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NEURAL CORRELATES OF ENVIRONMENTAL NOISE SOUNDSCAPES: AN EEG STUDY

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Environmental noise has documented effects on productivity in the workplace, and suggested impacts on health and wellbeing. However, there remains a gap in knowledge in determining whether there are neural markers for these effects that might be used in design, planning, and stakeholder engagement. Neuro-physiological measurement has become practical in laboratory listening tests, due to advances in in dry electrode technology, fast analogue-to-digital conversion, and cross-platform synchronisation, allowing for simultaneous ambisonic playback and collection of listener response data in multimodal contexts. The datasets created by such measurement are large and typically impractical to analyse over significant numbers of trials without modelling. In this work we present results from a pilot study (number of participants N=37), in which listeners were exposed to a randomised playback of first-order ambisonic recordings of typical urban environmental soundscapes (aircraft, trains, road traffic, and construction noise). Electroencephalograph (EEG) measurements were captured synchronously across a 10/20 scalp position. Data for each subject was normalised and smoothed before being filtered into alpha and beta frequency bands using PSD calculations, before being further filtered to remove artefacts including high frequency interference and event-related potential activity such as blinking and similar head movement. Self-reported data on perceived annoyance was also captured using the ISO 15666 scale from each participant in response to the stimulus set. We subsequently extract three acoustic components across the stimulus set using signal processing analysis techniques; loudness, sharpness (as a factor of spectral centroid), and mel-frequency cepstral coefficients (MFCC), and map these against neural activity indicated by correlates in the EEG recordings. We also compare EEG recordings with self-reported levels of annoyance. We plan further work to train a regression model with weighted vectors for EEG activity, acoustic features, and self-reported annoyance.

Keywords: Perceptual testing, Environmental Noise, Annoyance

1. Introduction

Increasingly soundscape measurement has suggested that our acoustic environment can exert an influence on both physical and mental health, with benefits of effective noise management including improvements in cardiovascular health, link to reduction of cases of dementia in elderly populations, and improvements in markers of general mental well-being such as stress reduction [1]. Here, we describe progress on a case study addressing the use of biophysiological metrics in combination with self-report techniques and acoustic feature extraction, towards fuller understanding of the underlying mechanisms between noise and health effects.

Previous work from this study, documenting the interaction between Galvanic Skin Response (GSR, interchangeably known as Electrodermal Activity) and self-reported perceived annoyance measured using the ISO 15666 standard, was presented and published in [2]. Perceived annoyance has been found previously useful in examination of urban spaces [3].

GSR was used as a marker of psychological arousal and as an estimate of emotional state. Measurement of GSR has been shown to be a robust metric for analysis of emotional responses to music [4]–[6]. Thus, there is a potential crossover between mental state, physiological reaction, and auditory stimulation. Chambers [7] showed that states of relaxation have correlations GSR, heart rate variability, and the ratio of alpha and beta waves in electroencephalographic measurement. The electroencephalograph (EEG) is a technique for metering electrical activity from the scalp used to infer patterns of brain activity. Bondolfi [8] and Economides [9] proposed that proactive training and entrainment of mental states might thus contribute to therapeutic treatment and physiological state improvement. In this paper we report on the next stage of analysis, incorporating acoustic feature extraction and moving towards the use of the synchronous (EEG) measurement which was collected during our experiments. This type of measurement has become practical in laboratory contexts in recent years, due to advances in 'dry' electrode technology and portable, near real-time analogue-to-digital conversion. This allowed for a multimodal experiment to be conducted capturing synchronous EEG data, GSR, heart-rate, and self-reported responses within the SoundLab listening environment, which provides first order ambisonic playback in a calibrated listening environment at <NC15.

