and rich spectral components, due to the plethora variety of sources. This wide number of indicators also results from their different uses and targets as each implies different prerequisites: evaluation of sound mitigation measures, communication with the citizens, decision making, etc. Within the framework of the ENERGIC- OD project, the sound indicators produced aim,

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on one hand, at intelligibly informing the users about their noise exposure and, one the other hand, at helping them to reduce this exposure through accessibility indicators. Consequently, the indicators are selected based on both their enforceability and transparency. Their calculation, outsourced to the cloud server, takes profit of the powerfulness of spatial SQL language features available through the H2GIS engine (see section 4.3).

Exposure indicators are dedicated at characterizing either the user own exposure or to the population exposure. At an individual level, the personal exposure is assessed by estimating and displaying within the smartphone application results screen both the $L_{A,global}$ and RNE values related to a measure (see section 5.4). At a population scale, the L_{den} and DANP maps are combined with occupation rates data (if available) in order to determine the number of persons exposed to a L_{den} level higher than a given threshold value or comprised within a range of values. In addition to these spatial indicators sought at a street scale or within selected buffered areas, the building facade exposures are investigated by extracting from the database the coordinates of the facades subjected to L_{den} levels over a fixed threshold value or between predefined noise levels ranges.

6.3 Data enhancement

The data forwarded by the application users are made more valuable at both an individual and public scales.

For the user, a valuable targeted feedback related to its own needs through devoted services which harvest the noise database (*i.e.* benefiting from the whole users' contributions) stands for an added-value information for the contributor. This shall moreover enable to motivate the participant to continue contributing to the crowd noise database by uploading geo-localized measurements. The proposed fully-interoperable infrastructure is also designed to encourage new development initiatives that reuse the built database for the purpose of user-centric services. For example, a few **accessibility indicators** can be designed that aim at offering tools dedicated to reducing its personal noise exposure. First, the participant's exposure is represented along its measurement track, as proposed in [23], through the Sound Exposure Level (SEL). This indicator corresponds to the sum of $L_{A,eq}$ values registered along the contributor trip that is deduced from the map of $L_{Aeq,1h}$ values assuming a configurable walking speed of 1.4 m.s^{-1}. Spatial SQL features can be used to estimate accessibility indicators by selecting the zones within a selected area that are exposed to a L_{den} value within a given range, the quiet zones within a selected area with L_{den} values below a given threshold, or the quietest zone within a selected area. Finally, a tool can be proposed to the user in order to help at reducing his noise exposure over a defined route. This service should rely on the Dijkstra shortest path algorithm that selects the route that reduces the SEL, as proposed in [23].

At a collective scale, the proposed system gives a free access for local authorities to view and discovery services that enable to generate the strategic noise maps demanded by the European union (see section 1). The regulation necessitates to provide noise maps for each type of source. Thus, future works will consist in developing outsourced processing methods to discriminate *a posteriori* the noise sources. Nevertheless, the present experimental approach also offers complementary information to simulation- based noise mapping that cannot account for all noise sources. Besides, accessibility to data shall act as an incentive for the collectivities to regularly update their noise maps and to easily analyse the impacts of achieved urban plannings. The built noise database and related services shall also initiate business actions. For example, the crossing of the noise data with building databases that contain information on the age of the buildings and from which the information concerning the noise insulation of the building can be deduced, can facilitate the commercial canvassing by the building professionals as as it allows to adequately target residents living in *a priori* poorly insulated houses.

7 Conclusion

In this paper, a Spatial Data Infrastructure is presented that relies on participatory smartphone-based noise measurements. The proposed architecture aims at handling a set of operations related to the characterization of sound environments. The first objective is to respond to the Environmental Noise Directive by elaborating noise maps that accurately account for all noise sources with a high spatial resolution. In addition, outsourced processes are designed and implemented for estimating advanced noise indicators, thus improving the characterization of sound environments. In return, valuable feedback information is offered to the user concerning its exposure and a few personalised solutions are proposed to the participant in order to reduce the noise exposure.

The novelty of the approach, in comparison with the existing participatory noise mapping tools, stands in three points. Firstly, specific outsourced treatments of the col-

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lected raw data are designed for both eliminating outliers and correcting the smartphones's microphone response through an *a posteriori* cross-calibration procedure, thus improving the confidence in the produced noise maps. Secondly, upgraded information are furnished to the contributor, what stands for an interesting feedback for the user. Thirdly, the described outsourced infrastructure is fully based on open source tools and programming languages that perfectly comply with geographical standards and facilitates data exchanges toward a global centered hub.

The next step of the project will concern the deployment of smartphones, in order to experience the proposed set of dedicated treatments outsourced on the server through real case conditions. The critical concern and challenge of engaging participants and stakeholders will be addressed by organising some "noise mapping parties" with the help of the open data services of a few cities in order to manage the user communities. Further studies will also investigate the reliability of the present noise mapping solution in comparison with simulation-based noise maps.

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