EEG correlates of environmental noise impact in daily life

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ABSTRACT

Although epidemiology has focused on equivalent level indicators to analyze the impact of environmental noise, several scholars blame not considering spectro-temporal fluctuations and meaning for the limited explained variance in exposure-effect relationships. This paper explores a possible pathway. We analyzed EEG data of 23 healthy volunteers exposed to sound of multi-talker babble, highway, and fluctuating traffic at 63 dBA. For each, three listening conditions were explored: attending to spoken text (LA), attending to environmental sound (BA), and not attending to any sound (BUA). Based on PCA and predictability of remembering the text, we found that the EEG principal component related to inhibition was strongest for multi-talker followed by fluctuating traffic in the BUA condition, while in the LA condition, it was stronger for highway than for fluctuating traffic. The principal component related to cognitive prediction was strongest for highway in the LA condition but strongest for fluctuating traffic in the BUA condition. As these principal components depend on EEG-factors that have been connected to cognitive load, this explains a different impact of different types of environmental sound during daily activities.

INTRODUCTION

The impact of long exposure to environmental noise on people has been studied through epidemiologic research, mainly cross-sectional, and mainly using the equivalent noise level or the derived quantity annual façade L_{den} as an exposure indicator. Based on this research, the world health organization concluded that there is sufficient and qualitative evidence to relate this exposure indicator to several health outcomes[1]. In this evidence review, L_{den} is always related to a particular sound source: road traffic, rail traffic, air traffic, etc. Hence the relationships found implicitly include the meaning of the sound and its spectro-temporal character. Yet, when sound source characteristics change due to the introduction of new technologies or new operation procedures, the relationships may also change – even for a strong outcome variable such as reported source-specific noise annoyance. Such a significant change was e.g. observed for aircraft noise annoyance close to airports [2]

Over the past years, several suggestions were made to introduce new metrics for assessing exposure. From an attention perspective, we suggested the noticing event as a concept [3] while focusing on the tranquil intervals between events led Wunderli et al. to the intermittency ratio [4]. Although these and similar approaches have shown that they allow to predict reported annoyance more accurately, they did not convince health experts about their usefulness. We identify two main reasons for this. Firstly, in everyday noise exposure situations, all noise indicators strongly correlate as they merely indicate the presence of a sound source. Secondly, the influence of the characteristic of the sounds is not clear within the pathway leading to short-term and long-term health effects.

In the underlying study, the effect of different environmental sounds on the very first levels of processing by the human brain are investigated. Two pathways and corresponding hypothesis will be tested: (1) environmental sounds increase the effort needed to attend to everyday sounds such as listening, understanding, and memorizing in short term memory verbal information even if there is no noticeable effect on performance; (2) environmental sounds still affect brain functioning, even if a person is not paying attention to them.

Three very distinct sounds are used as exposures and EEG is used as bio-monitoring tool to show give proof of concept and show how a more elaborate study might be able to detect the fundamental differences between environmental sounds in the way they impact persons during everyday activities.

EXPERIMENT

To explore effects of environmental sound on brain functioning as a pathway to wellbeing and health impacts, an experiment was designed around three listening conditions:

1. Attentively listening to spoken text disturbed by various environmental sounds (LA). The text consists of a corpus of 13 5-minute lectures about recipes for Flemish dishes and Flemish literature. These were recorded in anechoic conditions in English, spoken by a native speaker. The topics were chosen so that the participants (Canadian) were not familiar with the content prior to the experiment. Participants were instructed to listen attentively in order to be able to take an exam afterwards.
2. Attentively listening to the same environmental sounds (BA). The environmental sounds were augmented with a few salient events matching the context (e.g. phone ringing in babble sound, emergency vehicle in highway sound, honking in urban traffic sound) and participants were instructed to count the number and type of audible events.
3. Inattentive listening while embedded in the same environmental sounds (BAU). At this point – towards the end of the experiment – participants were instructed to simply relax but they were still seated in the dark watching a white cross on a screen and hence did not engage in any other tasks part of the experiment or not.

Twenty-three young healthy adults (mean age = 27±3.18 SD, 13 females, 20 right-handed), all English speakers, participated in the experiment.

In total, participants listened to 13 lectures, and 12 excerpts of the background sounds twice. During the experiment 64-channel EEG was recorded continuously. Artefacts were removed from the EEG and the recordings were split according to the listening condition and fragment and were resynchronized with the exposure.

