BEYOND THE LABORATORY: COGNITIVE MARKERS OF AUDITORY AND VISUAL SELECTIVE ATTENTION IN ECOLOGICALLY VALID ENVIRONMENTS

by

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Abstract

There is currently a trend towards measuring brain activity in more ecologically realistic scenarios. Bringing EEG experiments outside of the lab requires understanding of the impact of features of an ecologically valid environment, including visual scenery, sounds, and complex movements. In the first experiment, participants performed an auditory oddball task while cycling outside and sitting in an isolated chamber inside the lab. Significantly increased N1 and decreased P2 amplitudes was observed evoked by both standards and targets during cycling outside. To test the conclusion that this was related to a process of filtering overlapping sounds between the task and environment, a second experiment was performed using sounds inside the lab. Participants performed an auditory oddball task while also listening to concurrent background noises of silence, white noise and outdoor ecological sounds. We replicated the previous effect, finding a significantly increased N1 and decreased P2 when participants performed the task with outdoor sounds and white noise in the background, with the largest differences in the outdoor sound condition. In the third experiment, participants performed a visual oddball task while either viewing a video, or static screen in the background. We again found that ecologically valid background stimuli in the video decreased the P2, compared to the synthetic background stimuli. In a fourth and final experiment, participants were asked to perform the same auditory oddball task while again cycling outside in two different environments: a quiet park and next to a noisy roadway. In this experiment, only the N1 was increased in the noisier environment. This led to the conclusion that the N1 is altered by attention in non-ideal task situations, and the P2 is related to a process of filtering out irrelevant stimuli. Future research needs to focus on these differences in the ERP when experiments are performed outside, in order better understand how the brain works in the real world.

Preface

This thesis is an original work by myself, Joanna Elizabeth Mary Scanlon. This research project, of which this thesis is a part, received ethics approval from the University of Alberta Research Ethics Board, "Electrophysiological marker of Cognitive Processes", Pro00050069, 7/12/2016. The first chapter, "Taking off the training wheels: Measuring auditory P3 during outdoor cycling using an active wet EEG system" is already published in *Psychophysiology.* The papers in both chapter 1 and 2 received contributions from Kimberley Townsend, Danielle Cormier, Jonathan Kuziek, and Kyle Mathewson. Kimberly Townsend and Danielle Cormier were central to the data collection, background research and some of the writing for these papers. Jonathan Kuziek played a large part in modifying the technology to fit the needs of the experiments. My role in these experiments was in planning, creating/coding, data collection, data analysis and writing.

The third chapter was originally written as an honors thesis for Tia McLean, under Kyle Mathewson's supervision, in which I designed, created/coded, collected and analyzed data for the project, and she also collected data, performed background research and writing for the project. The fourth chapter received contributions from Eden Redman, Jonathan Kuziek, and Kyle Mathewson. Eden Redman helped with planning and data collection for the project and Jonathan Kuziek helped again with modifying the technology to fit the needs of the experiment. My role was in planning, creating/coding, data collection and analysis for this project.

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Thank you to my supervisors, Dr. Kyle Mathewson and Anthony Singhal, for their support and guidance throughout the program. Also thank you to my committee members, Dr. Jeremy Caplan and Dr. Craig Chapman and the many members of the Mathewson and Singhal labs. Finally, thank you to my family for their dedication and unconditional love and support throughout all aspects of my graduate experience.

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Introduction

Currently, there is a trend towards measuring brain activity in more ecologically realistic scenarios. Normally, cognitive neuroscience experiments require the confines of a laboratory and sedentary tasks in order to mitigate sources of electrical noise on EEG measurement. Bringing EEG experiments outside of the lab requires understanding of the impact of features of an ecologically valid environment, including visual scenery, sounds, and complex movements. Previous research has demonstrated that EEG measures including the N1 and P2 components as well as alpha waves, are all related to attentional processes that allow one to selectively focus on important stimuli and inhibit processing of unimportant stimuli. The N1 has been shown to relate to a process of attenuating all uninteresting, unpleasant, and unimportant, sensory inputs while enhancing the processing of interesting, pleasant and important stimuli (Näätänen & Picton, 1987). The P2 appears to reflect a separate yet related function of sensory filtering, in which irrelevant information is suppressed to allow better stimulus discrimination within a primary task (Getzmann et al., 2016; Kim et al., 2008; Potts, 2004; Potts et al., 1996). Alpha waves are understood to be a measure of a pulsating inhibition of processing, particularly of visual stimuli, which increase when the eyes are closed as well as when there is nothing to visually draw one's attention (Mathewson et al., 2012).

