

# Sound-mapping Urban Noise Pollution

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## ABSTRACT

In 2011, the Citygram Project was launched to explore non-ocular spatio-temporal energies through strategies that address the collection, mapping, analysis, and archival of invisible spatial energies. Since then, our efforts in exploration, research, and engineering infrastructural frameworks to contribute to existing mapping paradigms by addressing critical components necessary for capturing *urban soundscapes* have lead to a multidisciplinary and multi-organizational collaborative efforts. Our current system captures spatio-acoustic energy via a flexible sensor network, which is then analyzed, visualized, and mapped. Our collaborative efforts also include advancing multimodal geospatial research by embracing the idea of time-variant, poly-sensory cartography to better understand urban ecological questions. In this paper we summarize efforts in developing concepts, technologies, and analysis techniques that render data-driven multi-format maps with an overarching aim to better understand of urban environments and of its often-neglected, yet serious byproducts – noise pollution, which is the no.1 complaint by New Yorkers as quantified by New York City’s (NYC) 311 non-emergency hotline.

## General Terms

Algorithms, Management, Measurement, Documentation, Design, Reliability, Human Factors, Standardization, Verification.

## Keywords

Soundmap, urban, noise pollution, cyber-physical system.

## 1. INTRODUCTION

In this paper we outline our Citygram-Sound Project, which focuses on the collection, analysis, mapping, archiving, and interaction with urban spatio-acoustic dimensions enabled through a comprehensive cyber-physical system (CPS). Key points discussed include design of real-time sensor networks, data analytics, data access and exploration, citizen-science and community engagement efforts, community, and the What, Who, How, and Why related to the Citygram-Sound Project.

## 2. Project Vision: What and Who?

The *Citygram-Sound Project* aims to create an interactive and dynamic soundmap of NYC with a primary aim of addressing one of City’s most serious problems – noise pollution. Citygram-Sound’s data-driven maps are based on spatial quantitative low-level feature vector data streams processed by remote sensing devices (RSD) and stored on our server. The system is built on so-called cyber-physical system (CPS) will ultimately enable the real-time measurement, analysis, mapping, visualization, and exploration of urban spatio-acoustics. The project has grown since its inception in 2011 (*Citygram Project* [1]–[5]) with early collaborators from California Institute of the Arts (CalArts) and more recently adding researchers from NYU Steinhardt School,

NYU’s Center for Urban Science and Progress (CUSP), NYU’s Interactive Telecommunication Program (ITP), and NYC’s Department of Environmental Protection (DEP). With our close collaboration with NYU CUSP and its *Sound Project* since 2013, our combined efforts have developed into the Citygram-Sound Project with a further narrowed research and development scope in urban noise exploration. An early proof-of-concept heatmap visualization of spatio-temporal acoustic energy is shown in Figure 1. The dynamic heatmaps is overlaid on a standard Google Maps API.

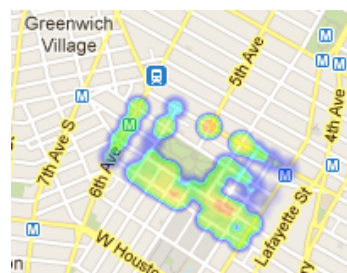


Figure 1. Citygram  $dB_{RMS}$  visualization

## 3. Project Vision: How?

### 3.1 Sensor Network

Creating a soundmap begins with addressing spatio-temporality. That is, capturing sound in real-time via an acoustic sensor network. Our sensor network design philosophy is based on adopting robust, cost-effective, and flexible remote sensing devices (RSD) that communicate in a cloud-computing environment to create a *dense* sensor network infrastructure. This includes addressing issues associated with traditional spatially *sparse* monitoring practices that cover large areas with a small number of bulky and often costly sensors. These designs have the advantage of very high sound quality, but at the same time suffer in the area of scalability. Our strategy also aims to address concerns related to an overreliance on consumer handheld devices (e.g. smartphones and tablets [6], [7]) for sensor network creation. Our sensor network strategy aims to create a dense sensor networks through rethinking of the functionality, utility, ubiquity, and adaptation of computing platforms to render seamless server-RSD interoperability via *fixed* and *crowd-sourced* environmental sensing paradigms. Figure 2 shows the sensor network infrastructure with a server and various forms of RSDs including desktop and laptop computers; handheld devices such as smartphones and tablets, and *fixed*, calibrated RSDs as further described below.

