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REVIEW

Smartphones, a tool for noise monitoring and noise mapping: an overview

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Abstract
Nowadays, environmental noise pollution is recognized as a major public health concern in big cities around the world. Therefore, it has been of great interest to measure the amount of noise that populations are exposed to as well as its evolution through time. In this work, citizen participation in noise sensing by using their smartphones as sound level meters is discussed. Specifically, relevant studies about this technique are described in the context of urban noise monitoring and noise mapping. There seems to be more studies supporting the use of smartphones for this matter. However, the authors have identified a series of limitations regarding proper calibration of the apparatuses, poor microphone response, and the not-utter control of the behavior of participants, among others. Despite this, the progress observed in this field suggests that there are high possibilities to continue working successfully toward the generation of quality noise maps by means of smartphones as sound sensors.

Keywords Noise map · Urban noise monitoring · Smartphone noise measurement · Participatory sensing

Introduction

Nowadays, environmental noise pollution is recognized as a major public health concern in big cities around the world (Berglund et al. 1999; Babisch 2002; Capolongo et al. 2018). Rapid growth of cities increases the exposure to prolonged or excessive noise levels that has been shown to cause several health problems, apart from hearing loss. The non-auditory effects of noise include cardiovascular disease, cognitive impairment, annoyance and stress, sleep disturbance, and tinnitus among others (Basner et al. 2014). In part, the cause can be explained in terms of urban soundscape degradation (Giglio, 2021), i.e., public's perception of the balance between harmless/pleasant sounds and annoying noise, but overall, it can be explained in terms of hazardous noise levels. Therefore, it has been of great interest to measure the amount of noise that populations are exposed to as well as its evolution through time (Zannin et al. 2002; Piccolo et al. 2005; Jakovljevic et al. 2009).

In order to characterize the variations of noise levels throughout different points of interest in cities, noise monitoring (i.e., a continuous logging of noise levels at one or more places) represents an essential activity in order to plan and take actions to mitigate population's noise exposure (Murphy and King 2010). Construction of noise maps requires measuring noise levels at points where workers and/or public are being exposed to potentially high levels. This construction also requires that these strategically chosen points of measure have uniform spacing between them as much as possible to be able to have a grid with reasonable resolution as a result. According to ISO 1996–2:2017, adjacent grid points should not have a difference higher than 5 dB. All this implies carrying out multiple measurements, some of which are not always practical to perform and might be both time-consuming and cost-intensive. One possible solution seems to be materializing from modern technology as it has proven successful at integrating

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multipurpose hardware and software tools with varied applications in one single gadget such as the smartphone.

Currently, smartphones are equipped with imbedded sensors to harvest physical parameters out of the surroundings. The most common and relevant examples are accelerometers, gyroscopes, GPS technology, ambient light sensor, barometer, proximity sensor, and sound sensor (microphone). Furthermore, the ubiquity of smartphones, along with that rich set of sensors, have fomented the development of plenty of useful applications including those related to sound analysis. This hardware/software amalgam offers the possibility of including the average smartphone users in the noise monitoring tasks; this is known as "participatory sensing" (Burke et al. 2006). According to (Burke et al. 2006; Kanhere 2013), the main objective of participatory sensing is to empower ordinary citizens to collect and share sensed data from their surrounding environments by using their smartphones, but the result of this participation goes beyond that. The possibility to have hundreds to thousands of participants/contributors who could accurately gather noise levels data through space and time would significantly improve grids' resolution and accuracy of noise descriptors.

In this work, we provide an overview of the use of smartphones as a new low-cost noise measurement tool within the context of techniques and methodologies found in studies where smartphones have been applied for tasks of noise monitoring and noise mapping. We contrast studies that the provide evidence of the advantages of these techniques to those that reveal drawbacks to overcome in the future. Furthermore, based on a comparison between characteristics of popular apps for noise measuring and the results with in-house developed apps reported in the literature, we propose what we consider the minimal features for better sound level measure app development. The articles selected were retrieved by searching for relevant keywords on scholar databases and by cross-referencing studies cited in the collected papers.

The rest of this paper is organized as follows. In Sect. "Urban noise monitoring", a review of the smartphone mobile technology applied to the measurement of urban noise is presented. Section "Noise maps" describes the methods of mapping environmental noise by using smartphones, acoustic instrumentation, and prediction models. In Sect. "Discussion", the advantages and disadvantages of smartphone mobile technology in urban noise measurements are discussed. Lastly, conclusions, recommendations and possible future lines of research are presented.

Urban noise monitoring

The in situ measurement is the traditional method to characterize urban noise. This method directly observes the real-world acoustic phenomenon. Unfortunately, it implies many drawbacks. For example, several measuring points are required in order to describe the acoustic environment within a specific area. Furthermore, it is extremely costly in time and money because it requires instrumentation that meets high specifications and sometimes hard to mobilize.

In general, urban noise measurements are carried out following guidelines established in ISO: 1996–2: 2017; ISO: 1996–1: 2016. These standards define the descriptors that should be used for monitoring the environmental noise. The most common used descriptors are as follows: Equivalent continuous sound pressure (L_{eqT}), Percentile level ($L_{N,T}$), Day-night equivalent sound level (L_{den}), Sound exposure level (L_E), Effective perceived noise level, Sound pressure level (L_p or SPL).