Many studies have investigated the functions of these cognitive markers, however few studies have looked at the way in which these electrophysiological measures may be affected by natural stimuli in an ecologically valid environment. The first study in this thesis was originally performed with the goal of investigating if we could perform an electrophysiological experiment during a mobile task outside of the lab. The following studies were born out of the unexpected results of this venture, with the goal of investigating the effects of ecological and ecologically

valid environments on brain activity during cognitive tasks. In particular, the auditory N1, auditory and visual P2 and alpha oscillation power were of interest. We used an oddball task for all of these studies, in order to allow us to make direct comparisons between the studies.

In my first experiment (Scanlon et al., 2017a) the goal was to look at the effects of cycling on EEG data. We had participants perform an auditory oddball task before, during and after a sub-aerobic stationary cycling task. We found increased noise in the EEG data during the stationary cycling task, despite this noise however, ERP signals were reliably recorded with no differences in the ERP components between any of the cycling conditions. In a follow-up to this study (Chapter 1; Scanlon et al., 2017b), we used compact technologies that could fit inside a backpack in order to have participants perform the auditory oddball task while cycling outside. Participants listened to the oddball task through headphones both while cycling outside and while sitting in the laboratory, responding with a mock-press button placed either on the handlebar of the bike or armrest of the chair. Baseline data noise was increased during the cycling condition, however the authors were successful in collecting laboratory quality ERPs in both conditions. Conversely to the stationary cycling study (Scanlon et al., 2017a), however, the outdoor cycling study (Scanlon et al., 2017b) demonstrated P3 amplitude and alpha band oscillations to be decreased while participants cycled outside, likely due to the sharing of attentional resources between the cycling and the oddball task. This study also found an unexpected increase in the N1 component and decrease in the P2 component of the ERP, during both standard and target tones while participants were cycling outside. In order to further investigate the effects that appeared when we performed the task outside, we made a follow-up study in which participants performed the same headphone auditory oddball task inside the lab with different sounds playing in the background of the task (Chapter 2; Scanlon et al., *In*

preparation-a). The background sound conditions included a recording of a noisy outdoor roadway, white noise, silent background with low-volume tones and silence. We found that we were able to replicate the N1 and P2 effects while playing outdoor noises and white noise in the background, indicating that the effect may have been due to a filtering of background noises in order to perform the task. No alpha differences were found in this study.

We then wanted to investigate whether an analog to this process existed in the visual modality. The next study (Chapter 3; Scanlon et al., *In preparation-b*) used a visual oddball task placed over two visual backgrounds. The first background was a point-of-view video of someone biking in traffic, and the second was a static 'snowstorm' screen. Here we found a significantly decreased visual P2 component and alpha spectra when participants were performing the task with the ecological video background, demonstrating that these measures appear to reflect similar functions whether the task is auditory or visual. Finally, to further investigate the N1, P2 and alpha waves in the real world, we performed a final study in which the auditory oddball task was performed in two different outdoor environments (Chapter 4; Scanlon et al., *In preparation-c*). These environments were a quiet park and next to a noisy roadway. Here we found evidence of P2 and alpha attenuation in both conditions, with an increased N1 in the roadway condition. This then demonstrated to us that even quiet outdoor environments can have the distracting effects on the P2 and alpha, and that the N1 and P2 while functionally similar, perform separate functions within the attentional system. Altogether these studies indicate that bringing EEG into the real world opens up the possibility of answering new questions about the way the mind works in the real world.

