Do Sound Meter Apps Measure Noise Levels Accurately?

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Worldwide adoption rate for smartphones is expected to hit 2 billion devices by 2015. As of the end of 2013, smartphone ownership in the U.S. market has reached more than 67% of all mobile subscribers, or more than 140 million devices. Apple iOS and Google Android platforms account for 93% of those devices [Nielsen, 2014]. Smartphones have evolved into powerful computing machines with exceptional capabilities; most now have built-in sensors such as microphones, cameras, global positioning system (GPS) receiver, accelerometers, gyroscopes, and proximity and light sensors. Smartphone developers now offer many sound measurement applications (apps) using the devices' built-in microphone (or through an external microphone for more sophisticated applications). Interest in such sound measurement applications is growing among audio enthusiasts, educators, acoustic and environmental researchers, and the general public.

Several government and research organizations have commissioned participatory noise pollution monitoring studies using mobile phones [Maisonneuve *et al.*, 2009, 2010; European Environment Agency, 2013; Kanhere, 2013]. The success of these studies relies on the public to report data using their phones' audio and GPS capabilities. However, none of these studies documented the accuracy or the limitations of the sound measurement apps used and whether they can adequately perform measurements similar to current sound measurement instruments in the field.

Currently, occupational noise exposure assessments require the availability and use of specialized and expensive instrumentation such as noise dosimeters or sound level meters, industrial hygiene and data collection expertise, and hundreds of manhours to assemble and analyze such data. In addition to the issues of instrumentation and expertise, workplace noise surveillance efforts have required extensive funding and large-scale government support because of the need for human expertise, accessibility to workplaces, and the use of expensive sound measurement equipment [Sieber, 1991].

The ubiquity of smartphones and the adoption of smartphone sound measurement apps can have a tremendous and far-reaching impact in this area, since every smartphone can be potentially turned into a dosimeter/sound level meter [Maisonneuve, 2010]. However, for smartphone apps to gain acceptance in the occupational environment, the apps must meet certain minimal criteria for functionality, accuracy, and relevancy to the users in general and the worker in particular.

The possibilities associated with collecting real-time occupational and environmental noise data can have a great impact on hearing health, environmental noise pollution, noise source identification, and may also impact decisions related to public health in a manner that could not be envisioned just a few years ago. Out of the box, mobile devices are uniquely suited to measuring sound in a manner that is not applicable to any other occupational or environmental hazard. Challenges remain with using smartphones to collect and document noise exposure data, mainly issues relating to privacy, motivation to participate in such studies, accuracy of applications, dealing with bad or corrupted data, and mechanisms for storing and accessing such data. Most of these issues are being carefully studied and addressed [Garcia *et al.*, 2012; Drosatos *et al.*, 2012; Huang et al. 2010].

Occupational and general-purpose sound level measurements are conducted using Type 1 (accuracy ±1 dBA) or Type 2 (accuracy ±2 dBA) sound measurement instruments that must meet the requirements of American National Standards Institute (ANSI) S1.4-1983 (R2007), Specifications for Sound Level Meters [ANSI, 1983 (R2007)]. ANSI S1.4 states the following: "the expected total allowable error for a sound level meter measuring steady broadband noise in a reverberant sound field is approximately ±1.5 dB for a Type 1 instrument and ±2.3 dB for a Type 2 instrument." For compliance with occupational and environmental noise requirements, standards and regulations in the U.S. require that instruments meet ANSI Type 2 specifications. The Occupational Safety and Health Administration (OSHA) noise standard [29 CFR 1910.95] considers Type 2 instruments to have an accuracy of ±2 dBA.

The National Institute for Occupational Safety and Health (NIOSH) received several inquiries and requests from occupational safety and health professionals, stakeholders, and members of the working public to address the issues of smartphone sound measurement apps accuracy and whether such apps are appropriate for use in the occupational environment. This report describes a pilot study to assess the functionality and accuracy of smartphone sound measurement apps, examines the variability of device hardware on the accuracy of the measurements, and aims to determine whether these apps can be relied on to conduct participatory noise monitoring studies in the workplace [Kardous and Shaw, 2014].

