Machine Learning and Regression Modelling of Dynamic Urban Soundscapes

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Declaration

I, Andrew Mitchell, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Abstract

Impact Statement

The statement should describe, in no more than 500 words, how the expertise, knowledge, analysis, discovery or insight presented in your thesis could be put to a beneficial use. Consider benefits from **inside** and **outside** academia and the ways in which these benefits could be brought about.

Acknowledgements

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Contents

List of Figures

List of Tables

1 Introduction

1.1 Research Summary

Urban noise pollution affects 80 million EU citizens with substantial impacts on public health which are not well addressed by conventional noise control methods. Traditional noise control methods have typically limited their focus to the reduction of unwanted noise, ignoring the potential benefits of increasing positive sounds and remaining restricted by practical limitations of noise reduction. Modern approaches to achieve improved health outcomes and public satisfaction aim to incorporate a person's perception of an acoustic environment, an approach known as 'Soundscape'.

Soundscape studies strive to understand the perception of a sound environment, in context, including acoustic, (non-acoustic) environmental, contextual, and personal factors. These factors combine together to form a person's soundscape in complex interacting ways (Berglund and Nilsson, 2006). In order to predict how people would perceive an acoustic environment, it is essential to identify the underlying acoustic and non-acoustic properties of soundscape.

When attempting to apply soundscape in practical applications in the built environment, it is immediately apparent that a predictive model of the users' perceptual response to the acoustic environment is necessary. Whether to determine the impact of a design change, or to integrate a large scale data at neighbourhood and city levels, a mathematical model of the interacting factors will form a vital component of the implementation of the soundscape approach. This work is intended to identify methods for incorporating contextual and objective information into a useable and interpretable predictive model of urban soundscapes. In order to achieve this, a protocol for collecting the multi-level, multi-factor perceptual assessment data has been developed and implemented, resulting in a large soundscape database. Several avenues of investigation are then drawn from the database. The primary research questions are:

1. What are the primary acoustic features involved in soundscape formation and what are the driving interactions between acoustic features and soundscape assessment?

2. How does the sound source composition in a complex sound environment mediate this interaction and how can this effect be simplified and modelled?

3. How can the multiple levels of soundscape formation be simplified and integrated into a cohesive predictive model, and what interpretations about the cross-effects of these levels can be drawn from the model?

4. How does the soundscape of a place vary over time, is this variation driven by environmental features or by context, and can this variation be predicted?

1.2 The SSID Project

1.2.1 Project collaborators

1.2.2 Motivation for the SSID Project

1.3 Research Aims

1.4 Soundscape Indices and Metrics

1.4.1 Standardisation

The soundscape community is undergoing a period of increased methodological standardisation in order to better coordinate and communicate the findings of the field. This process has resulted in many operational tools designed to assess and understand how sound environments are perceived and apply this to shape modern noise control engineering approaches. Important topics which have been identified throughout this process are soundscape 'descriptors', 'indicators', and 'indices'. Aletta et al. (2016) defined soundscape descriptors as "measures of how people perceive the acoustic environment"; soundscape indicators as "measures used to predict the value of a soundscape descriptor"; and soundscape indices can then be defined as "single value scales derived from either descriptors or indicators that allow for comparison across soundscapes" (Kang et al., 2019).

This conception has recently been formalised and expanded upon with the adoption of the ISO 12913 standard series (International Organization for Standardization, 2018). ISO 12913 Part 1 sets out the definition and conception of Soundscape, defining it as the "acoustic environment as perceived or experienced and/or understood by a person or people, in context". Here, the soundscape is separated from the idea of an acoustic environment, which encompasses all of the sound which is experienced by the receiver, including any acoustically modifying effects of the environment. In contrast, the soundscape considers the acoustic environment, but also considers the impact of non-acoustic elements, such as the listener's context and the visual setting, and how these interact with the acoustic environment to influence the listener's perception.

1.4.2 Soundscape Descriptors

In order to consistently discuss soundscape and the factors which influence it, it is important to understand what terms have been used to describe soundscapes and to construct a consistent framework within which to work. Both the traditional focus on the epidemiological impacts of noise and the development of the soundscape concept have used many different terms in order to describe the perception of a sound environment.

Noise annoyance is perhaps the best researched aspect of environmental sound perception.

