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Designing an Internet of Sounds Sonification System with FM Synthesis Techniques

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Abstract—**Sonification, the representation of data with sound to communicate information about the original data source, has the potential to become an important technique for the emerging Internet of Sounds (IoS) research field. This paper describes the design of a sonification system for sonification-enabled IoS networks in Smart Cities. It uses FM Synthesis techniques to map data from Smart City sensors to acoustic parameters. After a brief introduction considering topics in IoS and sonification, a formal definition of sonification for the IoS is introduced. The advantages of FM synthesis are explored before a discussion of psychoacoustic constraints specific to this approach. Three data sets for which the application was developed are introduced before design considerations are described apropos of each stage of the sonification process. The paper closes with a brief discussion of the design and its implications for IoS research.**

Index Terms—**Auditory Displays, Audio, Audio User Interfaces, Internet of Things, Internet of Sounds, Multimedia Computing, Sonification**

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I. INTRODUCTION

In their presentation of a research agenda for the Internet of Sounds (IoS) Turchet et al.. al. [1] call for the creation of "advanced IoS ecosystems" and discuss the potential of sonification techniques to enhance IoS architectures. Sonification involves the mapping of data to sound to obtain information about the original source of the data [2]. While it has become a critical tool for monitoring and understanding the flow of information across the Internet of Things (IoT) and Smart City networks, it has yet to be comprehensively explored for the IoS [1,3, 4]. This article envisions a sonification-enabled IoS network for Smart Cities, presented in Figure 1, and describes an interactive prototype for the sonification of device-level IoS data on the applications layer of this architecture. Sonification is a robust and flexible method that leverages the temporal and frequency resolution of hearing to convey complex time-series data that can be difficult to fully represent visually. This makes it particularly useful for data monitoring and exploration in IoS contexts.

The generic IoS architecture presented in [1] describes the basic configuration of an IoS network and defines a sound thing as "a networked computing device, equipped with sensors and/or actuators, with the capabilities to acquire, process, exchange, or generate sound or sound-related information". This architecture is extended in the sonification-enabled IoS network presented in Figure 1. This approach introduces four new components to the network infrastructure. Interactive sonification-enabled sound things receive data from IoT sensors and datasets on the storage layer and sonify this data at the device level. As such, they are capable of sonification and sound synthesis as well as playback of streamed audio. They are also interactive allowing users to define important parameters. More traditional IoT sensors are used for collecting the non-sound data generally associated with Smart City sensing. Both data types are kept at the storage and database level along with other relevant and useful datasets retrieved from the internet. The final components are real-time interactive sonification apps operating on the applications and services level, of which the prototype system outlined in this article is one example.

Applications of this nature are useful to three categories of Smart City stakeholders. The first category is citizens living and/or working in the city for whom these networks provide useful information and services. Tasks here involve exploring public noise level data to find which urban park might be right for a quiet picnic or monitoring public transport data for travel or commuting purposes. The second category is government stakeholders using the networks to support the management, governance, and administration of civil resources and policies in a Smart City. This includes urban planners exploring environmental data to better understand how humidity levels impact wear and tear on infrastructure, or transport authority stakeholders using inertial measurement units (IMUs) and GPS data to monitor public transport infrastructure such as

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Supplementary materials including a prototype implementation in Max/MSP along with audio and video examples is provided at: https://zenodo.org/records/11414299.

Color versions of one or more of the figures in this article are available online at http://ieeexplore.ieee.org buses, trams, and bikes. The final category involves the stakeholders who develop, operate, and maintain these IoS networks. For these stakeholders, the monitoring of both network-level and device-level data is key to ensuring the safe and effective operation of the network. Moreover, understanding these data through monitoring and exploration can provide the knowledge and insights to guide the further development of infrastructural resources and the design of future network infrastructures.