Experimental Setup

We selected and acquired a representative sample of popular smartphones and tablets on the market as of January 2013 (iPhone 3Gs, iPhone 4s, iPhone 5, iPad 4th generation, Samsung Galaxy S3, Samsung Note, Samsung Focus, HTC One X, and Motorola DROID RAZR).

Smartphone apps were selected based on occupational relevancy criteria:

- Ability to report unweighted (C/Z/flat) or A-weighted sound levels
- 3-dB or 5-dB exchange rate

Table 1. List of iOS smartphone sound measurement apps.

App	Developer	Features
Adv Decibel Meter	Amanda Gates	A/C weighting, int/ext mic, calibration
Decibel Meter Pro	Performance Audio	A/C/Z weighting, calibration
iSPL Pro	Colours Lab	A/C/SPL weighting, calibration
Noise Hunter	Inter.net2day	A/C/SPL weighting, int/ext mic, TWA, calibration
NoiSee	IMS Merilni Sistemi	A/C/Z weighting, ISO/OSHA, dose, calibration
Sound Level Meter	Mint Muse	A/C/SPL weighting, calibration
SoundMeter	Faber Acoustical	A/C/SPL weighting, leq, int/ext mic, calibration
(Real) SPL Meter	BahnTech	A/C/SPL weighting, calibration
SPL Pro	Andrew Smith	A/C weighting, leq, int/ext mic, calibration
SPLnFFT	Fabien Lefebvre	A/C/SPL weighting, leq, int/ext mic, calibration

Table 2. List of Android smartphone sound measurement apps.

App	Developer	Features
SPL Meter	AudioControl	A/C weighting, int/ext mic, calibration
decibel Pro	BSB Mobile Solutions	A weighting, calibration
dB Sound Meter	Darren Gates	Int/ext mic, calibration
Noise Meter	JINASYS	A/SPL weighting, calibration

Figure 1. The SoundMeter app on iPhone 5 (left) and iPhone 4S (right) compared to half-inch Larson-Davis 2559 random incidence Type 1 microphone (center).

- Slow and fast response
- Equivalent continuous sound level average (l_{eq}) or time-weighted average (TWA).

Considerations were also given to apps that allow calibration adjustment of the built-in microphone through manual input or digital upload files, as well as those with reporting and sharing features. For the purpose of this report, the apps were not calibrated to a reference sound level but were tested with their original calibration settings to simulate a typical user who may not have access to a calibrated sound source. Ten iOS apps out of more than 130 apps were examined and downloaded from the iTunes store. The list of the 10 iOS apps tested and examined in this paper is shown in Table 1.

A total of 62 Android apps were examined and downloaded from the Google Play store, but only four apps partially met our selection criteria (not all criteria elements highlighted above were available on all the apps). The Android apps are shown in Table 2. Only two non-commercial apps were available on both the iOS and Android platforms: Noise Exposure/Buller published by the Swedish Work Environment Authority, and NoiseWatch published by the European Environment Agency.

Only a few apps were available on the Windows platform but none met our selection criteria. As a result, no testing was conducted on Windows-based devices or apps.

The measurements were conducted in a diffuse sound field at a reverberant noise chamber at the NIOSH acoustic testing laboratory. The diffuse sound field ensured that the location and size of the smartphones did not influence the results of the study.

For our experimental setup, we generated pink noise with a 20 Hz-20 kHz frequency range at levels from 65-95 dB in 5-dB increments (seven different noise levels). The measurement range was chosen to reflect the majority of typical occupational noise exposures encountered in the workplace today.

Noise generation and acquisition were performed using the Trident software (ViaAcoustics, Austin, TX). Noise was generated through three JBL XRX715 two-way loudspeakers oriented to provide maximum sound diffusivity inside the chamber. Reference sound level measurements were obtained using a half-inch Larson-Davis (DePew, NY) Model 2559 random-incidence microphone. Additionally, a Larson-Davis Model 831 Type 1 sound level meter was used to verify sound pressure levels. The microphone and sound level meter were calibrated before and after each measurement using G.R.A.S. (Holte, Denmark) Model 42AP piston phone. All the reference measurement instrumentation used in this study underwent annual calibration at a NIST-accredited laboratory.