#### 3.1.1 Fixed RSDs

Fixed RSDs are permanently installed in “fixed” locations to provide consistent, reliable, secure, and calibrated audio data to our server. These RSDs, which constitute a distributed computing network, use identical hardware and software components to

ensure data consistency. To date, a number of initial systematic tests have been conducted to select suitable components for RSD development. Tests have included consideration of audio capture capability, processing power, RAM, onboard storage, OS flexibility, wireless connectivity, power consumption, I/O expandability, robustness/sturdiness, cost-effectiveness, and technology transferability. Our initial analyses have led to adopting the *Android mini-PC* platform for our system by considering the above factors as well hardware footprint: the mini-PC is approximately the size of a jump-drive as shown in Figure 3(a). Since April 2014, we have been conducting field tests via deploying a number of RSD nodes in normal outdoor weather conditions in the Brooklyn area. These low-cost, fixed RSDs capture, analyze, and transmit consistent soundscape reporting via distributed and cloud computing client-server architectures. Our current fixed RSDs can be built under \$90.

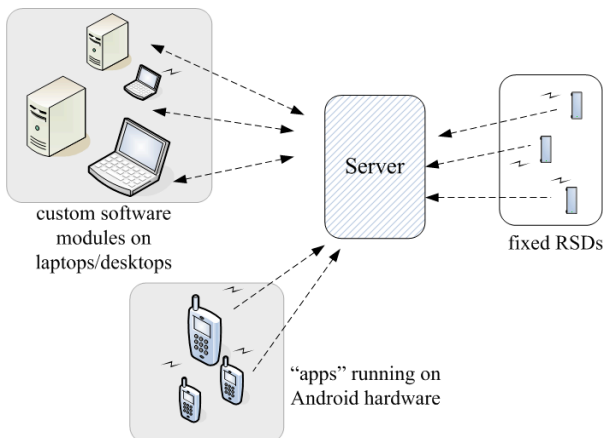


Figure 2. Sensor network infrastructure



Figure 3. Android fixed RSD proof-of-concept showing processor and audio CODEC (left-hand)

### 3.1.2 Crowd-Sourced RSDs

Our crowd-sourced RSDs are based on a design philosophy of *plug-and-sense* whereby any computing device with a microphone and Internet connection can be rendered into an RSD and allow users to become *streamers*. This includes smartphones, tablets, “phablets,” laptops, and desktop computers as standalone software or as add-ons for popular commercial software. We believe that our hybrid system consisting of a balance of fixed and crowd-sourced RSDs will accelerate the creation of a dense sensor network to produce high level of spatial granularity. A number of prototype software have been developed for Android and desktop platforms [2], [3]. These crowd-sourced RSDs are designed to capture, analyze, and stream audio data including feature vectors in *addition* to our fixed RSDs to facilitate the creation of a dense network while inviting meaningful community and citizen-science participation. These same RSD can also be used to access spatio-

acoustic data in real-time or historical data through client-server data access and streaming technologies as further described in Section 3.3.

### 3.1.3 Remote Software Update

Secure remote software updates for our RSDs are essential in allowing for efficient management and development of our sensor network. For our *mobile/crowd-sourced* RSDs, users via download links accomplish updates manually or built-in auto-update mechanisms in the case of registered mobile applications (App Store for iOS apps and Google Play Store for Android software). Our fixed RSDs, however, use a custom software update module to enable remote sensor network management, as manually updating large number of deployed RSD is not only impractical and costly, but also detrimental for system scalability.