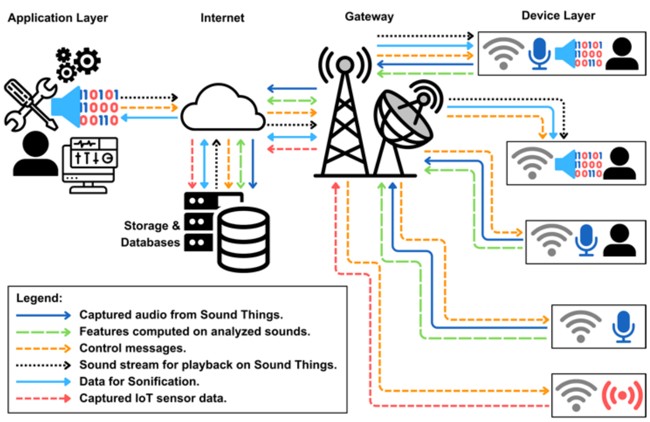

Fig. 1. Sonification Enabled-IoS Network w/ Associated Edge Devices

A. A Standardized Definition of Sonification for the IoS

Interoperability and standardization through shared protocols and ontologies are critical to the development of the IoS ecosystem [1]. As such, it is important to adopt an appropriate formalization of sonification that accounts for the specific kinds of tasks for which sonification is best suited in an IoS context.

$$s(t, X, \theta, I) = \sum_{i=1}^{M} \phi_i \left(t, \vec{\rho}_i\big(t, X(t), \theta(t), I(t)\big)\right) \quad (1)$$

To this end, Poret et. al. [5] recently presented an effective equation (1), the advantage of which will become clear when discussing psychoacoustic constraints as they apply to PMSon and FM Synthesis shortly. The left side of the equation accounts for key elements of a sonification: *s*, describing it as a function of the data: *X,* the acoustic parameters involved: θ, the users' interaction (if any): *I*, and the unit of time: *t* where $t \in \mathbb{R}^+$. The right-hand side focuses on meaning-making, describing how changes in data, sonic parameters, and interaction over time impact the listeners' perception of a sonification. It treats a sonification as a combination of meaningful perceptual units, termed sonic complexes, which consist of perceptual parameters, called sonic dimensions. Data are mapped to these sonic dimensions with some parameters constrained by the users' interactions [5]. In equation (1), M is the number of sonic complexes in a sonification. These are produced by: ϕ_i and the associated sonic dimensions are given by the vector $\vec{\rho}_i$ where $i \in [1, M]$. For example, consider a sonification consisting of ambient temperature data in a city, mapped to a single sine tone. The sine tone is the sonic complex representing the heat in the city. The acoustic parameters of the sine tone: frequency, amplitude, and phase, are the sonic dimensions to which changes in the measured data, temperature, can be mapped. How the data is mapped, may be moderated by user interactions given the design. Key components of this equation as they relate to the application described here are illustrated in Figure 2.

B. Sonification for the Internet of Sounds

Sarmento et al. [6] explore the sonification of Smart City data from a ubiquitous music angle. They highlight some relevant sonification techniques for Smart City, IoT, and IoS contexts. The most direct of these methods, Audification. translates time-series data with waveform characteristics into the audible range [7]. While it is ideal for use with data that conforms to a waveform model (e.g. seismometer and air pressure data) it is not as useful for data that do not, thus excluding much of the data associated with IoS networks. Auditory icons map data to familiar everyday sounds, and parameterized auditory icons are an iteration thereof that employs parameterized physical models to produce sounds in a data-driven manner. This approach is adopted in [3] to develop an interactive IoT sonification in the form of a smart sonic shoe for clinical applications. A related method involving models is model-based sonification (MBS) [8]. This approach involves the creation of dynamic sound-making models that are parameterized with the data set of interest. User interaction produces sonic results as a function of the original data and the interaction. Sonification is generally thought to work better when it is interactive and allows the user to define some aspect of the data to sound mapping [2]. Another sonification technique effectively applied to Smart Cities and IoT contexts is Parameter Mapping Sonification (PMSon). In [4] this involves multiple layers of complex data-to-sound-mappings but most relevant here is the mapping of Smart City data to control parameters of an amplitude modulation (AM) synthesis routine. Similarly, Gómez-Quintana et al. [9] apply a PMSon with AM and FM synthesis techniques to sonify neonatal EEG data on low-power IoT edge devices. Finally, Woo et al [10] apply interactive PMSon, and other, techniques to sonify environmental data captured from a bespoke IoT sensing platform, implementing the sonification in the Max/MSP graphical programming environment.