Smartphones were set up on a stand in the middle of the chamber at a height of 4 feet and approximately 6 inches from the reference microphone, as shown in Figure 1.

Results

iOS applications. The effect of primary interest, app, was highly significant ($p < 0.0001$) for both the unweighted and A-weighted sound level measurements. To see which apps provided measurements closest to the actual reference A-weighted sound levels, we

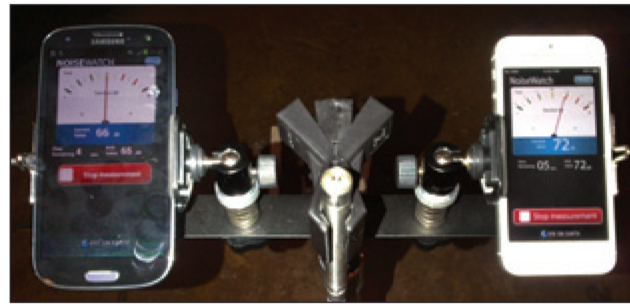

Figure 4. NoiseWatch app on the Samsung S3 Android device (left) and the iPhone 5 (right).

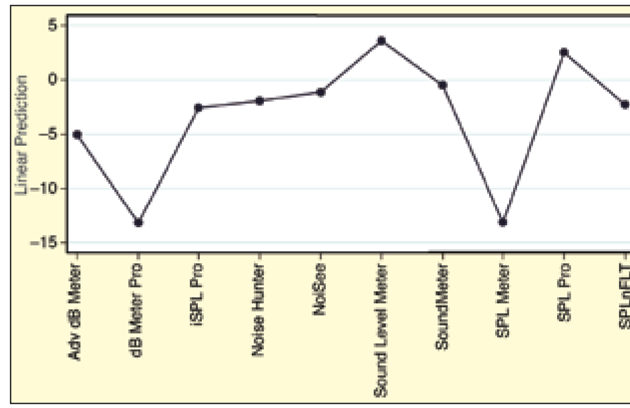

Figure 2. Marginal predicted means of differences in A-weighted sound levels (dBA) for the 10 apps.

compared the means of the differences using multiple pairwise Tukey comparisons, as shown in Table 3. Use of the Tukey approach ensures an overall significance level of 0.05. Note that the means with the same letter in Table 3 are not significantly different.

The effect of the device is also quite substantial. Again, to see which devices provided measurements closest to the actual reference sound level, we compared the means of the differences using the Tukey multiple pairwise procedure. A total of 420 sample combinations of different apps and noise levels were used to calculate the means of the differences for each device (see Table 4).

So we see that the SoundMeter app provides measurements closest to the actual values and that its mean is significantly different from that of any of the other apps. The marginal predicted means of the differences in A-weighted sound levels (dBA) with 95% confidence intervals are shown in Figure 2. The confidence

Table 3. Means of differences in unweighted and A-weighted sound levels using Tukey multiple pair-wise comparisons; means with same letter designation are not significantly different.

App	N	Mean, dB	SE, dB	Mean, dBA	SE, dBA
Adv Decibel Meter	168	3.8	0.3	-5.0	0.3
Decibel Meter Pro	168	–8.6	0.3	–13.2A	0.3
iSPL Pro	168	–7.4	0.3	–2.6C	0.3
Noise Hunter	168	–12.2	0.3	–1.9B	0.3
NoiSee	168	2.0D	0.3	–1.1	0.3
Sound Level Meter	168	6.8	0.3	3.6	0.3
SoundMeter	168	1.8D	0.2	–0.5	0.1
(Real) SPL Meter	168	–5.6	0.3	–13.1A	0.3
SPL Pro	168	2.8	0.2	2.5	0.1
SPLnFFT	168	0.1	0.4	–2.3B,C	0.3

Table 4. Means of differences in unweighted and A-weighted sound levls using Tukey multiple pairwise comparisons.

