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Crowdsourced Categorization of Environmental Noise Data by Wireless-Communication Devices

Tajinder Gadh

Marc Stogaitis

Praveen Chandran

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Abstract:

Exposure to noise pollution has been shown to contribute to cardiovascular effects in humans, can cause permanent hearing loss, and can interfere with the enjoyment of indoor and outdoor activities. As a result, there is a great need to aggregate and categorize environmental noise data to help the world both understand noise pollution as well as how to alleviate it.

This publication describes techniques for wireless-communication devices, such as smartphones, to categorize measured environmental noise data to generate location noise level information. For example, a wireless-communication device can categorize measured environmental noise data into a number of different categories utilizing an on-device machine-learned model to generate location noise level information. The location noise level information can then be utilized to build location area maps of the noise level which can, in turn, be utilized to aid in the global reduction of exposure to noise pollution.

Keywords:

Noise pollution, sound pollution, noise level, sound level meter, sound sensor, noise sensor, acoustic sensor, microphone, map, wireless-communication device, user equipment (UE), decibels (dB), machine-learning, categorize, location, monitoring, noise exposure, industrial noise, traffic noise, media noise, occupational noise, environmental safety, crowdsource

Background:

In industrial societies, multiple forms of pollution are often emitted, such as air and noise pollution. Many may not regard noise as a pollutant, but in excessive levels, it certainly produces adverse health effects. To be specific, noise pollution is the emission of harmful or aggravating levels of noise that are generated from a diverse range of sources, such as industry, traffic, or media. The presence of noise pollution is particularly prevalent in big cities. For instance, nine out of ten adults in New York City are exposed to levels of noise that the Environmental Protection Agency (EPA) considers harmful. Sound is measured in terms of decibels (dB) on a scale of zero to 180, where higher numbers correspond to a more intense sound. Values greater than 85 dB can permanently damage human hearing. Nearly 7.7 million adults in New York City alone are routinely exposed to sound in excess of 85 dB.

Noise level maps have been constructed in an effort to inform the public of heavily noise polluted areas. Current proposals and solutions rely on the deployment of hundreds if not thousands of acoustic sensors (*e.g.*, sound level meters, sound sensors, noise sensors, microphones) to measure and/or record audio to collect noise data.

It is desirable to utilize wireless-communication devices (*e.g.*, user equipment (UE), smartphones) to crowdsource the anonymous collection of environmental noise data to develop detailed real-time and historic noise level maps. To this end, techniques of aggregating and classifying noise data by means of a machine-learned model on wireless-communication devices may result in more thorough and accurate noise level maps.

Description:

This publication describes the techniques for anonymously aggregating and categorizing environmental noise data measured by a wireless-communication device to generate location noise level information. Such location noise level information can be plotted on a location noise level map. The crowdsourced noise data measured by millions of such wireless-communication devices may aid in the construction of a real-time, geographic noise level map. Through utilization of such techniques on a global scale, locations associated with high environmental noise and the sources of such environmental noise can be located. Utilizing location noise level information and location noise level maps, users as well as government entities can be provided with the noise level information they need to make decisions regarding avoiding and mitigating sources of environmental noise.

Wireless-communication devices are increasingly mobile and ubiquitous, while also advancing in their capabilities to measure various forms of input data. These features make wireless-communication devices perfect candidates for the evaluation and assimilation of noise exposure measurements. A wireless-communication device can employ different machine-learned architectures, including neural networks and convolutional neural networks (CNN) to support machine learning. Figure 1 illustrates the wireless-communication device including a machine-learned model with a learning-based framework to measure, aggregate, and categorize environmental noise.

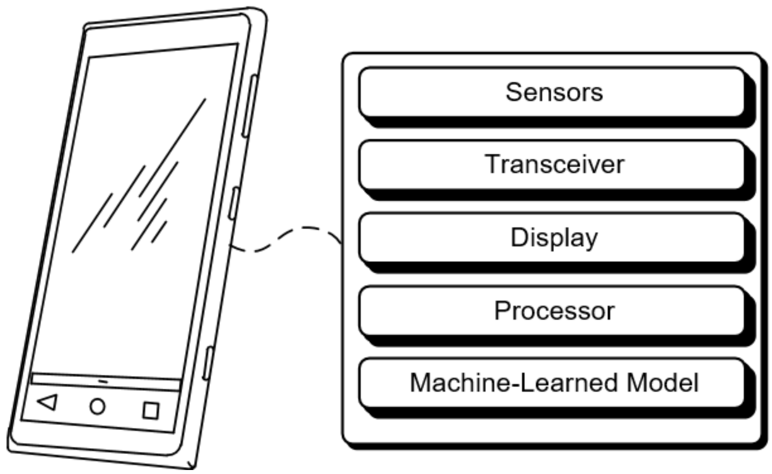

Figure 1

As illustrated in Figure 1, the wireless-communication device is a smartphone. However, other wireless-communication devices (*e.g.*, a laptop, a tablet) can also support the noise categorization process. The wireless-communication device includes a variety of sensors, for instance a location sensor (*e.g.*, a global positioning system (GPS) sensor), an audio sensor (*e.g.*, a microphone, an acoustic sensor), an accelerometer, a motion sensor, a gyroscope, and others. One or more of the sensors can be used to sense noise and generate a signal. The wireless-communication device further includes a transceiver (*e.g.*, a 4G LTE transceiver, a 5G NR transceiver) for transmitting data to, and receiving data from, an access point of a wireless network, a processor, and a display (*e.g.*, a light emitting diode (LED) display, liquid crystal display (LCD)).