When comparing multiple concurrent streams of sonified data, each stream must sound unique and distinct so that listeners can clearly discern and compare changes across them without confusion. Techniques producing sounds that are less perceptually distinct (e.g. pitch mapping of sine-tones) run the risk of masking one another and thus confusing the listener. FM synthesis proves useful for sonification tasks as it is a well-known method for synthesizing rich acoustic spectra with clearly distinct timbral profiles [11]. The technique involves the modulation of a carrier signal with a modulator (often simple sinusoidal waves) to create new sinusoidal partials, or sidebands (SB in Figure 2), at intervals equal to the carrier frequency plus and minus integer multiples of the modulator frequency. Applying a PMSon approach to FM Synthesis, data can be mapped to control these sidebands via the modulation index (MI) which determines the number and relative strengths of sideband partials, and the harmonic ratio (HR) which determines their frequencies of the sidebands and their relation to the original carrier. The design that follows applies both PMSon and FM synthesis techniques.

II. Design Considerations

A. Psychoacoustic Constraints

Addressing psychoacoustic constraints is an essential factor in sonification design. Critical bands are particularly important when working with FM synthesis. A critical band is the span of bandwidth around some central frequency, for which the cochlea has difficulty resolving an exact frequency. Where two tones fall within a critical band, the first will tend to be masked by the second making it difficult for a listener to perceptually resolve the tone. Given the use of sidebands in FM synthesis, care must be taken to ensure that auditory phenomena associated with critical bands, such as beating, roughness, and masking, do not become problematic. This is also linked to the concept of just noticeable difference, which refers to the smallest possible differentiable unit of change in a given stimulus. Changes taking place in a physical stimulus, do not become perceptually detectable to a listener until they cross the difference threshold. As such, sonification designs must ensure that a unit change in the original data variable maps to a perceptible change in the acoustic stimulus [12].

Entanglement across dimensions and nonlinearity within dimensions also pose a challenge to sonification [12]. Dimensional entanglement is concerned with the intermingling of auditory dimensions, which are sometimes mistakenly assumed to be distinct and separable. In PMSon, pitch, loudness, duration, and timbre can be mapped to unique data, however, because these dimensions are not independent, this can result in confusion as, for example, changes in timbre can interfere with pitch discrimination. Similarly, loudness perception does not proceed linearly with respect to amplitude across the frequency spectrum. Listeners can experience significant loudness differences between multiple sound stimuli presented with a common amplitude but with different frequency levels, a fact that complicates sonification design [12].

As per equation (1), the design outlined here accounts for these constraints by organizing sonification into meaningful acoustical units (sonic complexes) with unique subsets of perceptual parameters (sonic dimensions) that provide an aggregate of relevant channels for mapping data. In this approach, the data are not *directly* mapped to entangled perceptual parameters, such as the frequencies and amplitudes of individual sideband partials. Instead, as we shall see shortly, they are mapped to MI and HR across four FM synthesis routines for each sonified data stream. In essence, the data is redundantly mapped to a cluster of parameters that define the overall spectral shape of each sonified data stream. There is not a one-to-one correlation between values in the original dataset and individual partials in the synthesized sound but rather, they correlate to spectral shape as defined by MI and HR. As such, phenomena like roughness, beating and entanglement, where they might occur, do not obscure individual datapoints as they would if data were mapped in direct one-to-one relationships to the frequencies and amplitudes of the sideband partials.