The distinction between affective state, emotion, and mood, is complex, and is generally drawn along the duration of the response [10]. Various models of affective state exist, including models with dimensions for positivity and activation strength, such as the cirumplex model of affect [11]. This model places valence (as a measure of positivity) and arousal (as a measure of activation strength) on the horizontal and vertical axes respectively. Often, individual emotional descriptors can be plotted across these types of spaces [12], such as, in our example, perceived annoyance in the case of ISO 15666. We are interested in exploring biophysiological markers elicited synchronously to these self-reported responses, and correlating these with acoustic features extracted from real-world environmental soundscapes. The use of biophysiological measurement in these contexts presents the possibility of unconscious report, and the removal of the 'self-report confound' – listeners with environmental noise problems are, by-and-large, keen to voice their concerns, and by the time a sound has become a problem it may already be too late to mediate the likely effects on the listener.

1.1 Goals

The goal of this work is to move towards an understanding of the biophysiological mechanisms which occur in response to environmental noise, by determining acoustic correlates for physiological markers and self-reported responses. Based on previous work with GSR and EEG we hypothesise that where listeners described a soundscape as more annoying, there will be an increased level of beta waves in the EEG, and correlations in three acoustic features: spectral centroid, loudness, and mel-frequency cepstral coefficients, as extracted using traditional feature analysis from the stimulus set.

2. Method

Thirty-seven participants were recruited from a working office environment and were compensated for their time. All subjects were healthy, reported no medical problems or being under the influence of any medication at the time of taking part. Approval for the study was provided by University of York Physical Sciences Ethics Committee, including specific requirements for data storage and compliance with GDPR.

Participants were asked to listen to a series of first-order ambisonic recordings of urban environmental soundscapes, calibrated as shown in Table 1. The stimuli were played back through an ambisonic loudspeaker array at calibrated sound levels within the Arup SoundLab™ facility in Manchester to give an aural experience similar in level to the original sounds as recorded outside the laboratory environment. During a training exercise, participants were asked to conduct active and focused listening to the sound during the experiment, and to focus on how the sound made them feel.

The stimulus recordings themselves include aircraft, road traffic, construction noise, and other transport sounds. The order of stimulus presentation was randomised in each trial using a customised GUI created with Max/MSP. This GUI also allowed for synchronisation of audio playback and word clock with the biometric sensors.

One of the stimuli, the aircraft sound, was repeated (whilst maintaining an individually randomised order of stimulus presentation in each trial), in order to provide an anchor signal to facilitate within-participant comparison of variance if necessary.

Table 1: Stimulus set and calibrated playback level. Each stimulus was cropped with a linear fade in and fade out to a total duration of 30s.

Sound Stimulus	Playback level
High speed train	82 $dBL_{Amax,s}$
Urban Traffic	65 dBL_{Aeq}
Aircraft pass-by (650ft height)	82 $dBL_{Amax,s}$
Tram curving (wheel squeal)	82 $dBL_{Amax,s}$
Construction - Breaker	76 dBL_{Aeq}
Highway	76 dBL_{Aeq}

Electrical activity in the brain was recorded synchronously using an 8 channel, dry-electrode based electroencephalogram (EEG) with electrodes positioned in the 10/20 position [13], shown in Figure 1. Electrodes were recorded with a resistance of less than 1000m- ohms per channel.

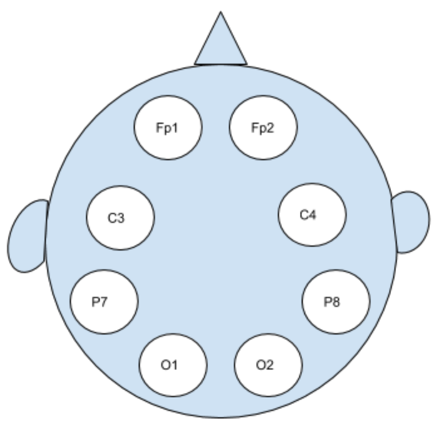

Figure 1. Eight channel configuration of EEG in the 10/20 position, where Fp = frontal parietal, C = central, P = parietal, and O = occipital regions

Each participant undertook the experiment in around 15 to 20 minutes, including time taken for familiarisation. This duration was only made possible due to the speed of calibration of dry electrodes, and was a length which should not create fatigue according to conventional listening test practices [14] – however, the biosensors themselves do create additional discomfort and fatigue for the wearer over time, which some participants remarked on informally after the experiment.