More details of the experimental setup can be found in our earlier publication [5]

Environmental sounds

Three types of environmental sounds were used in this work: (HW) highway traffic recorded at a distance of approximately 200 m from a busy highway; (FT) urban fluctuating traffic sound, recorded at approximately 20 m from an arterial road near a park hence with no street reverberation; (MT) multi-talker babble recorded at a social event with persons talking multiple languages but mainly English and Dutch further mixed to avoid understanding long conversations. These 3 types of sound were presented at an equivalent level of 63 dBA. Their spectrograms are however completely different as show in Figure 1. All sounds were presented from a loudspeaker in front of the participant thereby suppressing all spatialization effects.

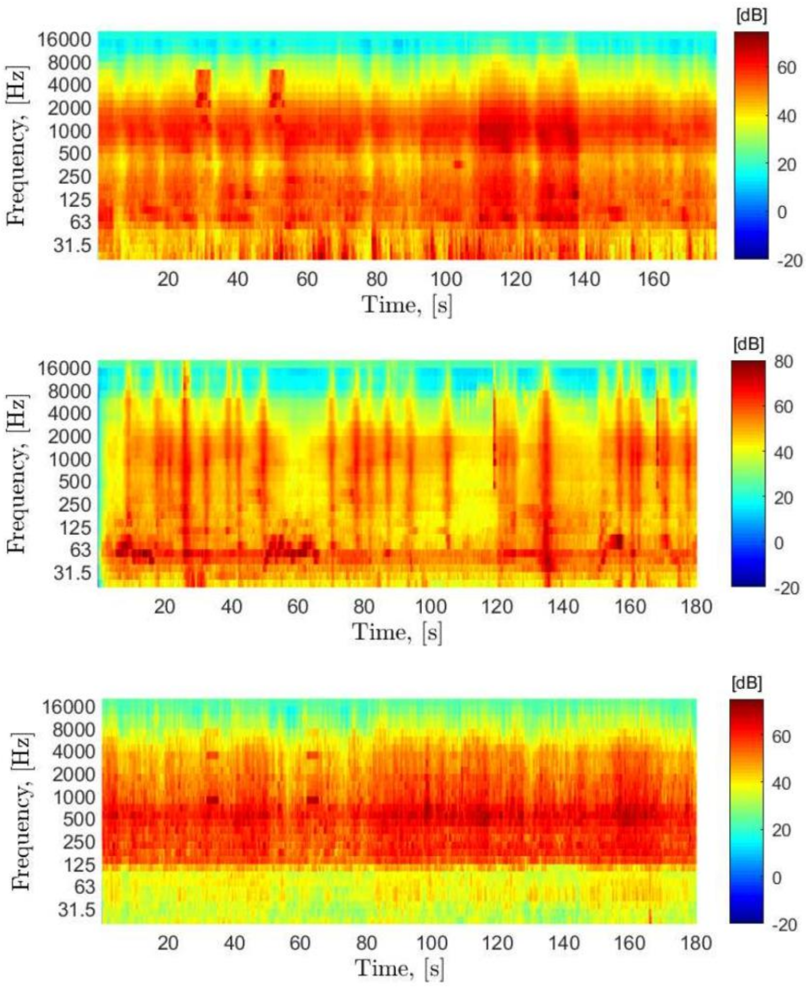

Figure 1: Spectrograms of the three sounds: HW (upper), FT (middle), and MT (lower)

RESULTS

Alpha power

It has long been established that alpha power, which is usually a strong and easily detectable EEG component, is related to sensory attention [6]. More recent work clearly illustrates the correlation of alpha activity with auditory distractor suppression, e.g. [7]. Although most of this evidence is given for 'simple' repeated stimuli. Considering alpha power as an indicator of effort needed to suppress a distracting environmental sound seems reasonable. Hence, alpha power (8-12 Hz) difference between background sounds was analyzed. To address the multiple comparison problem for comparing the channel-wise alpha power between the different conditions, we used the nonparametric cluster-based permeation testing across channel using 2000 permutations with a minimum of three significant neighboring channels [8]. Figure 2 indicates a stronger alpha power and thus distractor suppression for MT compared to FT in the LA condition and for FT over LA in silence. In the BUA condition on the contrary, FT evokes stronger alpha power than MT. The latter may indicate that MT is more easily suppressed but it could also indicate that participants are triggered to attend to multi-talker speech, even if instructed not to pay any attention to the sound.