### 3.1.4 Sensor Deployment

Our sensor deployment strategy follows a multi-stage procedure based incremental deployment steps. A small-scale sensor network step is currently being tested for seamless end-to-end functionality of physical and virtual components. As such, we are currently testing a small number of RSD deployed outdoors in the Brooklyn, Manhattan, and Valencia. Our long-term and large-scale deployment plans include activating citizen-scientists and adapting our CPS to existing urban infrastructures. This includes the application of *Citygram* for artistic purposes including real-time music performance and composition, real-time data-driven visualization, and development of interactive tools. One key future deployment strategy includes partnering with non-commercial (e.g. NYC currently has 59 unlimited free hotspots) and private sector organizations, which have taken initiatives to provide free and open Wi-Fi to urban city dwellers. For example, in 2013 Google sponsored the creation of free Wi-Fi to 2000+ residents, 5000+ student populations, and hundreds of workers in Manhattan’s Chelsea area. Another example is NYC’s initiatives to “reinvent” 11,412 public payphones<sup>1</sup>. These payphones produce approximately \$17.5 million annual revenue primarily from advertising but its function as a public telecommunication station has practically been rendered obsolete. NYC’s recent call-for-proposals to “reinvent payphones” aims to install, operate, and maintain up to 10,000 public payphone nodes with free Wi-Fi and other technologies. The urban payphone infrastructure could serve as an ideal large-scale deployment mechanism for our CPS sensor network as each station will include uninterrupted supply, communication line, additional weather protection, and as whole, provide an baseline for large-scale fixed RSD deployment. Such a model would be easily transferable to other cities around the world.

## 3.2 Machine Learning and Sound ID

An important focus of the Citygram-Sound Project is the real-time automatic ID of sound classes and noise in NYC. The field of automatic soundscape classification, however, is still in its nascent stages partly due to a number of factors including: (1) the lack of *ground truth* (annotated and label data) datasets [8], (2) the underexplored state of soundscape namespace, (3) the overwhelming emphasis on speech recognition [9]–[11], and (4) the sonic complexity/diversity of soundscape classes. A soundscape can literally contain any sound, making the sound

<sup>1</sup> <http://business.time.com/2013/01/09/google-brings-free-public-wifi-to-its-new-york-city-neighborhood/>

classification task fundamentally difficult [12]. That is not to say that research in this field – something we refer to as Soundscape Information Retrieval (SIR) – is inactive as research publications related to music, speech, and environmental sound as a whole has increased more than four-fold between 2003 and 2010 [9]; and numerous research *subfields* exist today, including projects related to monitoring bird species, traffic, and gunshot detection [13]–[16].

One of the notable initiatives in SIR research began recently in 2013 with the creation of the *IEEE D-CASE Challenge for Computational Audio Scene Analysis* (CASA) [8]. Although training and evaluation of SIR systems were primarily focused on indoor office sounds<sup>2</sup>, it is still worthwhile to note some of the SIR techniques presented at the Challenge. In the area of feature extraction, MFCCs were widely used, although in some studies, a case was made for time-domain and computer vision approaches realized via matching pursuit and a k-NN-based spectrogram image feature [17]. The former used a dictionary of atoms for feature presentation [18], [19] and the latter exploited spectrogram images for acoustic event detection and acoustic event classification. Both methods were demonstrated as alternative methods to MFCCs and showed robust performance in the presence of background noise. Some of the classifiers that were omnipresent included k-NNs, GMMs, SVMs, HMMs, and SOFMs based on expert-engineered feature vectors also reported in [12].

To address taxonomical and semantic side of SIR research we are currently developing crowd-sourced annotation tools to collect tags, labels, and soundscape descriptions through semantic data mining techniques. This has dual functionality of gaining insights into the soundscape *namespace* and also collecting *ground truth* data for machine learning. The latter research component entails crowd-sourcing multi-person tagged acoustic events in collaboration with various international universities. The database is projected to contain multiple annotations per sound class. The exact number of sound classes will be determined after careful analysis of tags/labels and community-provided noise complaint reports as further discussed below. Once our first phase tagging efforts are complete, we expect the creation of a rich dataset of ground truth data to enable our urban noise classification research.