In order to comply with the requirements for environmental and occupational noise measurements, for example, in the USA, it is necessary that the measuring instruments comply with certain specifications such as using at least type 2 sound level meters, in accordance with the ANSI Standard S1.4-1983 (R2007), specifications for sound level meters. In this regard, the Occupational Safety and Health Administration of the USA (OSHA) considers that type 2 instruments must have an accuracy of ± 2 dBA (OSHA 1971). It is important to mention that all these features and requirements make the standardized instrumentation expensive. For that reason, alternatives such as smartphones along with sound level meter apps have the potential to be used as a monitoring tool in noisy acoustic environments. These alternatives can be simple to use, functional and inexpensive.

Generally speaking, smartphones' sensors are useful to collect information about noise-related human activities. Recently, measurement of noise with smartphones has gathered attention in the environment monitoring area (Kardous and Shaw 2014; Nast et al. 2014; Robinson and Tingay 2014; Murphy and King 2016; Aumond et al. 2017). In addition, there are many applications available that allow recording of noise levels with a mobile phone. Tables 1 and 2 show a list of the applications found to hold the highest number of downloads, according to Google Play service site, i.e., the most popular among the users of that service distributor. Nine of these apps were developed for iOS and seven for Android operating systems. The characteristics of each app are presented in Tables 1 and 2 according to the information provided by the developer.

It is interesting to notice that most of the apps in Tables 1 and 2 include an option for calibration, but apparently, only iOS apps allow the use of an external microphone. This seems to be contradictory because, usually, smartphones' MEMS microphones display not completely linear frequency responses and limited dynamic ranges (Robinson and Tingay 2014), so not being able to use a better external microphone implies poor performance even whether a calibration was carried out. About 60% of the apps include the option to

Table 1 10 sound measuring apps characteristics developed for iOS

	Sound level analyzer Lite 5.2	Decibel meter Pro 5.1 (0.99 USD)	(Real) SPL meter	SPLnFFT 7.0 (3.99 USD)	NIOSH sound level meter 1.2.4	Noise hunter 1.0.1	SPL Pro 1.2.5	Decibel X: dB noise meter 9.3.3	NoiSee 2.2.0 (0.99 USD)
Weighting curves	A,C,Z	A,B,C,Z	A,C	A,C	A,C,Z	A,C,Z	A,B,C,D	A,B,C,Z	A,C,Z
Calibration	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time Weighting F/S	✓		✓		✓	✓	✓	✓	✓
Frequency analysis			✓	✓		✓	✓	✓	✓
Int/Ext Mic				✓	✓	✓	✓	✓	✓
L_{eq}	✓			✓	✓		✓	✓	✓
L_{max}/L_{min}		✓				✓	✓		
L_{avg}		✓				✓		✓	✓
Noise dose meter					✓				✓

Table 2 10 sound measuring apps characteristics developed for Android

	Noise Tube[a] 2.0.2	Sound meter 3.6.3	Decibel X Pro 6.3.5 (35 USD)	Sound level meter 1.4.8	Noise meter 3.9.2	SPL Meter 1.11	Decibel X 6.3.5
Weighting curves	A,C,Z		A,B,C,Z	A,C	A,B,C	A,C,Z	A,B,C,Z
Calibration	✓	✓	✓	✓		✓	✓
Time Weighting F/S				✓			✓
Frequency analysis				✓	✓	✓	✓
Int/Ext Mic							
L_{eq}	✓				✓	✓	✓
L_{max}/L_{min}	✓	✓	✓	✓	✓	✓	✓
L_{avg}		✓			✓	✓	✓
Noise dose meter			✓				

[a]Available for iOS

perform frequency analysis and to calculate equivalent continuous sound level (Leq). This appears to suggest that a significant 40% of noise-measuring apps are not originally aimed at more serious uses. The same scheme is reflected by the irregular appearance of features such as Lmax/Lmin, Lavg and time weighting. Several researchers have focused their effort to evaluate the accuracy of smartphone sound level measuring apps to assess occupational noise exposures in tests developed inside and outside a laboratory. An overview of this type of studies can be found in Table 3.

Kardous and Shaw (2014) examined a representative sample of smartphones and tablets on various platforms, more than 130 iOS and 62 Android apps. However, only about 8% of iOS and 6% of Android apps met criteria for an occupationally useful sound level meter. Their results show that three iOS apps (Noise Hunter, NoiSee, and SoundMeter) had mean differences within ± 2 dBA of a reference sound level measurement and a 65–95 dB test range. They also found that the iOS app SoundMeter had a better performance. For its evaluation, A-weighted reference sound levels were used for comparison between apps, all installed in four different iOS smartphone models (3Gs, 4 s, 4thGen, and 5) and corresponding discrepancies were averaged. The authors concluded that iOS apps have considerable potential to be utilized in occupational noise measurements whereas, in contrast, Android Apps showed poor performance. They attribute this conclusion to the fact that Android devices are built by several different manufacturers' components and features. These results are in agreement with those reported by Murphy and King (2016) who conducted tests with 100 smartphones (1472 tests in total) in these two different platforms in a laboratory environment. Their work