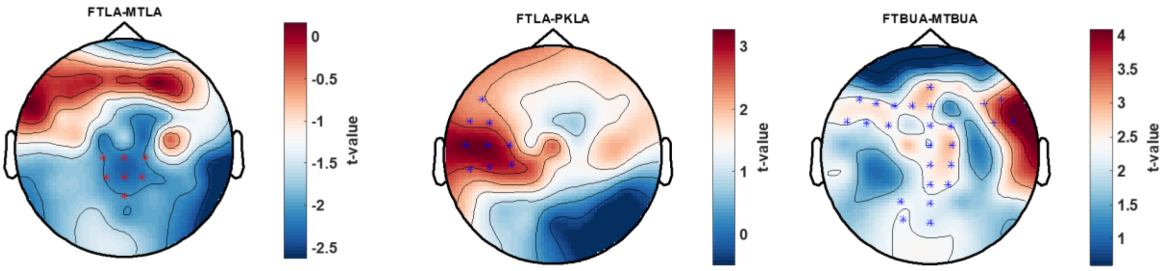

Figure 2: statistically significant differences in alpha power are indicated as stars on the topography (blue stars indicate positive difference, red starts negative difference); left: difference between FT and MT backgrounds during LA condition; middle: difference between FT background and silence during LA condition; right: difference between FT and MT background during BUA condition.

PCA analysis of multiple spectral components

In previous work [5], we combined multiple spectral indicators of the EEG signal at various brain regions in a principle component analyses that was conducted over all listening conditions and background sounds. Principle components (PCs) 6 and 7 showed the largest and most significant difference between background sound. There topographical map is shown in Figure 3.

PC 6 turns out to be significantly higher for HW background in the LA condition and for MT in the BA condition. PC 6 loads strongly on the gamma band (30 - 45 Hz) power and central frequency. Gamma activity has been related to creating the unity of conscious perception and semantic processing [9]. With this interpretation in mind, listening to a lecture in continuous background sound may require to evoke semantic processing and predictive coding more than other background sounds. When listening attentively to MT sound, semantic processing may likewise be more involved than when listening to HW or FT. In the BUA

PC7 increases with HW and more strongly with MT background in the LA condition. A similar trend is observed in the BA condition. It is also higher for MT compared to the other background sounds in the BUA condition. PC7 loads strongly on the long range temporal correlation (LRTC) of alpha activity [10]. LRTC measures self-similarity, in this case of the amplitude of alpha activity. It is a typical quantity for analyzing complex scale-free phenomena. Higher LRTC reflects that brain operates near a critical state. In fact, $0.5 < \alpha \leq 1$ indicates the presence of LRTC, whereas $\alpha = 0.5$ demonstrates that the data are completely uncorrelated. Considering the important role of alpha activity in inhibition, this component is expected to reflect a critical inhibition-excitation balance.

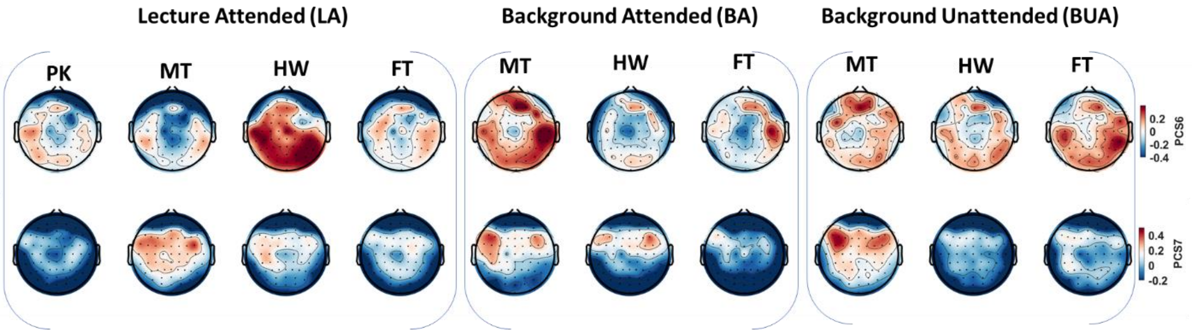

Figure 3: Principle components 6 and 7 from a PCA analysis including multiple spectral features.