Chapter 1: Taking off the training wheels: Measuring auditory P3 during outdoor cycling using an active wet EEG system

Authors: Joanna E. M. Scanlon, Kimberley A. Townsend, Danielle L. Cormier, Jonathan W. P. Kuziek, Kyle E. Mathewson

Abstract

Mobile EEG allows the investigation of brain activity in increasingly complex environments. In this study, EEG equipment was adapted for use and transportation in a backpack while cycling. Participants performed an auditory oddball task while cycling outside and sitting in an isolated chamber inside the lab. Cycling increased EEG noise and marginally diminished alpha amplitude. However, this increased noise did not influence the ability to measure reliable event related potentials (ERP). The P3 was similar in topography, and morphology when outside on the bike, with a lower amplitude in the outside cycling condition. There was only a minor decrease in the statistical power to measure reliable ERP effects. Unexpectedly, during biking outside, significantly decreased P2 and increased N1 amplitude were observed when evoked by both standards and targets compared with sitting in the lab. This may be due to attentional processes filtering the overlapping sounds between the tones used and similar environmental frequencies. This study established methods for mobile recording of ERP signals. Future directions include investigating auditory P2 filtering inside the laboratory.

1. Introduction

Brain imaging has made significant advances in recent years, providing insight into the functional relationship between cognitive processes and brain activity (Makeig et al., 2010). However, the use of non- invasive technologies to record brain activity often requires participants to remain stationary (Debener et al., 2012). This is because natural sounds and sensations, as well as movement all have the potential to introduce noise into the EEG signal (Schlögl et al., 1999; White & Van Cott, 2010), and this noise is typically what determines statistical power during EEG and ERP analysis (Luck, 2014). In efforts to begin expanding the limits of cognitive neuroscience recordings to mobile, real life settings, recent advances towards mobile electroencephalography (EEG) systems have provided a platform from which researchers can begin to study and understand the cognitive processes involved in critical human behaviours such as driving, exercise, and human interaction. The present study was conducted to attempt to overcome the limitations of measuring EEG on a moving participant, while determining the way in which cycling outside may influence auditory event related potentials (ERPs).

Recent progress in mobile EEG technology provides the possibility for significant developments in cognitive neuroscience. The majority of these studies make use of the oddball task due to this task's high signal to noise ratio when detecting the P3, as well as for the ability to infer the attentional effects of a concurrent task (Polich, 1987; Polich & Kok, 1995). Debener et al. (2012) collected data for an oddball task completed sitting indoors or walking outdoors while brain activity was measured using a small consumer wireless EEG mounted to a classic laboratory electrode cap. The results were analyzed using brain-computer interface (BCI) single-trial P3 classification with linear discrimination. This analysis revealed that both the indoor (77%) and outdoor (69%) conditions had high prediction accuracies and the P3 generated

indoors was significantly larger than the P3 found in the outside condition. However the authors noted that identifying whether the differences in P3 amplitude were a matter of added noise or distinct cognitive processes requires further research (Debener et al., 2012). The study aimed to reduce noise and signal degradation through the use of a small, wireless EEG system and concluded EEG data could be recorded while mobile in less than ideal conditions. While the authors showed that mobile EEG recordings are possible, the data collected did not achieve as high a quality as can be obtained from medical grade recording devices inside the lab. Additionally, Scanlon et al. (2017) collected EEG data with an auditory oddball task during sub-aerobic indoor stationary cycling and sitting in a laboratory environment. The authors found that stationary cycling added noise to the data during and after pedaling, however reliable ERP signals could be accurately recorded, with no differences between sitting and cycling conditions. These studies demonstrate that mobile EEG recording is feasible, yet requires further study to achieve the same quality as data collected within the laboratory.

Many mobile EEG technologies stem from work with brain-computer interfaces (BCI), which allows one to control a computer using the classification of signals from the brain, such as ERPs and oscillations (de Vos et al., 2014a,b). Using the same wireless mobile EEG system as Debener et al. (2012), de Vos et al. (2014a,b) compared outdoor walking and outdoor sitting conditions while participants performed a three-stimulus oddball paradigm. This follow-up study accounted for possible outdoor distractions that could potentially influence task performance. The noise was not significantly different between conditions and single trial classification was above chance for both sitting and walking. The P3 elicited in response to targets was 35% smaller in the walking condition (de Vos et al., 2014a,b). These results suggest that the differences in P3 are not a result of noise but instead some aspect of cognitive processing that

was different between the two conditions. Gramann et al. (2010) purposed that P3 was smaller in the walking condition because cognitive resources were divided amongst large amounts of incoming muscular and sensory information. In another study using a passive electrode wireless mobile EEG system, Zink et al. (2016) had participants perform an auditory oddball paradigm, while either sitting, pedaling, or cycling in an outdoor natural environment. They found no differences in RMS data noise or P3 between pedaling and sitting, but observed a nearly significant P3 amplitude decrease and increased RMS at outer electrode sites while participants were moving around. Additionally, BCI classification accuracies were significantly lower for the moving condition compared to the sitting still and pedaling conditions.