Table 3 Overview of studies for urban noise monitoring conducted with commercial apps

References	Operating system	SLM App	Smartphone's model	Environment test/Test signal	Calibration	SLM Reference	Remarks
Kardous and Shaw (2014)	Android	SPL Meter deciBel Pro dB Sound Meter Noise Meter	HTC One X Motorola Droid razr Samsung: Galaxy S3 Galaxy Note Focus	Laboratory environment/ Pink noise (20 Hz-20 kHz frequency range), at levels from 65 to 95 dB in 5 dB increments	No	Larson-Davis model 831 (Class 1)	Their results show that two apps achieved mean differences of 0.07 dB (unweighted) and -0.52 dB (A-weighted) from the reference values, while the other two apps had mean differences within ± 2 dB This study suggests that NoiSee, SoundMeter and SPLnFFT (for unweighted sound level), and Noise-Hunter, NoiSee and SoundMeter (for A-weighted sound level) may be appropriate for use in occupational noise measurements
	iOS	Adv Decibel Meter 2.0 Decibel Meter Pro 2.0.5 iSPL Pro 1.1.4Noise Hunter 1.0.1 NoiSee 1.0 Sound Level Meter 1.5 SoundMeter 3.3.1 (Real) SPL Meter 1.0 SPL Pro 3.6 SPLnFFT 4.0	iPhone: 3GS 4S 5 iPad 4^{th}Gen				
Nast (2014)	iOS	dB Volume SPLnFFT SPL SoundMeter	iPhone 4S	Laboratory environment/ Third-octave band noise with center frequencies at 0.25, 0.5, 1, 2, 4, and 8 kHz	No	Brüel&Kjaer 2250 (Class 1)	For all the applications analyzed, results varied significantly compared to references values They found that only one app (SoundMeter) was accurate within 5 dB across all frequencies and levels for both A- and C- weightings

Table 3 (continued)

References	Operating system	SLM App	Smartphone's model	Environment test/Test signal	Calibration	SLM Reference	Remarks
Robinson and Tingay (2014)	Android	NoiseMeter Noise-Watch +dB Sound Meter Decibel Pro +SPL Meter	Samsung Galaxy S2 Nexus 7	Workplace/ machinery noise, machinery and impulsive noise and Impulsive noise	No	Cirrus Research Model 171C	Considering the difference between smartphone and app combination used, an average of 12 dB from the level measured by a Class 1 SLM was obtained They concluded that, taking into account the limitations of the hardware/software, smartphone-based sound level measurement apps could be useful for a qualified professional, but not for the general public
	iOS	NoiseMeter	iPhone 5				
Roberts et al. (2016)	iOS	NoiSee SPLnFFT SoundMeter	iPhone: 4 4S 5S iPod	Laboratory environment/Pink noise from 60 to 100 dBA	A pure 1 kHz tone with intensity level of 94 dB	Trident Multi-Channel Acoustic Analyzer Software and Larson Davis 2559 1/2″ inch microphone (Class 1)	Their results show that both external microphones increased the accuracy and precision of noise measurements and reduced the measurement variability introduced by different iOS devices and apps The successful use of iOS smartphones is restricted to certain conditions and operation ranges of specific combinations of apps and external microphones

Table 3 (continued)

References	Operating system	SLM App	Smartphone's model	Environment test/Test signal	Calibration	SLM Reference	Remarks
Ibekwe (2016)	Android	Android Boy1	Samsung Galaxy Note 3 Nokia S Tecno Phantom Z	Real environment (Street, Hospital, Market)	No	Extech model 407,730 (Class 2)	The maximum difference in noise measurements between smartphone and SLM was 3 dB for daytime readings and 4 dB for night-time readings. All noise level measured were < 100 dB. Readings in dBA showed strong correlation (r = 0.9) between the mobile phone and SLM
Murphy and King (2016)	Android	Sound Meter 1.6 Noise Meter 2.1 Decibel Pro 1.4.22	Motorola Google Nexus 5 HTC: One One Mini 2 M8 LG: VS870 g2 Samsung: Galaxy Note 2 Galaxy Note 3 s3, s3 slim, s3 mini, s4, s4 active, s5	Laboratory environment/ Broadband white noise	No	Brüel&Kjaer 2250 (Class 1)	Their work concluded that apps developed for iOS are superior to those designed for Android and have a considerable potential to monitor urban noise in the near future Sound Level Analyzer Lite 1.3 is accurate to within ± 1 dB of true sound levels across a range of reference values
	iOS	Sound Level Analyzer Lite 1.3 SPLnFFT 1.1 Decibel Meter Pro 2.0 5 UE SPL 2.1.1	iPhone: 4 4S 5 5S 5C 6 +				
Aumond et al. (2017)	Android	NoiseTube (modified version)	HTC One X	Real environment	White noise	Standard monitoring sound station and RION NL52 (Class 1)	Noise levels measured with previously calibrated smartphones correlate strongly with those measured in the fixed station and sound level meter

Table 3 (continued)