App	N	Mean, dB	Mean, dBA
iPhone 3Gs	420	0.4	–0.7
iPhone 4s	420	–0.8	–2.6
iPad 4th Gen	420	–2.7	–5.4
iPhone 5	420	–3.6	–4.8

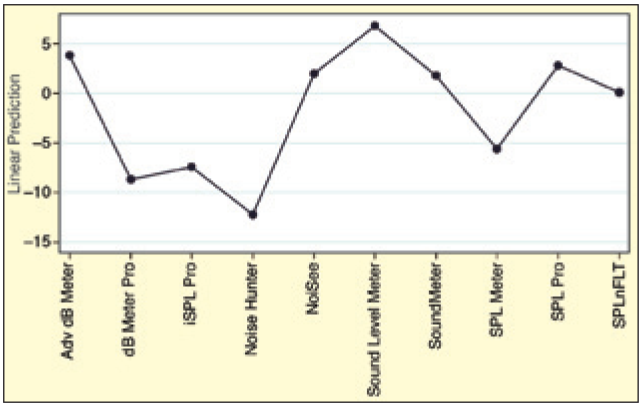

Figure 3. Marginal predicted means of differences in unweighted sound levels (dB) for the ten apps.

Figure 5. The MicW i436 external microphone (Type 2 compliant).

intervals, which are less than a few tenths of a dB, are obscured by the symbols.

For the differences in unweighted sound levels, we observe that the app SPLnFFT provides the closest agreement with actual noise levels. Furthermore, the mean for SPLnFFT is significantly different from all of the other means. The marginal predicted means for the differences in dB with 95% confidence intervals are shown in Figure 3. Again the confidence intervals are small and obscured by the symbols.

Android Applications. Four Android-based apps, (out of a total of 62 that were examined and downloaded) partially met our criteria and were selected for additional testing. Only one app, SPL Meter by AudioControl, met our criteria. The other apps did not offer all the features and functions that would be relevant to occupational sound level measurements. Some of the apps offered either unweighted or A-weighted measurements, but not both. As a result, a comprehensive experimental design and analysis similar to the iOS devices and apps study above was not possible. In addition to the low number of apps available with similar functionality, there was a high variance in measurements and a lack of conformity of features of the same apps between different devices. Table 5 shows the extent of the results from testing on Android devices and apps.

Table 5. Measurements of Android-based apps and devices at selected unweighted sound levels (dB).

App	Sound Level, dB	Samsung S3	HTC One X	Motorola Droid	Samsung Note
SPL Meter	70	62.5, ±2.5	72.4, ±2.0	73.6, ±2.5	66.7, ±1.2
	80	83.4, ±1.8	76.6, ±1.7	85, ±3.0	75.6, ±1.8
	90	91.2, ±2.2	85.4, ±1.5	93.6, ±2.8	92, ±1.6
deciBel Pro,dBA	70	69.8 ± 1.5	71 ± 0.8	81 ± 0.6	68.5 ± 1.2
	80	76.1 ± 1.5	79 ± 1.0	84.9 ± 0.8	75.8 ± 1.0
	90	87.2± 1.5	85 ± 1.2	82 ± 0.6	86.5 ± 1.5
dB Sound Meter	70	71, ±1.0	80, ±1.5	66, ±0.5	69, ±1.0
	80	78, ±1.0	91, ±1.3	80, ±0.7	77, ±1.0
	90	87, ±1.0	92 , ±1.2	93, ±0.4	86, ±1.0
Noise Meter	70	61, ±0.8	63, ±1.2	66, ±0.9	60.6, ±0.6
	80	68.5, ±1.2	71, ±1.0	75.6, ±0.6	69, ±1.1
	90	77.8, ±1	80.2, ±1.4	82.2, ±1.0	78.6, ±1.2

There were only two non-commercial apps available on both the iOS and Android platforms: Noise Exposure/Buller, published by the Swedish Work Environment Authority, and NoiseWatch, published by the European Environment Agency. The apps did not meet our criteria, but testing of the same apps showed a variance of ±6 dB between Android and iOS devices. Figure 4 shows the NoiseWatch app and the difference between the sound levels measured by a Samsung S3 Android device and the iPhone 5. Reference sound level was 70 dB.