In addition to ERPs, some studies have also looked at cortical oscillations during movement. Storzer et al. (2016) investigated oscillations in the motor cortex during stationary cycling and walking tasks of comparable speed. The authors demonstrated that while participants were cycling there were decreases in the high beta band (23–35 Hz) while movements were being initiated and executed, with subsequent increases in this band while movements were terminated. Additionally, both walking and cycling were associated with a decrease in alpha (8–12 Hz) power with a significantly larger decrease during walking. Jain et al. (2013) also measured motor cortex oscillations using EEG on a stationary bicycle, demonstrating significant increases in beta desynchronization during active pedaling compared to passive (low-effort) pedaling. These studies indicate that it is possible to measure cortical oscillations during movement tasks, and that cycling may have effects on alpha and beta band oscillations.

Several studies have investigated ways in which to optimize EEG technologies to be better used in mobile situations. Makeig et al. (2010) described numerous features that are required for an effective mobile EEG system. These include EEG sensors that are small and

lightweight to not hinder movement, removing the use of conductive gels to prevent electrical activity gathered from adjacent electrodes from combining together and finally, reducing the use of wires by implementing battery powered amplifiers and wireless data recording. Similarly, de Vos and Debener (2014) recommended that the mobile EEG technologies be small, lightweight and able to avoid cable motion (ideally wireless). In accordance with these recommendations, Debener et al. (2015) demonstrated that they could reliably record a P3 ERP component using a cEEGrid electrode array, made up of electrodes arranged in a flexible sheet and placed around the ear. A similar approach was used in a brain-computer interface (BCI) speller-task study by de Vos et al. (2014b), which showed equivalent results between a wired laboratory EEG system and a mobile wireless amplifier. Another study using a BCI speller by Bleichner et al. (2015) used a BCI system which could obtain significant P3 effects in a spelling task, while being small enough to hide under a baseball cap. The current study does not use many of the recommendations for an ideal mobile EEG system, and instead investigates the feasibility of using a regular (non-mobile) EEG system for a mobile task outside of the lab, as well as the ways in which the resulting data collected will differ from that collected within the typical laboratory environment.

An important consideration in the process of mobilizing our regular EEG system is the type of electrodes used, as this is the first source of data collection and can affect data quality in every stage of analysis. Several studies have investigated which electrode types might be best for non-ideal recording conditions such as mobile EEG in natural environments. Mathewson et al. (2017) compared active-dry electrodes to passive-wet and active-wet electrodes with the same amplifier. The electrodes were compared on single trial noise, event-related potentials, scalp topographies, ERP noise and ERP statistical power. The results showed that active-dry electrodes

had comparatively higher levels of noise than the passive-wet and active-wet systems, indicating that wet electrodes result in more statistical power and require fewer trials to get the same quality of data as dry electrode systems. Oliviera et al. (2016) investigated different electrode types in mobile studies by comparing BioSemi (active amplification) wet electrodes to Cognionics dry and wet electrodes (passive electrodes with active shielding) during an oddball task while participants were either walking or sitting. The BioSemi active wet electrodes showed the best results, with no difference in data noise between seated and walking conditions, while both passive dry and passive wet electrodes demonstrated significantly increased pre-stimulus noise and P3 time window amplitude variance, as well as decreased signal-to-noise ratio. While it may be argued that this study could have been confounded by the electrode caps and amplifier types used, active electrodes appear to offer some benefit to mobile EEG that warrants further study. Further, Laszlo et al. (2014) investigated the difference between active and passive electrodes using the same amplifier and different levels of impedance. The authors showed that while passive electrodes had ideal results in extremely low-impedance conditions (<2 k Ω), active electrodes had the best results for all impedance levels above this point. With increased electrical noise and impedance due to wire movements being a major concern when recording EEG during mobile activity, this study adds to evidence that active amplification and wet electrodes may be the ideal for mobile EEG studies. While future research is needed to indicate the best type of electrodes specifically for mobile EEG research, the current study uses active wet electrodes based on the evidence available.