References	Operating system	SLM App	Smartphone's model	Environment test/Test signal	Calibration	SLM Reference	Remarks
Ventura et al. (2017)	Android	Ambiciti (not commercial app)	OnePlus One (OPO)	Laboratory environment/ Pink noise (20 Hz-20 kHz frequency range), at levels from 40 to 95 dBA in 5 dB increments	Pink noise	Cirrus Optimus Red (Class 1)	On a selection of smartphones available in the market, the responses authors obtained are linear for levels in the 45 to 75 dB(A) range
Celestina et al. (2018)	iOS	NoiSee	iPhone 6 (external microphone: MicW type i436)	Laboratory environment/ Continuous sinusoidal signal of 4 and 8 kHz	A pure 1 kHz tone with intensity level of 94 dB	Brüel&Kjaer 3630	Their results show that the SLM app and an external microphone can achieve compliance with most of the requirements for Class 2 of IEC 61,672/ANSI S1.4–2014 standard
McLennon et al. (2019)	Android	Noise Exposure 2.0.1 Decibel X 1.4.1 Sound Meter- Decibel Sound Meter 3.1.6 Sound Meter & Noise Detector	Samsung: Galaxy S4 Galaxy S7	Laboratory environment/ Steel making, conveyor belt, speech, white noise, pink noise All acoustic stimuli at: 60, 70, 80 and 90 dB(A)	No	Larson Davis model LxT (Class 1)	They conclude that most of the apps cannot be used for accurate determination of sound levels. However, SLA Lite app has the potential to be used as a screening tool in occupational scenarios
	iOS	Noise Exposure 2.0.1 Decibel X 4.3.5 Sound Meter-Noise Power Level and Decibel Meter 1.0.0 Sound Level Analyzer (SLA) Lite- Simple dB Meter 2.2 Sound Level Meter 1.8	iPhone: 6 6 Plus 5 s SE 4 s				

also concluded that apps developed for iOS are superior to those designed for Android and have a considerable potential to monitor urban noise in the near future. Their results show that Sound Level Analyzer Lite app is accurate to within ± 1 dB of true sound levels across a range of reference values. In a later study, Kardous and Shaw (2016) evaluated four apps (Noise Hunter, NoiSee, SoundMeter, and SPLnFFT) using external calibrated microphones. Their results showed measurements within ± 1 dBA compared to the reference. Aumond and his collaborators (2017) carried out a total of 3409 environmental noise measurements by 60 volunteers using a modified version of the NoiseTube app at 28 locations. Simultaneously, measurements were made at fixed stations for environmental noise monitoring by means of a reference sound level meter. Their results showed that the noise levels measured with previously calibrated mobile phones correlate strongly with those measured in the fixed station and sound level meter. It is important to notice that their research was performed on Android-based devices only (HTC-One X).

In contrast, Robinson and Tingay (2014) claim that most studies on this matter try to erroneously control most of the variables that affect the variability of this type of measurements. In their tests, a wide variety of factors are taken into account, some of which are not usually found in other studies. For example, device size, subjects who would carry out the measurements, wind noise, variability in the characteristics of sound sources and characteristics of the surroundings are the most relevant variables included. The sound level meter apps used in this study were selected randomly from the list of ten used in the Kardous and Shaw (2014) study. Their results show that considering the difference between smartphone and app combination used, an average of ± 12 dB from the level measured by a Class 1 sound level meter was obtained. They concluded that taking into account the limitations of the hardware/software, smartphone-based sound level measurement apps could be useful for a qualified professional; however, there are also some drawbacks in the use of smartphone sound level meter (SLM) apps by the general public. This seems to suggest that including more variables typical of the participatory process would derive in poorer, yet more realistic results.

Nast et al. (2014) report even less optimistic results. According to their study, SLM apps are not accurate enough to replace professional sound level meters. They carried out sound level measurements and tested five different apps using an iPhone 4S (dB volume, Advanced Decibel, SPLnFFT Noise Meter, SPL, and SoundMeter). Their results show that, for all the applications analyzed, results varied significantly compared to references values. They found that only one app (SoundMeter) was accurate within ± 5 dB across all frequencies and levels for both A- and C-weightings.

Noise maps

Urban noise monitoring and noise maps keep a close relationship. In order to know and visualize the spatial distribution of noise, the sound levels measured previously in the noise monitoring process can be used for the development of noise maps of the area under study. This spatial distribution allows to identify the acoustic quality of the environment within zones of interest and to assess the effects of noise levels exposure in the population.

Noise maps constitute a useful instrument for the planning of activities diverse in nature, but with specific necessities of quietness. A noise map is a cartographic projection of the distribution of noise levels in a certain geographical area in a given period of time (Murphy and King 2010). In addition, in the European environmental noise directive (Directive 2002/49/EC), a strategic noise map is defined as a map designed for the global assessment of noise exposure in a given area due to the different sound sources in such area. Therefore, the former definition is related to the presentation of the data only, while the latter is focused on the evaluation of human exposure to sounds that may be potentially harmful for the population, being the starting point to improve or preserve the quality of an acoustic environment (Murphy and King 2010). In terms of usefulness, according to the British Department of Environment, Food and Rural Affairs (DEFRA 2012), the use of noise maps allows to quantify noise in a specific area in order to model and predict acoustic environments which, in time, will be useful as databases for urban planning, noise-mitigating public policies design, and noise-related public health issues assessment. The resulting benefits include proper designing to avoid the mix of noisy activities locations with sensitive areas such as hospitals, schools, etc. Noise maps are also helpful to monitor the implementation of specific noise-reductive actions or any not-planned changes in an acoustic scenario (Lam and Ma 2012).