One of the key issues in SIR is its sonic, spatial, and temporal diversity. These factors make SIR-based machine learning fundamentally difficult. The aim at this stage, however, is not to *solve* the urban SIR problem per se. Rather, the goal is to develop automatic urban sound classification algorithms that can detect and classify the most “popular” noise pollutants in cities like NYC; benchmark classification performance, and progressively improve and expand soundscape class identification. And although developing a comprehensive soundscape classifier with large number classes is the ultimate goal, if we can identify a smaller but significantly impacting *subset* of noise pollutants as determined by city-dwellers, the problem then becomes more manageable and a iterative procedure can be applied. Thus, for the classification portion we are focusing on (1) classifying some of most “popular” noise polluting agents and (2) strategically increasing the collection of noise classes guided by a sound class priority scheme, based on crowd-sourced *noise agent rankings*. To get preliminary assessment of this notion of *noise agent ranking*, we have analyzed the NYC 311 noise

complaint dataset which shows the following class distributions representing four years of data: 54% complaints *included* words *car* or *truck*, 49% *music*, 20% *people* or *talking*, 14% *construction*, and 10% the word *dog*. In other words, if we focus our attention to a smaller subset of soundscape classes (those that are most “popular”) and expand our algorithms to automatically recognize classes in an incremental methodology (include less “popular” ones), then the classification task can be divided into a number of iterations that are more manageable. In addition to the 311 dataset we aim to analyze other similar datasets [20] from cities like Chicago, Atlanta, Philadelphia, San Francisco<sup>3</sup>, and Houston<sup>4</sup> to validate the efficacy of such a noise ranking system – in the European Union, for example, road traffic noise accounts for 32% of noise events that are above 55 dB(A) [21]. With the amalgamation of fundamental knowledge gained in the analysis research part, we aim to transition from a position of questioning, – “what is noise?” – to a position of enunciation – “this is noise.”

### 3.3 Interaction and Exploration

One of the goals of creating a comprehensive CPS includes mechanisms for interactive exploration. We are thus developing online access exploration technologies not only for researchers but also for citizen-scientists, students, artists, and the general public. One such exploration mechanism is our current proof-of-concept web interface, which is designed to function as an interactive environmental exploration portal and is built on the Google Maps API. Also, a number of visualization prototypes have been realized [2], [3] providing real-time visualizations and accompanying interfaces for standard web browsers. The interface dynamically visualizes RSD-streamed audio data and also provides the ability to animate historical data stored in the server database. The historical data serves as an archival module, which stores low-level spatio-acoustic feature vectors. To enable users to hear the “texture” and characteristics of spaces without compromising private conversations that may be inadvertently captured in public spaces, we employ a custom voice blurring technique based on a *granular synthesis* [22]. To accomplish these conflicting tasks – blurring the audio while retaining the soundscape’s texture – a multi-band signal processing approach has devised as detailed in [3]. In addition to online-based tools that can be used to “find the nearest quiet part – right now”, “to measuring and visualizing noise in various areas”, to “determining what bars play your favorite style of music,” a number of current prototype software tools also allow users to interact with our soundmaps whereby: stream data to their computer and stream spatio-acoustic data to the server.

## 4. Project Vision: Why?

Humans have shown a remarkable ability to adjust to changing environments and studies suggest that we “have undergone rampant adaptation” in the last 200,000 years of history [23]. In the last 200 years, however, the size of cities, population growth, and accompanying urban infrastructural complexities along with its multimodal byproducts have reached astonishing numbers. The industrial revolution in particular has been a cataclysmic contributor to rapid worldwide population growth and change in

<sup>2</sup> dissimilar to music and speech sounds although arguably a type of “environmental sound”

<sup>3</sup> [www.sf11.org](http://www.sf11.org) lists barking dog, people talking, and car alarms as top 3 examples for noise complaints.