B. The Data

This system is intended for application layer monitoring and exploration of time-series data collected from both sound things and traditional IoT devices embedded in Smart Cities. As such, two Smart City datasets comprised of measurements from environmental sensors were chosen for sonification. These contained noise level and heat-related measurements. A third dataset comprised of synthetic data generated by random walk algorithms was chosen to simulate the highly variable readings produced by inertial measurement units (IMUs) and GPS sensors affixed to public transport infrastructure such as buses, trams, and bikes. These datasets were chosen to support the needs of the stakeholders outlined in the introduction.

Noise level data were collected between February 28th, 2020, and February 28th, 2024, at three locations around Dublin City. Data were captured by a network of noise monitoring sensors operated by Sonitus Systems for the Dublin City Council. The sensors capture measurements at approximately real-time speeds and log a single measurement of the equivalent continuous sound level (LAeq) was calculated per hour using the database. These data are archived by Smart Dublin's open data store, Dublinked, and are accessible through a series of APIs and/or data stores [13]. Data from three locations were used in this project. Data from Ballymun on the north side of the city and Strand Road on the south side were collected with EM2030 sensors, while data from Chancery Park, a more central location, were collected with an EM2010 sensor.

Both sensors capture audio clips at a rate of 48KHz across the audible range of, 20 Hz-20KHz, with robust dynamic ranges of 33 to 121 dB(A) and 16 to 121 dB(A). Hourly LAeq values were calculated from these clips. These data are not as rich as audio-rate data, but they still constitute a useful dataset for IoS contexts. This is the exact kind of Smart City data we would expect to see computed on-device from a captured sound stream or measured by a traditional IoT sensor in an IoS network.

Temperature, humidity, and heat index data were collected in Mexico City between April 4, 2022, and the 19th of January 19, 2023 [14]. The heat index is an indexical measure computed as a function of ambient air temperature and humidity values and is intended to represent the perceived or felt experience of temperature as mediated by humidity levels.

The sensor used was a DHT22 (AM2302) interfaced with an ESP32 microcontroller, which relayed the values to a database for storage and analysis. The data were measured at a rate of one sample per minute, resulting in 385,872 observations. As with the noise level measurements, this is precisely the kind of Smart City data we would expect to be collected and stored in an IoS network.

Random walk data were generated with a classic one-dimensional random walk, a stochastic process that describes a path as a series of random steps across a given mathematical space. It is a Markov process and thus indexed by time with future step states being independent of past states and reliant only on the present state. These data consist of random numbers normalized to a range of 0. to 1. At each iteration, a new random step size was chosen between 0. and 0.1. The data were produced at a default rate of 50 samples/s. Random walks can be used to model a wide range of phenomena and are used here to simulate the kinds of highly variant Smart City data (e.g., IMU and GPS data from trams, buses, and bicycles).

III. Design Overview

As referenced previously, the design was prototyped in the Max/MSP. The design involves three distinct acoustic units, which act as channels for sonified information. Each one represents a unique data stream. The signal chain and data-to-sound mapping strategy is common across all 3 channels as shown in Figure 2. Additional details of the system design are provided below.