Different methodologies for preparation of a noise map have been well studied: it can be done by performing in situ measurements at previously defined points and by using the required specialized acoustic instrumentation, as described in Sect. 2 (ISO 1996–2:2007(E); Tsai et al. 2009; Sommerhoff et al. 2004); by using prediction models (Lee et al. 2008; Suárez and Barros 2014; Aletta and Kang 2015; Ryu et al. 2017; Zhou et al. 2017); in a mixed system, i.e., by using both techniques mainly to complement and verify the measurements obtained through prediction programs (Manvella et al. 2004; Fiedler and Zannin 2015; Cai et al. 2015); or, more recently, by taking advantage of the flexibility of smartphones as sound receivers (Kanjo 2010; D'Hondt et al. 2013; Aumond et al. 2018; Picaut et al. 2019; Lee et al. 2020; Dubey et al. 2020).

For the case of software-aided prediction models, there are different types of acoustic software for conducting noise maps such as IMMI software and MITHRA SIG Software. SoundPLAN, Predictor-LimA, and CadnaA are among the most important software used in this field of research. This type of programs are aimed for simulating sound in open spaces by calculating airborne propagation for point and/or extended (line) sources, such as industrial machines and vehicle traffic, respectively. The programs include libraries of typical noise sources whose acoustic power has been previously characterized. They consider acoustic barriers (that is, reflection and absorption coefficients) and pavement acoustical characteristics. It is also important to feed the simulation with geographic information systems (GIS) data in order to include accurate information about topography and roads of the site to be mapped.

Although modeling techniques seem to fulfill most expectations, they have limitations as well. On the one hand, prediction models are useful to assess road noise (Steele 2001), railroads (Szwarc et al. 2011), airports (Isermann and Vogelsang 2010) and industries which are usually treated as either point or extended acoustic sources with previously characterized acoustic profiles. On the other hand, many factors are involved in urban noise pollution, and they are not usually taken into account into the modeling because they are difficult or almost impossible to predict mathematically. Examples of this wide variety of factors are citizen's behavior on the streets, concentration of activities, existence and location of pedestrian crossings, bus stops, traffic lights, tunnels, peddlers, etc. All of them are impractical for inclusion in these types of software, yet they could significantly contribute to the distribution and characteristics of environmental sound levels (Manvella et al. 2004).

One way to estimate the magnitude and significance of the differences between the models and reality is to perform in situ noise measurements for comparison with predictions (Mioduszewski et al. 2011; Can et al. 2014). As it has been discussed, standardized measurements, though reliable, tend to be complex, expensive and time-consuming. It is yet to be completely demonstrated whether measuring noise levels with smartphones for this purpose is up to the task, but it is an interesting avenue that has been explored in recent years because of its potential for contributing to this field. Figure 1 shows how smartphones could contribute to the measurement processes of urban noise monitoring and noise mapping.

The development of mobile technology has evolved significantly, and it is currently a fundamental part of people's life. According to Statista site, by the end of 2025, the number of smartphone users worldwide will reach 5,575 million (Statista 2021). Currently, most smartphones have several sensors, such as microphones, cameras, and GPS. Combined with a large number of mobile devices' users, this might imply a significant increase in efficiency and spatial resolution for city noise surveying. It also has been shown that citizens' participation enables the formation of big interactive sensor networks (Burke et al. 2006; Campbell et al. 2006; D'Hondt et al. 2013;), allowing real-time data collection with high temporal resolution. Hence, the potential use of smartphones enables the build-up of more detailed noise maps than those made from laboratory instrumentation measurements. In addition, citizen participation in noise mapping is a way to empower the citizen; it could be used as a tool to measure their individual exposure to noise in their everyday environment, and as a tool for raising awareness of noise pollution and the associated hearing damage. In summary, bearing in mind all the technical differences between state-of-the-art laboratory equipment and smartphones as noise sensors, the latter have the potential to become a valuable tool for the development of noise maps in cities.

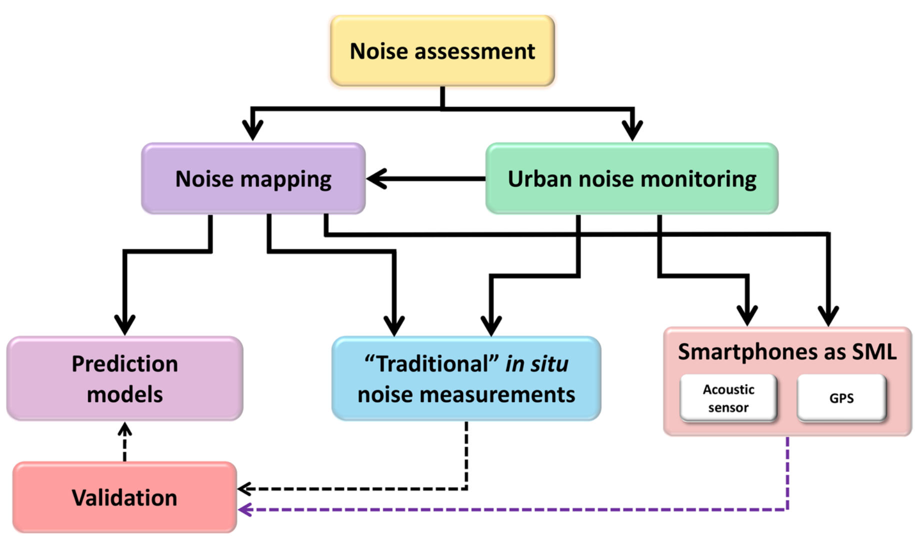

Fig. 1 Schematic view of the use of smartphones within the most common procedures for noise assessment: Noise maps construction and urban noise monitoring