Few previous studies have directly measured whether accurate and statistically reliable ERP data can be collected during outdoor cycling. The current study is an extension to the findings of Scanlon et al. (2017), using similar methods and analysis. It is of particular interest to

examine the potential ERP component variations between indoor laboratory conditions and outdoor path cycling, as well as how these conditions differ in statistical noise and power. Each participant completed four 6-min. blocks of an auditory P3 task while both sub-aerobically cycling on an outdoor path and sitting inside a laboratory Faraday cage. Active, low-impedance wet electrodes (*actiCAP*) were used. The noise levels and power spectra were analyzed, as well as ERP morphology, topography, and magnitude for P3, P2 and MMN/N2b. Our first hypothesis is that due to a larger degree of movement during recording, the outside cycling condition will show an increased amount of ERP and single-trial noise, leading to decreased statistical power. Our second hypothesis is that even with the effects of this movement, we will be able to accurately record ERPs in both the inside sitting and outside cycling conditions, with a high enough level of accuracy to detect possible differences between conditions. Furthermore, our third hypothesis is that in accordance with previous mobile EEG evidence, attention will be split between cycling and the oddball task, demonstrated by a decreased P3 component during the outdoor cycling condition.

2. Materials and methods

2.1 Participants

A total of 12 members of the university community participated in the experiment (Mean age = 22.9; Age range = 31–20; 4 female), and each participant was compensated $20. Participants all had normal or corrected-to-normal vision with no history of neurological problems. The experimental procedures were approved by the Internal Research Ethics Board of the University of Alberta.

2.2 Materials

During the ‘outside’ condition, participants selected one of two bicycles (Kona Mahuna), differing in only frame size (17 in or 19 in) based on participant’s height. Seat height was adjusted to a comfort level as indicated by the participant. The bicycles were equipped with a small mock-press button (button which can be pressed but does not collect data), fastened on the right handlebar. Resistance was kept constant for all participants at a set level of 2nd gear in both the front and back in order to allow participants to pedal evenly and constantly throughout the trials at a sub-aerobic level.

In the ‘inside’ condition, participants were seated in front of a 1920 × 1080 pixel ViewPixx/EEG LED monitor. A fixation cross was presented using a windows 7 PC running Matlab with the Psychophysics toolbox. Video output was via an Asus Striker GTX760. On the right armrest of the participant's’ chair was a mock-press button identical to the one placed on the bicycle. In both conditions, data was recorded and observed using a Microsoft Surface Pro 3 running Brain Vision recorder (Brain Products), and powered by an Anker Astro Pro2 20,000 mAh Multi-Voltage External Battery. The mentioned technology was connected using a Vantec 4-Port USB 3.0 Hub.

A Raspberry Pi 2 model B computer, which was running version 3.18 of the Raspbian Wheezy operating system, using version 0.24.7 of OpenSesame software (Mathôt et al., 2012), was used both to run the oddball task and to mark the data for ERP averaging (see Kuziek et al., 2017 for validation study). Audio output was via a 900 MHz quad-core ARM Cortex-A7 CPU connected through a 3.5 mm audio connector. Coincident in time with sound onset, 8-bit TTL pulses were sent to the amplifier by a parallel port connected to the General Purpose Input/Output (GPIO) pins to mark the data for ERP averaging. A start button was affixed to the

Raspberry Pi to simplify the beginning of a trial. Participants wore a two-pocket backpack (Lululemon; Figure 1.1A and B) which contained all of the recording and stimulus generating materials. When outside, participants rode along a 1.4 km shared use path on Saskatchewan Drive in Edmonton, Canada (Figure 1.1C and D).