<sup>4</sup> Houston noise code lists vehicles, amplified sound from vehicles, and noise animals are top noise examples

our natural environment [24], and this includes *soundscapes* [25], [26]. Modern city-dwellers are all *too familiar* with the constant cacophony of urban machinery and ubiquity of a myriad of noise pollutants, regardless of time and space. For New Yorkers, the city's noisy soundscape has become second nature. Adapting to noise pollution, however, comes with serious associated health risks: according to Bronzaft, one of the leading experts in environmental psychology, "It means you've adapted to the noise ... you're using energy to cope with the situation. That's wear and tear on your body" [27]. Studies show that such "wear and tear" does not just contribute to hearing impairment, but also non-auditory health risks, including adverse effects on children's learning skills, hypertension, and sleep deprivation, as well as gastrointestinal, cardiovascular, and other physiological disorders [28]–[36], [37]–[39]. This notion of human "adaptation" is especially concerning if we consider how little adaptation time we have had since the expansion of manmade urban environments. There is a strong case to be made that the current noise pollution situation will significantly worsen with rapid population growth, which in turn will likely contribute to the expansion of ever denser and larger megacities worldwide: by 2050, it is projected that 3/5 of the global population is expected to live in one of these megacities. New York City (NYC) has been particularly sensitive to its noisy soundscape, and for good reason: since 2003 more than 3.1 million noise complaints have been logged by NYC's 311 city service hotline<sup>5</sup> representing the top category of complaints as quantified by the 311 reporting mechanism. Other cities nationwide that have implemented 311-style citizen hotlines have figures comparable to NYC: recent consumer ranking of the noisiest cities in the United States include Chicago, Atlanta, Philadelphia, San Francisco, and Houston [40]. Noisy urban environments – something that acoustic ecologist Schaefer refers to as *lo-fi* soundscapes [41] – is unsurprisingly an international phenomenon and continues to be one of the main environmental problems facing Europe today. For example, studies in the United Kingdom have shown that the general population lives above WHO noise level recommendations (WHO Guidelines for Community Noise) where an increase of noise has been recorded between 1990 – 2000 [42]. In another study, it has been shown European Union households willingness to annually pay upwards to 34 Euros per decibel of noise reduction [21], [43].

Although we have come a long way since recognizing that noise is not just a mere *nuisance* or *irritation* [42] for humans, noise codes as written *and* enforced today are problematic in several respects:

- (1) The *metrics* by which noise is defined are based on definitions of excessive "volume" that are either severely subjective or, when standard SPL measurements are used, fail to reflect how sound is perceived. For example, soothing ocean waves at 80 dB and the sound of blackboard fingernail scratching at the same level are not perceived in the same way.
- (2) Cities' capacity to effectively monitor, quantify, and evaluate urban noise is very limited.
- (3) The mechanism for noise enforcement is impractical as noise is fleeting in nature: even when law enforcement officers do make it to a reported noise "crime scene", chances are that any noise pollution traces will have disappeared completely by the time they arrive.

- (4) Noise complaints are typically reported via 311 hotlines or directly reported to the police. However, these tools are inadequate for reporting or combating noise. For example, studies show that only 10% of surveyed residents who were experiencing noise issues bothered to contact authorities: most directly confronted the person responsible [42] which may partly explain the 4.5 annual killings due to noisy neighbor disputes [44].

With the recent maturing of cost-effective technologies including wireless communication networks, cloud computing, crowd-sourcing/citizen-science practices, and the explosion of Big Data science as a growing research field, the past few years has provided an opportunity to re-examine many of the issues pertinent to capturing soundscapes – in particular noise pollution – by creating a comprehensive real-time and interactive cyber-physical system (CPS) for collecting, analyzing, mapping, and archiving soundscapes. Additionally, considering the increasing willingness of cities to provide public access to spatial data<sup>6</sup> and integrate data science techniques and civic participation towards public policy-making decisions [45], an even more compelling case for developing an adaptive, scalable, and comprehensive CPS system for mapping our hyperdimensional environment can be made.

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<sup>5</sup> <http://www.amny.com/news/noise-is-city-s-all-time-top-311-complaint-1.7409693>

<sup>6</sup> <https://nycopendata.socrata.com/>

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