Immediately prior to the start of the listening test sequence, participants were asked to rate their own noise sensitivity on a scale of 0-7, following an existing protocol by Clark *et al*., [15]. Responses received ranged between 2-6. Participant ages varied from 17-55 years of age, the majority of respondents being between 25-35 years old. No participants declared a history of hearing impairment. Participants were also allowed time to acclimatise to the laboratory environment and the biosensors, which allowed for baseline levels to be captured for use in subsequent signal cleaning.

2.1 Data Cleaning

Several metrics for extracting meaningful control data from EEG are common. The ERP (or 'oddball' paradigm) has been used to allow active control in brain-computer interfacing systems [16], [17]. Stimulus-responsive input measures, for example, the SSVEP[1] [18], have been adapted to real-time audio and music applications [21]. However, the intended use of our system is unconscious auto-nomic measurement in noise evaluation, and as such we focus on preparing data for analysis by means of spectrum and spatial distribution. Alpha bands in EEG can be extracted by means of filtering the power spectrum of a recording between 8-12 Hz, and beta bands in the region 12-28 Hz [22]. Nevertheless the EEG data is challenging to interpret [23], [24] and remains the subject of further work. EEG was filtered with a high pass filter at 3Hz to remove offset and a lowpass filter at 40Hz to restrict the spectrogram. Our dataset for each subject was further filtered to remove artefacts including high frequency interference and event-related potential activity such as blinking and similar head movement. There were marked event-related potentials (ERP) in the occipital cortex which we used an interpolation across the other remaining channels to remove. Data was then normalised and smoothed before being filtered into alpha and beta frequency bands using PSD calculations, and a full data process flow chart is shown in Figure 2.

[1] SSVEP is a response to visual stimulation at a given frequency and integer multiples thereof, measurable in the visual cortex. For a detailed explanation of the signal characteristics under analysis, the reader is referred to [18], [19], and to [20] for a review of use in various BCMI platforms