Pleasantness

Quietness / Tranquillity

Acoustic Comfort

Perceived sound level

Music-likeness

Restorativeness

Soundscape quality

Appropriateness

Perceived Affective Quality (PAQ)

1.4.3 Soundscape Indicators

Several studies prior to the formalisation of the ISO standards on soundscape demonstrated the general, but inadequate, relationship between traditional acoustic metrics, such as L_{Aeq}, with the subjective evaluation of the soundscape (Berglund and Nilsson, 2006; Yang and Kang, 2005; Aumond et al., 2017; Alsina-Pagès et al., 2020). These have typically aimed to address the existing gap between traditional environmental acoustics metrics and the experience of the sound environment. *cite Yang2005Sheffield* showed that, when the sound level is "lower than a certain value, say 70 dBA", there is no longer a significant change in the evaluation of acoustic comfort as the sound level changes. However, the perceived sound level does continue to change along with the measured sound level, showing that (1) measured sound level is not enough to predict soundscape descriptors such as 'acoustic comfort', and (2) there is a complex relationship between perceived sound level and soundscape descriptors which is mediated by other factors.

Subsequent studies have shown that, even with large data sets and several possible acoustic indicators examined, models that are based on objective/measurable metrics under-perform in predicting soundscape assessment when compared to models based on perceptual responses. Ricciardi et al. (2015), with a methodology based on smart phone recordings, achieved $R^2 = 0.21$ with acoustic input factors L_50 and $L_10 - L_90$, whereas the same dataset and model building method achieved $R^2 = 0.52$ with perceptual input factors overall loudness (OL), visual amenity (VA), traffic (T), voice (V), and birds (B). This indicates that merely examining the acoustic level is not sufficient for predicting the assessed soundscape quality, and that additional objective factors and a more holistic and involved method of characterizing the environment is required. These previous studies have generally been limited by one or many of the following factors:

- limited number or types of locations;
- limited responses sample size;
- no non-acoustic factors.

These factors generally limit the generalizability of their results beyond the investigated locations.

1.4.4 The need for predictive soundscape models

The ability to predict the likely soundscape assessment of a space is crucial to implementing the soundscape concept in practical design. Current methods of assessing soundscapes are generally limited to a post-hoc assessment of an existing environment, where users of the space in question are surveyed regarding their experience of the acoustic environment (Engel et al., 2018; Zhang et al., 2018). While this approach has proved useful in identifying the impacts of an existing environment, designers require the ability to predict how a change or proposed design will impact the soundscape of the space. To this end, a model that is built upon measurable or estimate-able quantities of the environment would represent a leap forward in the ability to design soundscapes.

Developing soundscape indices is a process that requires consideration of how people perceive, experience, and understand the surrounding sound environment. For the purpose of modelling and comparisons,

Previous soundscape research has demonstrated that perception of the acoustic environment, while primarily driven by sound level, is mediated heavily by non-acoustic factors which interact with the sound level, spectral information, and temporal acoustic behaviour in complex ways. The soundscape is influenced by several levels of factors: the immediate and long-term acoustic environment, other environmental factors (e.g. temperature, air quality), the physical / visual characteristics of the space, the type of architectural space, and even cultural and country-level expectations. When approached in a predictive model context, the acoustic data must form the core components, but a coherent framework for describing how the influence of the acoustic factors is affected by the non-acoustic factors is required.

Simpler analyses have taken a fragmented approach, for instance where separate acoustic-factor models are built independently for each type of architectural space considered in the data set and, separately, statistical models are built to investigate another non-acoustic factor, e.g. visual greenness vs lack of greenness. In order to properly extract the influences of all of these levels of factors as well as to build a generalisable model which can be used in practice, this fragmented approach should be combined into a single multi-level model.

The first key step for this approach is the creation of a coherent, large-scale, multi-factor database of objective environmental measurements and subjective perceptual responses. My research makes use of in-person field questionnaires, long-term manned questionnaires, and multi-factor characterisation of the environment as part of the ERC-funded project Soundscape Indices (SSID) and in collaboration with The French Institute of Science and Technology for Transport, Development and Networks (IFSTTAR) to collect this database across a wide range of locations and soundscape types. This work has already been mostly completed and the database is now ready to be put to use in building the overall soundscape predictive model.