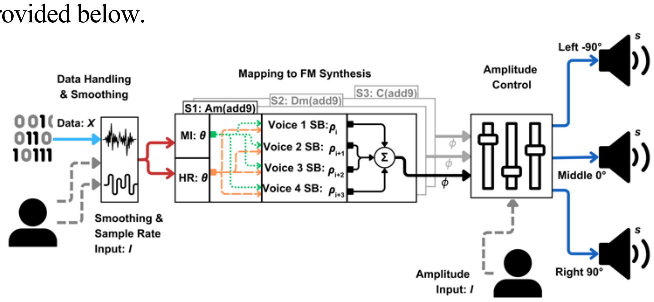

Fig. 2. Sonification process for each data stream

A. Data Handling

Data values, X in equation (1), are passed in delimiter separated format with two fields, timestamp, and sensor value, are separated by a comma (,) semicolons (;) close records and ASCII new line characters (\nl) close outlines. The overall sampling rate (SR) of sonification is defined as the rate at which data are read and fed forward along the signal chain. SR can be defined at this point in the sonification. After reading data are rescaled with min-max normalization for a range of 0-1. Default SRs of 12hz and 30hz are assigned for the Dublin City noise data and Mexico City environmental data. This results in the presentation 24hrs of data over 2s for the noise and 1hr of data in 2s for the environmental data. The random walk data was produced at a rate of 25hz. These initial SRs can be changed by user input.

B. Data Smoothing

The next step was interactive data smoothing, a component of *I* in equation (1). A drawback of working with PMSons for complex, high-frequency time-series data is that the rapidly varying components of the data can dominate the acoustic result and obscure any components of the data that might evolve at a slower or more intermediate pace. Allowing the user to control the application of a simple smoothing filter (2) to the data pre-sonification can address this issue:

$$Yn = \left(Y_{n-1} + \frac{X_n - Y_{n-1}}{\alpha}\right), \quad 0 < \alpha \geq X_n - Y_{n-1} \qquad (2)$$

The filter divides the difference between the current input Xn and the previously output filter value Yn−1 by a smoothing variable α. The result is added to the previous filter value Yn−1 to compute the current filter output Yn. This allows the listener to focus on different portions of the dataset, thus better understanding the relationship between moment-to-moment changes, as well as broader, more slowly evolving trends. The smoothing filter is useful with noisy data, where intermittent noisy events litter the dataset and thus benefit from some smoothing. It becomes less useful with temperature data because the difference between measurements evolves at such a slow pace that smoothing is not required. This is mostly true for the heat index, but it is useful for humidity data spikes and declines that can occur rapidly. Smoothing proves much more useful with random walk data owing to its highly variable and noisy nature. Given that random walks can be used to model sensor readings from a wide range of sensing devices, some form of data smoothing may be required in the sonification of IoS data more generally. Care should also be taken so as not to over-filter the data, obscuring relationships therein.

C. Mapping to FM Synthesis

The next step involves mapping the data to FM Synthesis parameters. Individual sonified data streams (S1, S2, and S3 in Figure 2) are assigned unique chords created with four FM synthesis voices. For the first data stream, the chord is Am(add9) consisting of frequency components at 110hz, 130.81hz, 164.81hz, and 233.08hz respectively. The data are redundantly mapped to control the HR and MI, elements of θ in equation (1) of each synthesizer voice, generating these frequencies. For each voice, the HR was modulated on a scale from 1 to 4, and the MI was modulated on a scale of 0-3 both with positive mapping polarities. These mappings result in pronounced effects across the sidebands (SB in Figure 2), which reflect changes in data as temporally evolving patterns across the frequency spectrum.

The configuration is the same for the other two streams but with different chords. The middle stream consists of Dm(add9) with components at 146.83hz, 174.61hz, 220hz, and 329.63hz. The final stream was set to C (add9) 261.63hz, 329.63hz, 392hz, 587.33. These chords roughly fall into the key D minor, although the only harmonic confirmation of this is on the 9th added to our A minor chord, which is Bb. These 9th notes were added to help separate the chords from one another. It should be noted that this chordal arrangement provides an acoustic baseline or zero point for the system. Because the data control the number of sidebands, their relative amplitudes, and their harmonic relation to their fundamental frequencies, these chordal configurations are only obvious when the value of each data point approaches zero.