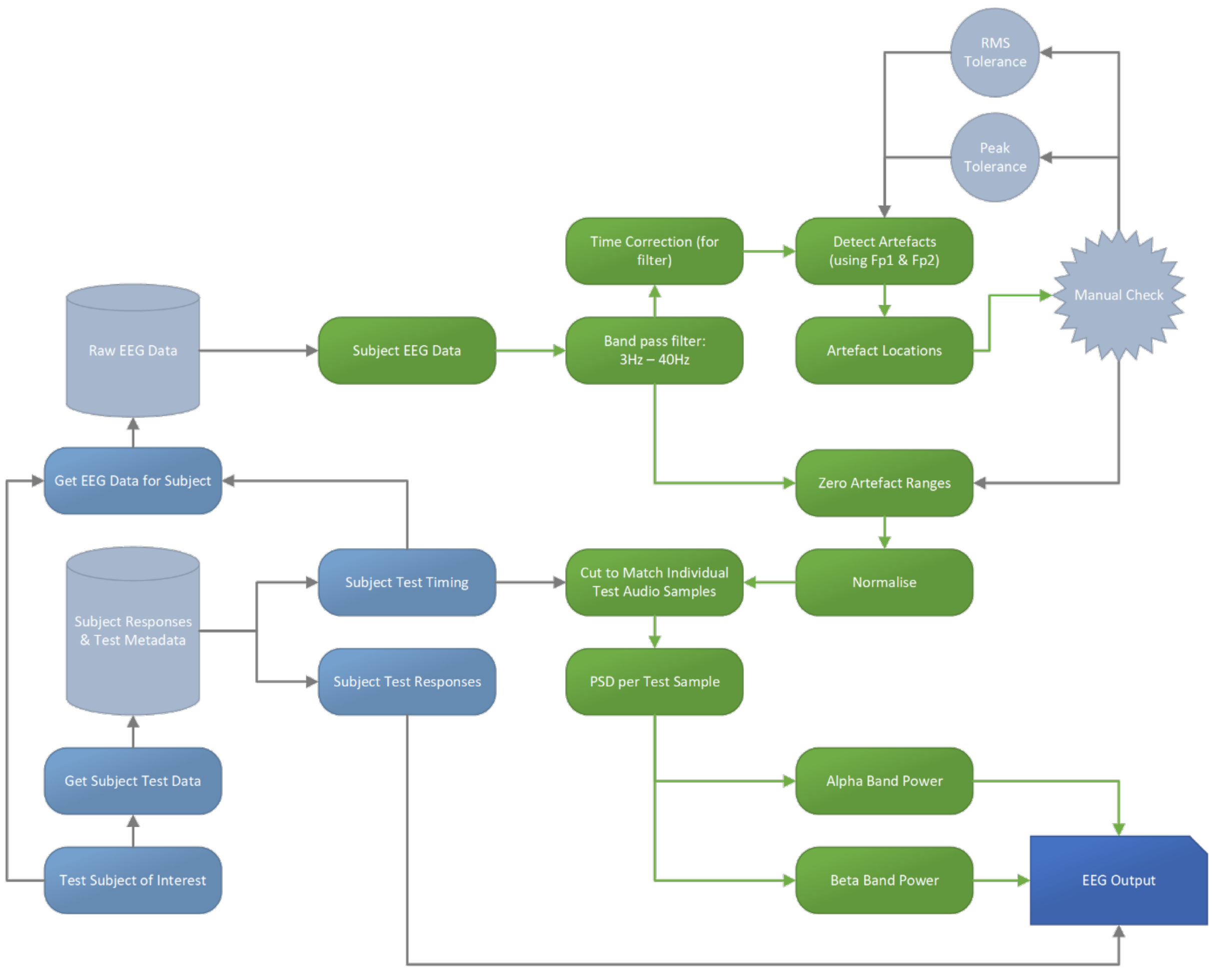

Figure 2: Data cleaning process for EEG data.

Figure 3 shows wave and spectrogram data from the frontal parietal channels, with marked interference at 25Hz, whilst Figure 4 shows spectrogram of frontal parietal channels for a complete trial with more successful cleaning and artefact removal (prior to 40Hz lowpass filtering).