Environmental noise data samples can be collected and categorized with corresponding correct noise classifications (*e.g.*, industrial noise, media noise, occupational noise, traffic noise) to train a machine-learning model (*e.g.*, neural network). After sufficient training, the machine-learned model can be deployed to the operating system (OS) of a wireless-communication device. Figure 2 illustrates an example of how the OS may use the machine-learned model for noise classification to classify sensed noises.

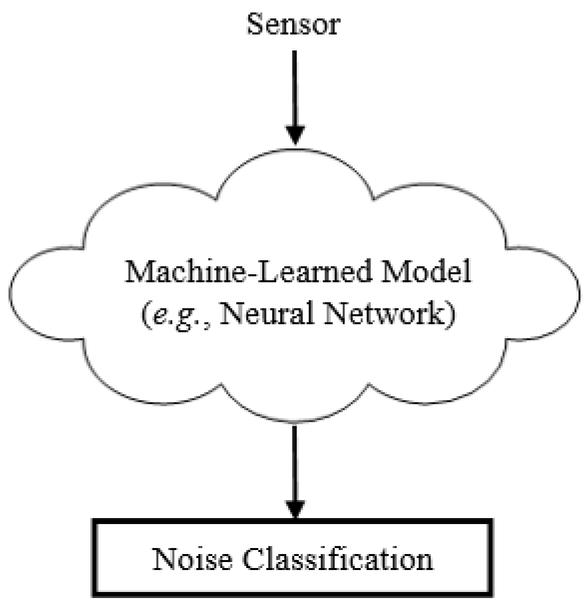

Figure 2

In Figure 2, sensor of a wireless-communication device can sense noise and generate a signal. Utilizing this signal as an input, the machine-learned model can then categorize the noise represented in the input. For example, the machine-learned model could categorize the noise as being in a category (*e.g.*, industrial noise, traffic noise, media noise, occupational noise) and/or based on a noise level (*e.g.*, based on a decibel level).

The wireless-communication device can generate location noise level information utilizing a determined noise classification and noise level with associated geolocation information from a sensor (*e.g.*, a GPS sensor) and time information from an internal clock. Location noise level information may be uploaded to a remote server via the transceiver for the purpose of training or retraining a machine-learning model. Location noise level information may be aggregated to form crowdsource-generated location noise level information which can, in turn, be utilized to construct location area maps of associated location noise levels.

Location area maps of associated location noise levels could be utilized to display a warning notification on a user device to a user upon entrance into an unsafe noise region, as illustrated in Figure 3.

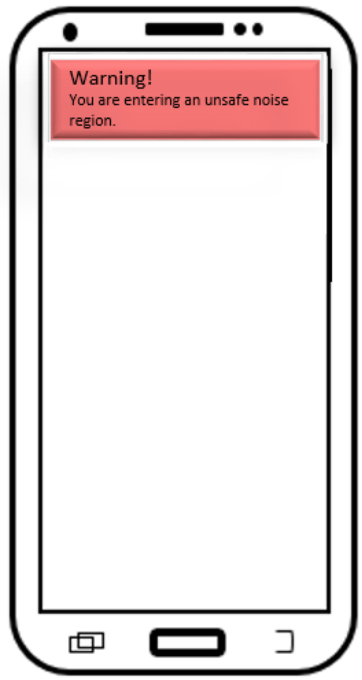

Figure 3

Location area maps of associated location noise levels could be utilized to provide real-time or historic noise level information for geographic locations to users to enable them to minimize their contact with noise pollution, to display information to users relating to their daily exposure to noise pollution, and to enable users to request information regarding how noisy a selected area is. Further, location area maps of associated location noise levels could be utilized to provide cities and local governments information to help with noise pollution reduction, awareness, and infrastructure planning.

In addition to the descriptions above, a user may be provided with controls allowing the user to make an election as to both if and when systems, programs or features described herein may enable collection of user information (*e.g.*, information about a user's social actions, information about a user's activities, information about a user's profession, information about a user's current location), and if the user is sent content or communications from a server. Furthermore, certain data may be treated in one or more ways before it is used, so that personally identifiable information is removed. For example, a user's geographic location may be generalized where location information is obtained (such as to a neighborhood, a district, a city, a ZIP code, or at a state level), as well as related time information may be generalized (*e.g.*, taken on an hourly basis), so that the specific location of a user at a specific time cannot be determined. Thus, the user may have control over what information is collected about the user, how that information is used, and what information is provided to the user. Further, no audio from the wireless-communication devices is recorded during any of the processes described herein.

Aggregating and categorizing anonymous noise data measured from wireless-communication devices to generate crowdsource location area maps of associated location noise levels are effective methods for collecting and utilizing environmental noise information. With these available noise data, global mitigation of negative health effects from noise pollution on humans can be realized.

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