As it could be noticed in Tables 1 and 2, different commercial apps show different features, so during the stage of collecting data, the researcher should stick to the use of only those apps that have in common the features of her interest. Besides, for a long-term study, there is no certainty of a continuous support service from part of the developer. Because of this, developing specific-purpose apps is highly recommendable. For that matter, new apps have been developed by researchers (see Table 4) in order to explore the use of smartphones with noise map purposes (Maisonneuve et al. 2009; Kanjo 2010; Rana et al. 2010; Becker et al. 2013; Yao et al. 2013; Wisniewski et al. 2013; Ruge 2013; García et al. 2012, 2013; Dutta et al. 2017; Nugent and Stanners 2014; Picaut et al. 2019). For example, Kanjo (2010) developed a monitoring environmental noise application called NoiseSpy, an open platform to measure, annotate and localize noise pollution by individual citizens by using their mobile phones as noise level recorders. In this platform, it is possible to share data between users and update noise maps dynamically and in real time. One interesting highlight of Kanjo's app is its capability to assess personal exposure level in their everyday environment, which might be a motivating and useful compensation for the user. Lee et al. (2020) developed an app for both Android and iOS and ask 29 graduate students to collect noise recordings and data in the streets. Smartphones were calibrated with a method in (Garg et al. 2019) which basically consists in applying a correction factor for each frequency to the recordings made with the smartphones. The correction factors are calculated from WAVS of environmental noise simultaneously recorded with a SLM and the smartphones. The authors claim that this calibration method ensures an accuracy of ± 1 dB, except for models with built-in noise cancellation and/or signal processing. The obtained data are uploaded to a website, and includes the calibration WAV, the smartphone recorded WAV, SPL levels, and location of the smartphone log files. The authors conclude that "crowdsourcing" for noise maps using smartphones is viable.

In a study described by Picaut et al. (2019), an in-house developed for Android app called Noise Capture was used by a group of participants with different levels of expertise in acoustic measurements ranging from "expert and "novice contributors" to non-experienced contributors who were trained for the data collecting. The app displays the usual sound level meter descriptors: A-weighting, Min/Max, mean, from 100 Hz to 16 kHz real-time sound spectrum, spectrogram, percentile indicators and average sound spectrum, and it works in the integrating 'fast'-only mode. It also allows setting up the smartphone GPS accuracy and shows real-time position in a map. The contributor may provide subjective feedback on her perception of the registered noise. Afterward, data are transmitted to a remote server. The calibration method of the smartphone is performed with single tone calibrator whenever a 1/2 inch external microphone is used, or by performing a comparison between measurements the smartphone and a calibrated sound level meter in the same noise conditions. In both cases, a global or frequency band calibration factor is applied. Even though the calibration method used is not as meticulous as that used by Lee et al. (2020), interesting perspectives regarding contributors' behavior are provided. As a result, the authors established a series of criteria in order to discard poor quality measurements. Some of these criteria are as follows: pedestrian speed limit of 5 km/h, geolocation accuracy of less than 15 m, whether the calibration factor was applied by the user, not desired indoors data, among others.

Even commercial apps have been used successfully for this type of testing; in a work by D'Hondt et al. (2013), 13 volunteers used the Noise Tube application to make a noise map by using mobile phones. This work aimed to show that these applications can be used by ordinary citizens as a form of participatory evaluation of public noise in big cities. The authors point out that whenever noise measurements based on mobile phones are correctly implemented (in terms of well-motivated citizens, statistical considerations, logistics and data evaluation and interpretation), it is possible to obtain margins of error of about ± 5 dBA, which is comparable with those obtained by acoustic simulation models.

Discussion

The evolution of the use of smartphones as an instrument to sense noise levels is relatively recent. For example, for sound environmental monitoring, several authors have reported results that seem promising (Kardous and Shaw 2014 and 2016; Murphy and King 2016; Aumond et al. 2017). Also, some studies have shown the good performance of sound level meter apps specifically under controlled environments (Murphy and King 2016; Ventura 2017; Kardous 2014). Outdoor measurements also showed strong correlation between noise levels measured with smartphones and those measured with reference sound level meters (Can et al. 2016) or professional noise monitoring stations (Aumond et al. 2017). Most recent studies have attempted to obtain noise maps by means of smartphones-only noise measurements (Lee et al. 2020; Picaut et al. 2019).