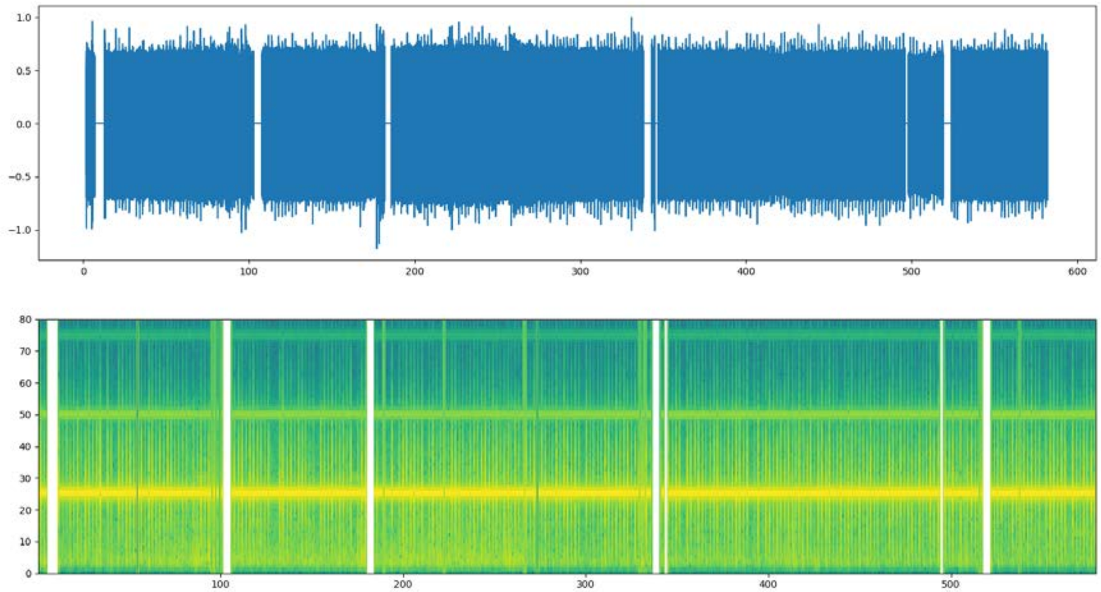

Figure 3: Complete trial data prior to cleaning (prior to lowpass filtering at 40Hz) in the frontal parietal electrodes

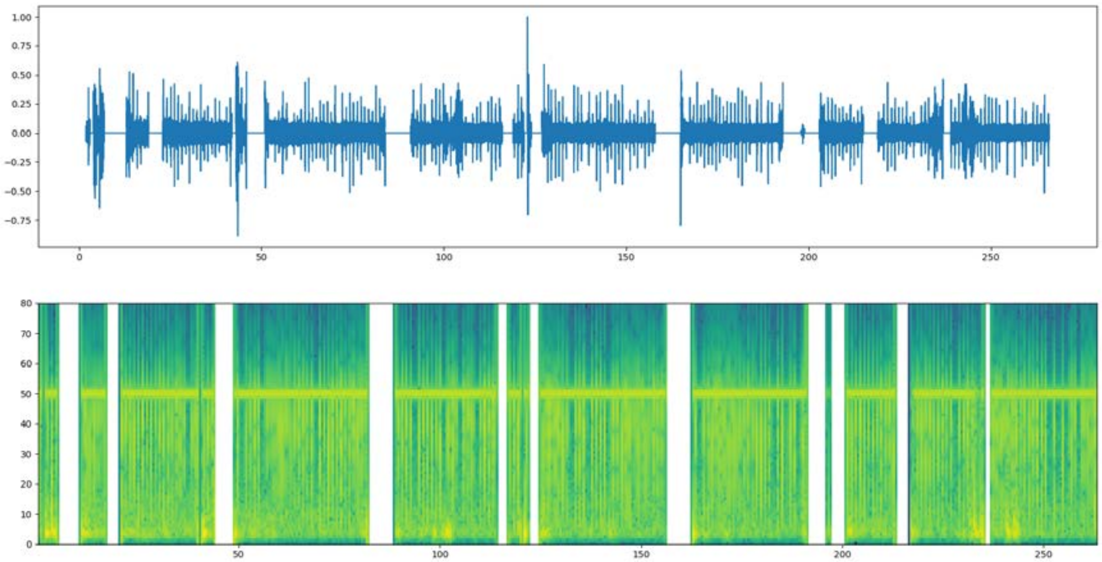

Figure 4: Complete trial data for a cleaned subject (prior to lowpass filtering at 40Hz) in the frontal parietal electrodes

3. Results

Spatial distribution and band power analysis for a single subject are shown in Figure 5.

Figure 5 Spatial distribution of activity and bandpower analysis from participant #35

Initial examination of self-reported annoyance rankings using a single factor ANOVA and a two-sample t-test assuming equal variance (p=<0.05) indicated that participants found sounds with temporal or impulsive spectrums and high frequency tonal components to be most annoying. Participants would likely be most familiar with the urban traffic sound, which notably they reported as the least annoying of the stimulus set, whilst the construction sound was reported as the most annoying. For more detailed results analysis of the perceived responses and GSR recordings the interested reader is referred to previous work in [2].

We extract three acoustic components, chosen on the basis of previous work reducing acoustic featureset choice for maximal correlation with annoyance [25] - integrated loudness, sharpness (spectral centroid), and mel-frequency cepstral coefficients (MFCC). Results are shown in Table 2 across the stimulus set with mean and standard deviation rankings for perceived annoyance.