Discussion

The results reported in Table 3 show that the SoundMeter app had the closest agreement in A-weighted sound levels, with a mean difference of –0.52 dBA from the reference values. The SPLnFFT app had the closest agreement, in unweighted sound pressure levels, with a mean difference of 0.07 dB from the actual reference values. For A-weighted sound level measurements, Noise Hunter, NoiSee, and SoundMeter had mean differences within ±2 dBA of the reference measurements. For unweighted sound level measurements, NoiSee, SoundMeter, and SPLnFFT had mean differences within the ±2 dB of the reference measurement.

The agreement with the reference sound level measurements shows that these apps may be considered adequate (over our testing range) for certain occupational noise assessments. The evidence suggests that for A-weighted data, SoundMeter is the app best suited for occupational and general-purpose noise measurements. In addition to having the smallest mean difference for the A-weighted data, SoundMeter had one of the narrowest distributions of differences. The apps with differences outside the ±2 dB/2 dBA are considered not to be in good agreement with un-weighted and A-weighted measurements.

The effect of the four different iOS devices used in this study on sound level measurements as demonstrated in Table 4 shows that the older iPhone 3GS model produced the best overall agreement between app and reference sound level measurements, with mean differences of 0.4 dB and –0.7 dBA. The variability in the results could be due to the different microphone elements in each device since Apple moved to a new supplier of microphones with the introduction of the iPhone 5 and iPad 4th Generation devices. The differences could also be related to the introduction of a new operating system (iOS 6) that allowed developers to bypass speech filters and input gain control on older devices.

Almost all smartphone manufacturers use microelectromechanical systems (MEMS) microphones in their devices. MEMS microphones typically have a sensitivity between 5 mV/Pa and 17.8 mV/Pa and can capture signals as low as 30 dB SPL and as high as 120-130 dB SPL (signal-to-noise ratio > 60 dB). MEMS microphones also have a flat frequency response similar to ceramic and condenser microphones used in Type 2 noise dosimeters. With the introduction of the iOS 6 operating system in late 2012, Apple allowed developers to bypass the high-pass filter that degraded the quality of acoustical measurements on older iPhones. This development also allows users of Apple smartphones to connect external microphones through the headset input jack. External microphones such as the MicW i436 (Beijing, China) Omni-directional measurement microphone comply with the IEC 61672 Class 2 sound level meter standard (Figure 5).

Overall, the Android-based apps lacked the features and functionalities found in iOS apps. The development ecosystem of the Android marketplace and users' expectations tends to promote free or low-priced apps. A comprehensive testing procedure could not be carried out to show conclusive evidence of differences, since not all apps shared features and metrics that met our selection criteria. The limited testing showed a wide variance between the same app measurements on different devices. This variability can likely be attributed to the fact that Android devices are built by several different manufacturers and that there is a lack of conformity for using similar microphones and other audio components in their devices.

Challenges remain with using smartphones to collect and document noise exposure data. Some of the main issues encountered in recent studies relate to privacy and collection of personal data, sustained motivation to participate in such studies, the overall accuracy of the sound applications, bad or corrupted data, and mechanisms for storing and accessing such data. Most of these issues are being carefully studied and addressed [Maisonneuve, *et al.*, 2009; Kanjo, 2010].

This study is not a comprehensive assessment of the application market for mobile sound measurement. Apps are added and removed on a daily basis and features and updates occur regularly. This study had several limitations, mainly because of the small number of devices that were acquired and tested. Furthermore, this study examined these apps in a controlled noise environment. Field measurement results may vary greatly due to the effect of temperature, humidity, long-term use, object interference, and overall stability of the microphone and electronics in these devices. Finally, smartphone apps cannot be relied upon to conduct compliance assessments in the workplace until the devices and apps meet national and international standards for sound measurement instrumentation, such as ANSI S1.4 and IEC 61672-1.