The advantages of using smartphones in combination with citizen participation in noise monitoring and noise mapping have been discussed throughout this article and can be summarized in the next list:

- No need of expensive equipment or noise levels predictive software
- Faster data acquisition

Table 4 Overview of studies for noise mapping conducted with in-house developed apps

References	App	Operating system	Calibration	Location	Remarks
Maisonneuve et al. (2009)	Noise Tube	Android and iOS	Yes	Paris, France	This platform comprised of a mobile phone application and the Web-based community memory The mobile phone application can sense noise level in dBA and users can tag sound level measurements and level of annoyance. These tags can describe the source. The mobile application provides users with a personal noise exposure dosimeter. The mobile application provides users with a personal noise exposure dosimeter. Noise descriptor: Equivalent continuous sound level
Kanjo (2010)	Noise Spy	Android	Yes	Heavy traffic streets of Cambridge, UK	Noise Spy is defined as “low cost data logger for monitoring environmental noise”. The mobile phone application allows to assess personal exposure level. The mobile phone application allows to assess personal exposure level. The software combines sound-level data with external GPS receiver locations to generate a map of sound levels, so a collaboratively visualizing noise levels in real time is possible
Rana et al. (2010)	EarPhone		Yes	Both major heavy traffic road intersection, and quieter branch road in Brisbane, Australia	EarPhone is an end-to-end noise pollution mapping system which uses Microphone, GPS receiver and System Clock in a mobile. It was implemented on Nokia N95 and HP iPAQ mobile devices and Java J2ME platform (it is now obsolete). Their results show differences in noise levels when the mobile phone was carried in hand, bag, pocket and waist. Noise descriptors: Equivalent continuous sound pressure. Noise descriptors: Equivalent continuous sound pressure
Becker et al. (2013)	WideNoise	Android and iOS	Not mentioned	London, UK; Rome, Italy; Antwerp, Belgium; and Birmingham, UK	Smartphone application that has been designed to record both noise samples (objective) and opinions and feelings (subjective) data. In the context of hearing loss, user can post measurements on social media in order to raise awareness. The measure noise levels are sent to a server for mapping the measurements
Yao et al. (2013)	Day Day Noise Monitor (DDNM)	Android	Not mentioned	1.4 km section of Lu Mo Road and University of Geosciences north campus, Wuhan, China	Users can download maps through WiFi for offline usage

Table 4 (continued)

References	App	Operating system	Calibration	Location	Remarks
Wisniewski et al. (2013)	NoizCrowd	iOS	Not mentioned	Fribourg, Switzerland	This system collects urban noise levels. Provides dynamic visualizations of both sensor and model data. When data is missing, an interpolation over time and space is autonomously generated
Ruge (2013)	Sound Of The City	Android and iOS		Lübeck, Germany	It collects noise measurements and send it to a central server. Users can annotate the noise readings using semantic tags
García et al. (2012, 2013)	Noise battle	Android		Castelló, Spain	This app is designed and presented for the user as a game. This technique is chosen in order to motivate people to participate voluntarily. Within the game, the user "conquers" areas of the city which is divided into cells, areas being won by providing more noise samples than other participants
Dutta et al. (2017)	NoiseSense	Android	Not mentioned	Kolkata, India	This system monitors the present noise level in the user environment and generates city's noise pollution footprints
Picaut et al. (2019)	Noise capture	Android	Yes	Center of Lyon city, France	Userscan supply additional information (text or photographs). Also, an opinion about his/her perception of the sound environment. The app allows collect both physical sound level data and perceptual data on the acoustic environment. Noise descriptors: Equivalent continuous sound level over 1 s LA_{eq} distribution of $LA_{eq,1s}$ over the measurement time minimum and maximum values of $LA_{eq,1s}$ percentile indicators LA_{10}, LA_{50} and LA_{90} and average sound spectrum over the duration

- Feasible and significant increase in spatial and temporal resolution
- Additional benefit of raise awareness about noise exposure

Although there are numerous advantages to the use of smartphones for urban noise monitoring, there are also some limitations that must be discussed. One major limitation of smartphones for urban noise monitoring is the microphone. The microphones used in smartphones, typically MEMS, are designed to respond to speech signal. The frequency range for the speech signal is between 250 and 4 kHz, so attempting to use certain MEMS microphones outside this interval might result in nonlinearities. Potentially, this limitation of the smartphones could be overcome by the use of external and calibrated microphones (Kardous and Shaw 2016; Celestina 2018; Roberts 2016), but not all devices have this compatibility (as it was seen in Tables 1 and 2).

On the one hand, the calibration option is not available for all commercial smartphone apps. On the other hand, several studies show that calibration of the pair app-microphone is of paramount importance to ensure accurate noise measurements (Aumond et al. 2017; Ibekwe et al. 2016; Celestina 2018; Garg 2019). Besides the fact that not all the apps incorporate the flexibility to make a compensation or calibration, procedures for successful calibration might be too complicated for the average app-user, mainly because the user might not have an appropriate calibration reference at hand. Unless the aim of a study was to evaluate the results obtained in cases when calibration is not possible (Nast 2014), calibration features in the app are mandatory.

In our opinion, another important aspect needs to be in consideration: app users should be warned about intrinsic health risks of measuring high levels of noise when helping create a noise map. This could also represent a limitation for smartphones use for noise mapping because not all users may have hearing protection available, thus exposing them to possible hearing damage and/or discouraging them to collect data in "noisy" locations. Even if the user is not being exposed to high levels, an estimation of noise dose in the app interface can be helpful for them to take care of their health and raise awareness in that sense. A lucky contradiction in this complication is that users might feel motivated to keep participating because of the knowledge they acquire through their contributions.