Regarding short term memory, it was also observed that both PC6 and PC7 negatively correlate with the z-score of the exam on the lectures taken after the exposure. For PC6 this could be related to the observation that relying more on predictive coding may result in a less precise encoding of the information, while for PC7 the stronger need for inhibition may result in loss of information discrimination from distractors.

Microstate analysis

The EEG signals observed at the skull originate at different locations and depth in the brain. Hence, several techniques have been designed to reconstruct the origin of the signals – so called source reconstruction techniques. Optimally, they are based on an MRI image of the brain. As this information is seldomly available, the identification of microstates from the observed EEG signals may be seen as an alternative. Based on the abundance of data (several hours for 23 participants at 100 ms time step) the main topographic maps can be identified using a principle component techniques. The name microstate reflects that the observed patterns switch very quickly between states [11]. In resting state the spatial patterns that are thus identified seem very similar across persons and can serve as a diagnostic tool for disturbance of mental processes [12]. In these studies, transition probabilities between states, duration in each states, and complexity indicators are used to identify the persons state-of-mind. Here, in a first step we use the global map dissimilarity (GMD) [13] to calculate the distance from each state at each 100 ms time step to the 7 prototype microstates derived from all data. This results in a representation in this new state space at every time interval. Finally the t-distributed stochastic neighbor embedding (t-SNE) technique is applied to visualize the dissimilarity distribution between the EEG topographies and template maps.

In Figure 4, each dot represents a 100 ms instance of the listening experience averaged over all participants and averaged over the same conditions (e.g. LA-MT). In the upper left part of the figure, dots are colored by listening condition. It shows that BUA condition has a tendency to cluster in the upper right part, LA in a belt left of the middle while BA condition clusters in the same region but slightly more to the upper and lower parts.

As expected, listening condition has a stronger effect than background noise. Concentrations of points in small areas are related to individual persons which was also expected to have a strong influence. Small effects of background noise can mainly be observed for the outliers. In the LA condition, colors related to listening in background sound are usually found away from the clusters of black dots related to listening to lectures in quiet. For the BA condition, there is a slight tendency for red (MT) and green (HW) dots are found more often in the upper left and right areas while blue dots (FT) reside more in the lower and upper areas.