This approach is unique in that it:

1. fundamentally incorporates all identified factors of soundscape perception in a coherent manner;

2. is extensible and interpretable;

3. considers how soundscape change over both multi-hour and multi-day timescales and incorporates this dynamic behaviour for increased accuracy.

1.5 Application of SSID

1.6 Summary of Novel Research

1.7 Chapter Summary and Thesis Overview

2 Literature Review

2.1 Impact of Urban Noise on Health and Wellbeing

Give a full formal background to why noise control is important for public health.

2.2 Current Methods of Assessing and Addressing Urban Noise

2.2.1 Acoustical Parameters

2.2.2 ISO Environmental Acoustics Standards

ISO 1996-1, esp sections on annoyance, e.g. Annex F, G, H

2.2.3 EU Noise Mapping

2.2.4 Shortcomings

2.3 Soundscape Studies

2.3.1 Soundscape Descriptors and Indices

2.3.2 World Soundscape Project

2.3.3 Swedish Soundscape Quality Protocol

2.3.4 Demographic differences

Several studies have attempted to study the degree to which personal and demographic factors influence a person's soundscape perception. In some conceptions (Kou et al., 2020) these personal factors are classed as 'contextual' soundscape indicators - features which influence or, in a modelling context, be used as independent variables to predict the value of a soundscape descriptor. The personal factors help to create a personal soundscape interpretation model which is individual to each person.

In this way, a person's individual state-of-mind, ethnic identity, educational background, gender identity, etc. form a pseudo-deterministic framework through which the physical inputs from their environment are filtered. Clearly, many of these personal factors could never be measured and even those which are measurable will have wide ranges of legitimate effects, however estimating the degree and type of effect they may have can both help us better predict individual soundscape assessments and understand how group identities influence sound perception.

Section on Erfanian et al. 2020, Psychological Well-being

Low-income and minority evidence A consistent limitation of soundscape studies investigating the influence of personal factors is a sampling bias towards majority ethnicities (typically White British for UK studies and ethnic Chinese for Chinese studies) and middle-class and highly educated groups. This results in not only incomplete information about how demographics influence soundscape perception, but also represents a systemic under-representation of certain environments. While it may be unclear to what extent ethnicity and social class internally influence a person's perception, it is clear that these groups are exposed to different sound environments and therefore studies which do not include under-represented groups are also by definition not including those sound environments which those groups inhabit.

A recent study by Kou et al. (2020) was successful in making inroads in these under-represented environments by studying the Humboldt Park neighbourhood in Chicago, USA. Their study included

2.4 Existing Predictive Models

(Lionello et al., 2020)

2.4.1 Models based on non-acoustic data sources

(Verma et al., 2020), (Gasco et al., 2020)

3 Methods

This protocol is trying to extend the scope of objective measurements that are being collected in conjunction with perceptual responses by including other environmental and visual data.

3.1 Data Collection

3.1.1 Spatial Recording

3.1.2 Ambisonic Encoding

3.1.3 Lab Design?

3.1.4 VR Reproduction

3.2 Questionnaire

3.3 Psychoacoustics and Auditory Perception

3.3.1 Psychoacoustic Parameters

Loudness

Zwicker and Fastl, Chap 8, see Mendeley notes and python-acoustics development notes.