Each sonified data stream is spread across the stereo space with two panned 90° hard left and right, and the third presented centrally, with equal amplitude across the right and left channels. This helps keep them distinct from one another. In addition, gain controls are provided for all three sonified data streams, another component of I in equation (1). This allows listeners to focus on a single stream of interest or compare two or more streams simultaneously by making amplitude adjustments. Given the musical parameters of this design, users familiar with and/or trained in the functional harmony of Western tonal music would likely find this system easier to use than those without familiarity or training. In more general terms, having a musically trained ear attuned to small changes in frequency spectra would no doubt be a boon also. The sonification system, along with example sonification outputs, is provided in [15].

D. The Sonified Result

The noise level data comprised roughly 35,000 values per measurement. Sonifying at the default SR (12hz presenting 24hrs of data in 2s) allows us to hear the values rising and falling across day/night cycles. As the data approaches night, the HR decreases, causing sideband frequencies to move toward, and cluster around, their respective fundamentals. This effect is enhanced by the redundant mapping of data to the MI, which results in a drop-off in sideband amplitudes starting with the partials furthest from the fundamental. As the values increase, the sidebands spread across the frequency range again, and their relative amplitudes increase. This results in a spectral pulsing pattern representing a sequence of day/night cycles in which a wider frequency range on the pulse suggests a noisier day overall and a tighter one a suggests relatively quiet day. Small details, such as the slope (or rate of attack) and smoothness of the expanding and contracting sections of the pulse, represent noise levels during the corresponding periods. This is evident in the spectrogram in Figure 3. Similarly, increasing the SR to 56hz, (7d in 3s) reveals a pattern in which sequences of five pulses are often followed by two narrower pulses. This is evident in the Chancery Park data and to a lesser extent the Ballymun data. This likely reflects activity patterns over a week at these locations. The Strand Road sensor remains somewhat stable throughout, possibly given its proximity to the bay and near continual exposure to the sounds of wind and waves. A comparison of the sounds of all three data streams highlights the differences and commonalities across the three locations, revealing patterns specific to individual sites and patterns common across all two or more. The smoothing filter is useful here in removing the rapidly varying components at each site so that the overall trend in noise levels across both the day/night cycles and week cycles becomes more obvious.

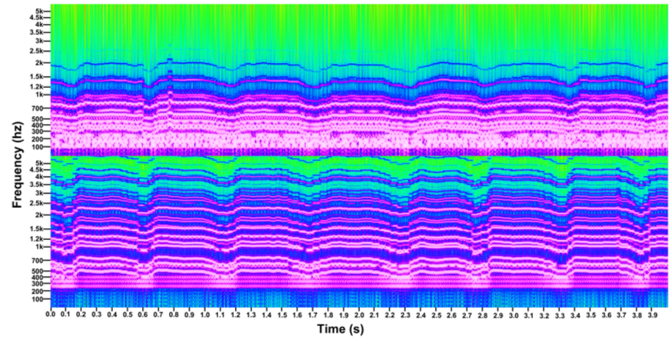

Fig. 3. Spectrogram of Day-Night Cycles in the Noise Level Sonification

The system rendered the changes in temperature from the Mexico City as relatively flat for the default SR of around 30hz reflecting the general stability of these values the dataset. At 30hz a new data point is sonified roughly every 33ms. On average, it takes a minimum of 13ms for the ear to pick up a shift in frequency. As such 33ms is within the safe range for representing the data. The temperature and heat index evolve slowly over the course of the data, with temperature spanning a range of roughly 13°C and a heat index range of 40. This is also true at rates of 480hz (1d in 3s). At 480hz, subtle sequences of day/night cycles start to become apparent, albeit with a spectral shape that slowly spreads and contracts over time. Dramatic shifts in the humidity measurements, likely coinciding with precipitation or similar weather events, presented as pronounced changes in the shape, and spread of the sidebands across both SR. At 480hz a new datapoint is sonified about every 2ms, well below the 13ms threshold. While much information is lost to the human ear, in this case the resulting sonification nonetheless provides a good overview of trends taking place at longer timescales. This effect is exaggerated on approach to high SR values (circa 999hz). This is useful for monitoring and exploring broader trends in a dataset. For example, as SR is increased, broader seasonal patterns may be better tracked. As mentioned, the humidity data are far more variable than the temperature data and, as such, benefit from some smoothing to remove noise and transients and to reveal broader trends to the ear. The heat index proves to be an interesting case, as it broadly correlates with the actual temperature for large portions of the dataset. This means that both sounds follow a similar pattern of sideband expansion and contraction across spectral space. As a result, when these measures diverge, the acoustic changes across the frequency spectrum are stark and pronounced. This result is less impactful when comparing the heat index with humidity because, while they obviously correlate, it is often the case that comparatively large degrees of change are required to impact the heat index.