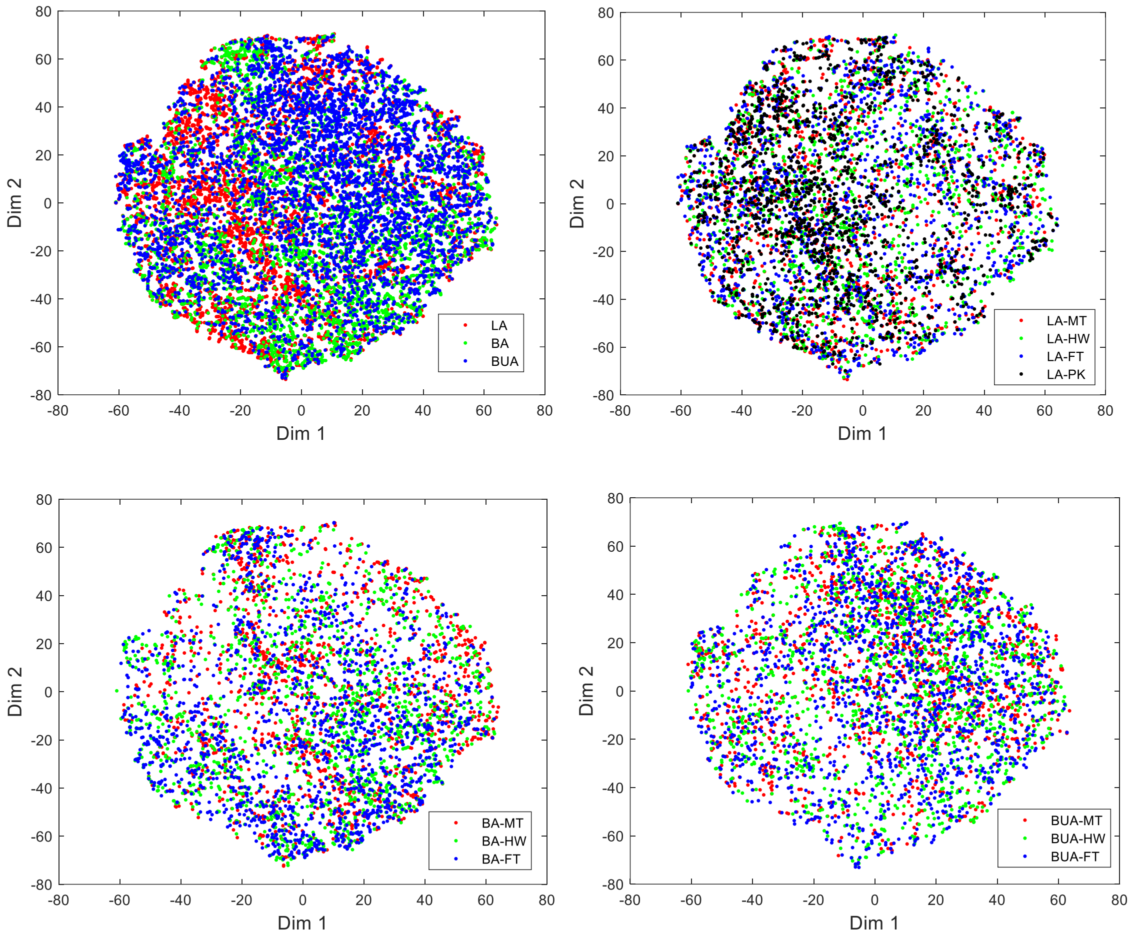

Figure 4: t-SNE mapping of the 100 ms brain state mapped to a 7-dimensional micro-state space; upper-left: colored by listening state; upper-right: colored by background (black indicates silence) during LA condition; lower-left: colored by background during BA condition; lower-right: colored by background during BUA condition.

DISCUSSION AND CONCLUSIONS

This publication explored the possibility to identify the impact of environmental sound on attentive listening to lectures and backgrounding the sound in skull EEG. To this end, the EEG of 23 participants under three listening conditions and with three types of background sound were explored using three different techniques.

It was shown that background sound influences the alpha power – indicative of distractor suppression processes – both during a task, listening to a lecture, and while ignoring the sound. This effect was significantly stronger in some brain areas for multi-talker sound than for fluctuating traffic while listening to lectures. While backgrounding, fluctuating traffic sound evokes stronger distractor suppression than multi-talker sound. Due to the similarity between the lecture and the multi-talker sound, the former could be explained. The stronger effect of fluctuating traffic sound on distractor suppression during backgrounding may be related to the unpredictability of the fluctuating sound.

Based on the PCA analysis of multiple indicators, the long range temporal correlation of alpha power – an indicator for switching between excitation and inhibition – was shown to increase for the multi-talker background over HW and FT in the LA condition. This seems to be consistent with the observation based on overall alpha power. However, it also seems higher for MT than for the other background sounds in the backgrounding condition which calls for a refinement of the conclusion drawn on the basis of alpha power on itself. This might be caused by the participants occasionally eavesdrop on the multi-talker sound even while instructed not to attend to it and hence excitation and inhibition switches.

By including more EEG oscillation frequencies, and using PCA to group them, it could further be shown that listening to lectures in high level continuous highway sound triggers the semantic network more strongly probably leading to higher levels of prediction. The same network is triggered by attending to multi-talker babble. At the same time this leads to a lower recall of information from short term memory and thus less efficient learning. Thus the semantic networks may have been over solicited in this noise condition.

Finally the complex transitions between microstates was investigated. Although this showed clear differences between the listening states, differences between type of background sound were less easily detected. During the LA condition, background sound seems to divert the brain from attractors in microstate space occasionally. This may correspond to epochs of distraction, but no clear evidence could be given at this stage.

At the very least, this study showed that the effect of environmental sound on a listening task and during backgrounding on brain functioning depends on the type of sound and not only on the equivalent level (all sounds were presented at the same L_{Aeq}). It also shows that the effects are diverse. Some background sound may required higher attention regulation during an auditory task but also while persons are not attending to the environmental sound, others may solicit semantic processing and predictive coding more during auditory tasks.

In general inhibition and predictive coding increase cognitive load and reduce task efficiency which relates these findings to mental fatigue caused by extensive exposure to environmental sound.

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