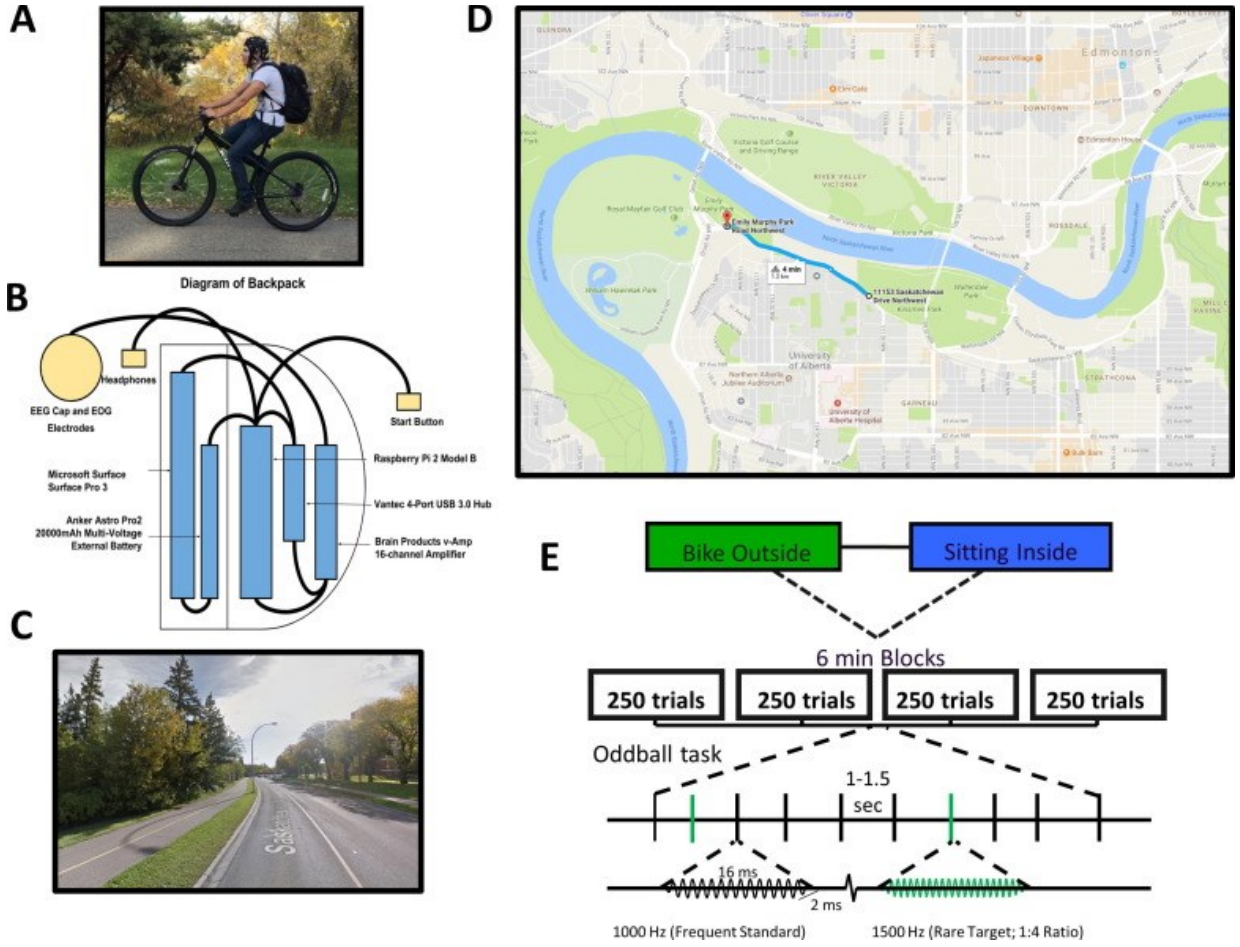

Figure 1. 1 Mobile EEG biking apparatus and procedure.
Mobile EEG biking apparatus and procedure. A: Participants performed the task while cycling on the bicycle, wearing the EEG cap and backpack containing the EEG equipment. B: Schematic layout of mobile EEG backpack contents. The two-pocket backpack contained the following: a Microsoft Surface Surface Pro 3, Anker Astro Pro2 20,000 mAh Multi-Voltage external battery, Raspberry Pi 2 model B, Brain Products v-Amp 16-channel amplifier, Vantec 4-Port USB 3.0 hub. C: The Procedure had two conditions: Biking outside and sitting inside. C: Shows the shared-use path participants rode on beside a 50 km/h two-way road. D: Shows the path on a map. E: Both sitting inside and outside on the bike, participants performed four 6 min blocks of an auditory oddball tasks, with breaks in between. Within the oddball task, 80% of the tones

were frequent low-pitched tones (1000 Hz), while 20% were rare high-pitched tones (1500 Hz), each played for 16 ms with a 2 ms ramp-up and down. Tones were played 1–1.5 s apart.