The synthetic random walk data were highly variable and did not exhibit the cyclical patterns present to differing degrees in the other two datasets. As such, the cyclic pulsing effect is replaced with spectral spreading wherein sidebands spread out across their frequency range as the data values increase, and contract as they decrease. This produces a sonic equivalent to the stacked area charts that are common in data visualization. As the data values decrease in each sonified data stream, the stream morphs back to its default chordal configuration. As such, data streams with decreasing values become less salient, returning to their original harmonic center, while those with increasing values rise to the fore as their sidebands spread across the available spectral space. The variance between successive data values is also critically important. High levels of variance between values result in near-instantaneous changes in the number of sidebands and their spectral spread. Successive data values tightly clustered around an average will result in a sustained configuration of sidebands, whereas the opposite is true for highly variable sequences that tend to dominate by virtue of the complex spectral shapes they produce. The smoothing filter is particularly useful for filtering out these values and can be further applied to reveal lower-frequency information.

IV. Discussion

Despite its potential, sonification for the IoS has not been thoroughly explored. Sonification has been applied in IoT contexts for clinical applications [3,9], weather monitoring [10], and music making [6]. The system here differs in its focus on Smart Cities, building on [4, 6] and integration of the IoS as described in the introduction. In IoS contexts, monitoring and exploring datasets are key tasks for the Smart City stakeholders.

They are also important for patient monitoring in healthcare applications, suggesting that the approach detailed here might find more broad applications in this field going forward.

Attention to detail is central to monitoring tasks, such as the tracking and comparison of noise levels at cultural events by governmental and administrative stakeholders. In such cases, lower SRs ensure that each discrete value is audible, and light smoothing can reduce the impact of high-frequency transients. For exploratory tasks where a general overview of dataset trends is required, higher SRs compress more values into less time, and filtering can reveal broader patterns in the data that might otherwise remain obscured by rapidly varying components. This has applications for urban planners, designing new public transport connections, and IoS network operators examining and comparing sensor readings across locations. The stereo configuration of the system supports the cross-comparison of individual data streams for data monitoring and exploration tasks. By controlling their amplitudes, users can compare individual streams to understand how data differ and relate across multiple locations (e.g. the Dublin City noise data). This configuration is also useful for understanding phenomena measured at a single location with multiple sensors (e.g. the Mexico City dataset).

The application of PMSon with FM Synthesis proved a useful method for rendering changes in the data audible. Treating MI and HR as sonic dimensions for mapping data, as in equation (1) was a novel strategy for revealing structures and features in the IoS data. It rendered the finer details of the Dublin City noise data audible allowing for careful tracking and comparison of changes between streams based on shared day/night cycles. Longer broader trends were revealed about the temperature and humidity levels in the Mexico City data, information which may be of use to citizens living and working in the area.

The random walk data provided a proxy for IMU and GPS readings from public transport infrastructure. These data are far less correlated with one another and tend to wander across the frequency spectrum and undergo distinct spectral transformations when sonified. As such, these data are more easily tracked than the more highly correlated noise and environmental datasets. This suggests the system might also be applied to monitoring and exploring tasks for highly variant and uncorrelated IoS data. This is of particular use to Smart City stakeholders monitoring multiple streams of transport information for travel purposes, and administrative stakeholders monitoring the operation of that infrastructure.

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