Table 2: Mean responses to each stimulus type (rounded up to 1 decimal place), with values for two acoustic features extracted using the MATLAB audio toolbox. Integrated loudness calculated according to ITU-R BS.1770-4

Stimulus	Mean annoyance	St. Dev annoyance	Integrated loudness	Spectral Centroid
High speed train	6.3	2.2	-30.4	14
Urban Traffic	4.3	2.4	-45.8	14
Aircraft pass-by (650ft height)	6.5	2.2	-33.7	14
Tram curving (wheel squeal)	7.1	2.2	-34.0	14
Construction - Breaker	7.2	2.3	-28.3	14
Highway	5.1	2.4	-26.6	14

Note that whilst there appears to be no variation in the spectral centroid across the stimulus set, the time-varying spectral centroid, shown in Figure 6, does vary across each stimulus. Figure 6 also shows the time-varying MFCC (due to space restrictions it is not possible to reproduce all MFCC and time-varying spectral centroid plots here).

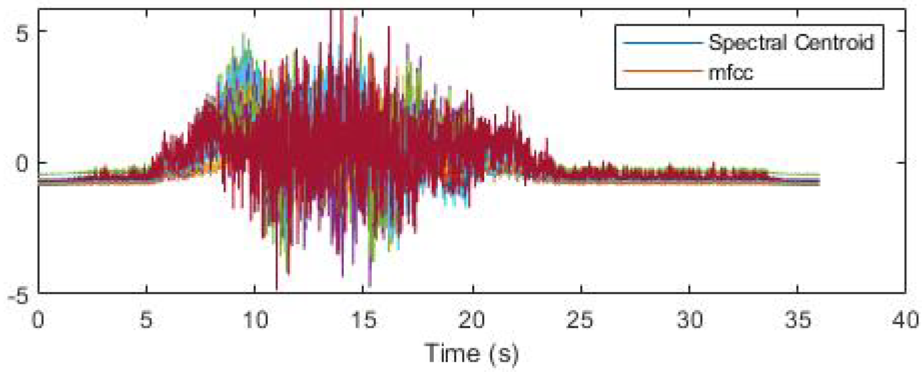

Figure **6**: MFCC and spectral centroid change over time for first stimulus – high speed train.

4. Conclusions and further work

Environmental noise has documented effects on productivity in the workplace, and significant impact on health and wellbeing. However, there remains a gap in knowledge in determining whether there are neural markers for these effects. Real-world testing of systems using bio-signal mappings in audio laboratory contexts has become an emerging field of research, partly due to recent advances in portability, wearability, and affordability of biosensors.

Metrics like the ISO 15666 for perceived annoyance used here have emotional connotations. The distinction between affect, mood, and emotion is complex, but in the context of sound evaluation the temporal nature of such responses can be useful [26]. Previous work has shown that there are measurable neurological and physiological responses to sound stimuli [27]. When listening to sound, our bodies may respond by inducing reactions such as pupil dilation, increased heart-rate, blood pressure, and skin conductivity [4].

The potential use of biophysiological data to help understand the mechanism of health effects caused by noise is therefore appealing, as biophysiological regulation may also help to circumvent some of the problems of self-reported emotion (e.g., users being unwilling to report particular felt responses, politically motivated responses, or perhaps simply confusing perceived responses with felt responses [28]).

In this work, analysis of perceived responses suggests that participants found sounds with certain acoustic correlates (temporal impulsive content, and high frequency tonal components), were most annoying. In future work, we plan to train a regression model with weighted vectors for EEG activity, our acoustic featureset, and self-reported annoyance, to analyse the large biometric dataset resulting from these experiments. We hope to harness these findings to create a prediction system which can help correlate affective state and biophysiological response with quantifiable acoustic features and qualitative self-report data from listeners. Beyond understanding the mechanisms at play there is potential for self-mediation and mood-based regulation (becoming less annoyed by disturbing sounds), by empowering the stakeholders/end users with their own data in the future.

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