Conclusions

This study shows that certain sound measurement apps for Apple smartphones and tablets may be considered accurate and reliable for use in certain noise assessments. From an occupational perspective, these apps can serve to empower workers and help them make educated decisions about their work environments. They may be useful for industrial hygienists and safety and health managers to make quick spot measurements to determine if noise levels exist in a workplace that can harm workers' hearing.

Bibliography

ANSI [1983]. Specification for Sound Level Meters, ANSI S1.4-1983. American National Standards Institute, New York. (1983 (R2007)).

Drosatos, G., Efraimidis, P. S., Athanasiadis, I. N., D'Hondt, E., & Stevens, M. [2012]. A privacy-preserving cloud computing system for creating participatory noise maps. In Computer Software and Applications Conference (COMPSAC), 2012 IEEE 36th Annual (pp. 581-586). IEEE.

European Environment Agency. (2013, June 23). eyeonearth.org. Retrieved June 23, 2013, from eyeonearth.org: http://eyeonearth.org/map/NoiseWatch/

Garcia Martí, I., Benedito, M., Trilles, S., Beltran Fonollosa, A., Díaz Sánchez, L., Huerta Guijarro, J., & Rodríguez, L. E. [2012]. Mobile Application for Noise Pollution Monitoring through Gamification Techniques.In Entertainmnet Computing-ICEC 2012 (pp.562-571). Springer Berlin Heidelberg.

Huang, K. L., Kanhere, S. S., & Hu, W. [2010]. Are you contributing trustworthy data? the case for a reputation system in participatory sensing. In Proceedings of the 13th ACM international conference on Modeling, analysis, and simulation of wireless and mobile systems (pp. 14-22). ACM.

IEC [2002]. Electroacoustics – Sound level meters 0 part 1: Specifications, IEC 61672-1, International Electrotechnical Commission, Geneva, Switzerland.

Kanhere, S. S. [2013]. Participatory sensing: Crowdsourcing data from mobile smartphones in urban spaces. Distributed Computing and Internet Technology. Springer Berlin Heidelberg, 19-26.

Kanjo, E. [2010]. NoiseSPY: A Real-Time Mobile Phone Platform for Urban Noise Monitoring and Mapping. Mobile Networks and Applications, 562-574.

Kardous, C.A. and Shaw P.B. [2014]. Evaluation of smartphones sound measurement applications. J. Acoust. Soc. Am., 135, (4).

Maisonneuve N., Matthias N. [2010]. Participatory noise pollution monitoring using mobile phones. Information Polity, 51-71.

Maisonneuve N; Mattias S.; Nissen M.E.; Hanappe P.; & Steels L. [2009]. Citizen Noise Polution Monitoring. In Proceedings of the 10th Annual International Conference on Digital Government Research: Social Networks: Making Connections between Citizens, Data and Government (pp. 96-103). Digital Government Society of North America.

Nielsen [2014]. Mobile Majority: U.S.smartphone ownership tops 67 %. Retrieved 2/24, 2014, from http://www.nielsen.com/us/en/newswire/2014/how-smartphones-are-changing-consumers-daily-routines-around-the-globe.html

NIOSH [1998]. Criteria for a recommended standard—Occupational noise exposure (revised criteria 1998). Cincinnati, OH: U.S. Department of Health and Human Services, Public Health Service, Centers for Disease Control and Prevention, National Institute for Occupational Safety and Health (NIOSH) Pub. No. 98–126.

OSHA [1992]. Occupational Noise Exposure. Code of Federal Regulations 29 CFR 1910.95. U.S. Government Printing Office, Office of the Federal Register. OSHA, Washington, D.C.

Sieber, W. K. [1991]. Development, use, and availability of a job exposure matrix based on national occupational hazard survey data. American Journal of Industrial Medicine, 20(2), 163-174.

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