3.3.2 Feature Selection

3.4 Machine Learning and Regression Techniques

3.4.1 Clustering Analysis

K-means

nbclust

3.4.2 Modelling Likert-type Data

Multiple Linear Regression

Ordinal Logistic Regression

Multi-output Regression

3.4.3 Multi-level Models

3.4.4 Bayesian Regression

4 Characterizing the Temporal Behaviour of Dynamic Urban Soundscapes

4.1 Introduction

4.2 Methods

4.3 Results and Discussion

4.3.1 Presence of 1/f in urban soundscapes

4.3.2 Statistical relationship to pleasantness ratings

4.3.3 Ordinal logistic models based on temporal and acoustic features

4.4 Conclusion

5 Combined Multi-level Regression Model for Predicting Soundscape

5.1 Introduction

5.2 Methods

5.2.1 Multi-level regression modelling

5.2.2 Feature Selection

5.3 Results

5.3.1 Simplified predictive soundscape models

COVID-19 Model

5.3.2 Multiple levels of soundscape formation

5.3.3 Feature selection

Acoustic features

Non-acoustic factors

5.3.4 Model design

5.4 Discussion

5.4.1 Interpretation

5.4.2 Implementation and use cases

6 The Influence of Sound Source Composition in Soundscape Formation

6.1 Introduction

6.2 Methods

6.2.1 Data collection

6.2.2 Clustering analysis

6.3 Results

6.3.1 Sound source profiles

6.3.2 Perceived affective quality ratings

6.3.3 Psychological well-being mediates soundscape formation within different sound source profiles

6.3.4 Regression models

6.4 Discussion

6.5 Conclusion

7 A Bayesian Hierarchical Predictive Soundscape Model and a Proposed Soundscape Index

7.1 Introduction

7.2 Methods

7.3 Results

7.4 Discussion

7.5 Communicating SSID on the Basis of Percentages

7.6 Conclusion

8 Soundscape Modelling for Smart Cities: A case study

8.1 Introduction

8.2 Methods

8.2.1 SSID Data Collection

8.2.2 Sensor network and IFSTTAR data collection

8.3 Results

8.4 Discussion

9 Conclusions

9.1 Summary

9.2 Findings

9.3 Limitations and Recommendations for Future Research

Bibliography

Aletta, F., Kang, J., and Axelsson, Ö. (2016). Soundscape descriptors and a conceptual framework for developing predictive soundscape models. *Landscape and Urban Planning*, 149:65–74.

Alsina-Pagès, R. M., Freixes, M., Orga, F., Foraster, M., and Labairu-Trenchs, A. (2020). Perceptual evaluation of the citizen's acoustic environment from classic noise monitoring. *Cities & Health*.

Aumond, P., Can, A., De Coensel, B., Botteldooren, D., Ribeiro, C., and Lavandier, C. (2017). Modeling soundscape pleasantness using perceptual assessments and acoustic measurements along paths in urban context. *Acta Acustica united with Acustica*.

Berglund, B. and Nilsson, M. E. (2006). On a Tool for Measuring Soundscape Quality in Urban Residential Areas. *Acta Acustica united with Acustica*, 92(6):938–944.

Engel, M. S., Fiebig, A., Pfaffenbach, C., and Fels, J. (2018). A Review of Socio-acoustic Surveys for Soundscape Studies. *Current Pollution Reports*, 4(3):220–239.

Gasco, L., Schifanella, R., Aiello, L. M., Quercia, D., Asensio, C., and de Arcas, G. (2020). Social Media and Open Data to Quantify the Effects of Noise on Health. *Frontiers in Sustainable Cities*, 2:41.

International Organization for Standardization (2018). ISO/TS 12913-2:2018 Acoustics - Soundscape - Part 2: Data collection and reporting requirements. Technical report, ISO, Geneva.

Kang, J., Aletta, F., Oberman, T., Erfanian, M., Kachlicka, M., Lionello, M., and Mitchell, A. (2019). Towards soundscape indices. In *Proceedings of the 23rd International Congress on Acoustics*, number September, pages 2488–2495, Aachen.

Kou, L., Kwan, M.-P., and Chai, Y. (2020). The effects of activity-related contexts on individual sound exposures: A time-geographic approach to soundscape studies. *EPB: Urban Analytics and City Science*.

Lionello, M., Aletta, F., and Kang, J. (2020). A systematic review of prediction models for the experience of urban soundscapes. *Applied Acoustics*, 170:107479.

Ricciardi, P., Delaitre, P., Lavandier, C., Torchia, F., and Aumond, P. (2015). Sound quality indicators for urban places in Paris cross-validated by Milan data. *The Journal of the Acoustical Society of America.*

Verma, D., Jana, A., and Ramamritham, K. (2020). Predicting human perception of the urban environment in a spatiotemporal urban setting using locally acquired street view images and audio clips. *Building and Environment*, page 107340.

Yang, W. and Kang, J. (2005). Acoustic comfort evaluation in urban open public spaces. *Applied Acoustics*, 66(2):211–229.

Zhang, X., Ba, M., Kang, J., and Meng, Q. (2018). Effect of soundscape dimensions on acoustic comfort in urban open public spaces. *Applied Acoustics*, 133.