Overall, there is a lack of a methodology for noise measurements with smartphones, let alone noise map making based in these techniques. What is usually found in articles is that authors have based their proposed methodologies on noise measurement standards (ISO, IEC), for the calculation of acoustic descriptors, but they apply different criteria for the rest of the procedure (i.e., calibration, smartphone location/position, measurements duration, etc.). It is therefore necessary to establish consensuses and guidelines aimed at ensuring that common criteria are being applied to noise environmental monitoring with smartphones and, subsequently, to noise mapping.

Nevertheless, the articles analyzed for this review offer evidence of what could work and what could not work in their own specific experimental setups and conditions, so that some recommendations are possible to abstract. Based in what has been found in the literature and discussed in this manuscript, we also offer a list of features required for common noise-measuring app-smartphones pair:

- Acoustic calibration module available in the app
- Use of external microphones
- Frequency A-weighting option
- Calculation of the Equivalent Continuous Sound Level (L_{eq})
- Frequency spectrum visualization
- Noise dose monitoring for the app user
- Optional deactivation of any automatic internal processing of the signal (equalization, compression, etc.)

Conclusion

In this work, participatory noise monitoring by means of smartphones used as sound level meters was reviewed. Relevant studies about this technology were described in the context of urban noise measurement and noise mapping. A description of various sound measuring apps developed for Android and iOS was presented. Also, the advantages and limitations of participatory noise monitoring for the creation of noise maps were addressed.

Active involvement of the population in the making of noise maps might have the positive effect of empowering them and conveying an understanding of the effects of high noise level exposure during their daily activities. This awareness, in turn, motivates more participation and yields more useful data as a result. In general, most studies tend to point out that use of smartphones for participatory noise monitoring is viable within an acceptable margin of error (consider those that report a ± 5 dB maximum uncertainty). The problem with obtaining more accurate measurements lies in part in that there are no unified criteria for calibration procedures and adjustments to achieve measurements of this quality. Apparently, because of the multiple factors and variables involved, a standardized methodology is far from being proposed in this field. However, most studies agree in that there are some crucial aspects to take care of in order to reach the common goal of a quality noise map.

An appropriate app design seems to be feasible by including the calculation of meaningful sound descriptors such as those that typically are found in sound level meters plus the flexibility to attach location, images and subjective information to each measurement. Although remote calibration of every smartphone involved is still a drawback to be tackled, an effective calibration of the software-hardware setup can be achieved as long as the app developer grants access to supervised in-person calibration procedures (for example, by recording the same noise both with a smartphone and a SLM, so that a frequency correction function can be obtained). If the hardware allows the use of an external microphone, the chances of accurate measurements might significantly increase as external microphones use to have better performance than that of smartphones. We believe that following these suggestions, researchers developing new dedicated apps might be able to succeed in this field.

Because the smartphone market has been dominated by two operating systems, most studies centered their attention in iOS and Android. In general, it was observed that iOS smartphones and apps were reported to be better equipped for noise monitoring than Android's. The apparent reason is the high variety and variability in the features and quality of the equipment using Android, whereas iOS apps are always installed in devices with more homogeneous technical characteristics. However, some authors still prefer to carry out their research based on Android-using devices because there are more Android users, and because those devices are still able to do the task, nonetheless. Evidently, probing for what devices would be used for a specific study should be carried out before measurements in order to estimate the attainable accuracy.

Future work

The progress observed in this field suggests that there are high possibilities to continue working successfully toward the generation of quality noise maps by means of smartphones as sound sensors. In the following, we attempt to provide potential future lines of research.

In addition to a good app design and calibration of a smartphone, the challenge of picking up valid measurements among the heap of data received from the participants remains to be properly approached. Basic training of participants will save time and money when the time of data debugging comes. Unfortunately, there are no guidelines on what the participant's behavior should be when registering noise levels of their surroundings. For example, there is a lack of studies addressing the right position of the smartphone or an external microphone with respect to the user's body and the noise sources as well as defining a range of ideal time lapses of measuring for each location according to their characteristics (land use, population density, type of nearby sources, etc.). Overall, more attempts on construction of noise maps with data collected via smartphones will be required to gather enough evidence to develop regional directives and international standards in this regard.

Different ways for making noise maps can also be explored. Recent studies (Bravo-Moncayo 2019; Green 2020) have explored the use of Machine Learning (ML) techniques to produce more accurate predictions of noise levels within urban areas. The typical problem with this technique comes when training the neural network, which requires enormous amounts of data and which is not always easily available. Combining smartphones sensing with ML might provide new avenues in which noise mapping could find good chances of improvement. ML approaches allow incorporation of otherwise qualitative-only characteristics of sound such as annoyance and perceived loudness, as well as giving information about the sound sources that conform the overall noise. This conveys more relevant results from the human hearing experience perspective. In that sense, the inclusion of qualitative aspects of the process through the use of artificial intelligence might reveal factors that could be at play in the noise monitoring and noise mapping processes.

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