2.3 Procedure

Each participant completed an auditory oddball task to measure their P3 response to target tones in both the 'inside' and 'outside' condition (Figure 1.1E). Condition order was counterbalanced across participants, and was separated by a ten minute break and impedance check. Both inside and outside, participants completed four blocks of 250 trials separated by a 30 s break for a total of 1000 trials. Each trial had a 1/5 likelihood of being a target trial. Each block began with a 10-s countdown to ensure the oddball task only took place when the participant was already pedaling steadily. Each trial began with a pre-tone interval between 1000 and 1500 ms, followed by the tone onset. The next trial began immediately after the tone offset, with participants responding to targets during the following pre-tone interval. The headphones played one of two different frequency tones (either 1500 or 1000 Hz; sampled at 44.1 kHz; two channel; 16-ms duration; 2-ms linear ramp up and down), with the rare target tone always being 1500 Hz. In both conditions, the participant's task was to press the mock-press button with the index finger of their right hand when the rare tone was heard. During the outside cycling condition, participants were instructed to pedal slowly and evenly, and try to mostly stare forward while performing the oddball task, and to limit eye movements. In the inside condition, participants were instructed to sit still and stare at the fixation while performing the identical oddball task.

2.4 EEG recording

Based on previous lab work by Laszlo et al. (2014) comparing active and passive amplification electrodes at various levels of impedance, as well as a comparison by Oliviera et

al. (2016) of active wet, passive wet, and passive dry electrodes during a mobile task, active wet electrodes (BrainProducts actiCAP) were selected for the study, as both of these studies demonstrated that they afford cleaner and better quality signals in non-ideal recording conditions. Ag/AgCl pin electrodes were used and arranged in 10–20 positions (Fp2, F3, Fz, F4, T7, C3, Cz, C4, T8, P7, P3, Pz, P4, P8, and Oz). Additionally, a ground electrode, embedded in the cap at position Fpz, and two reference electrodes, clipped to the left and right ear, were used. SuperVisc electrolyte gel and mild abrading of the skin with the blunted syringe tip were used to lower impedances of all the electrodes. Gel application and aforementioned techniques continued until impedances were lowered to <10 kΩ, measured using an impedance measurement box (BrainProducts) and until data quality appeared clean and free of excessive noise. In addition to the 15 EEG sensors, 2 reference electrodes, and the ground electrode, the vertical and horizontal bipolar electrooculogram (EOG) was recorded from passive Ag/AgCl easycap disk electrodes affixed above and below the left eye, and 1 cm lateral from the outer canthus of each eye. Passive electrodes were used for the EOG as the AUX ports of our amplifier did not support active electrodes and we did not want to give up 4/16 EEG channels. These EOG channels can nonetheless record a reliable signal because of their placement on the face, where there is usually less hair to impede the signal, and any dirt and oils are removed before electrode placement. NuPrep preparation gel was applied to the applicable areas of the face, followed by wiping of the skin using an antibacterial sanitizing wipe, both used to lower the impedance of these EOG electrodes based on visual inspection of the data. These bipolar channels were recorded using the AUX ports of the V-amp amplifier, using a pair of BIP2AUX converters, and a separate ground electrode affixed to the central forehead.

EEG and EOG was recorded with a Brain Products V-amp 16- channel amplifier powered by the laptop USB port. Data were digitized at 500 Hz with a resolution of 24 bits. Data were filtered with an online bandpass with cutoffs of 0.1 and 30 Hz, along with a notch filter at 60 Hz. The narrow filters used were recommended in the actiCAP Xpress manual as ways to increase reliability and signal quality in mobile settings (Brain Products GmBH, 2014).

2.5 EEG analysis

EEG analyses were computed using MATLAB 2012b with EEGLAB (Delorme & Makeig, 2004), as well as custom scripts. After recording, EEG data was re-referenced to the average of the left and right ear lobe electrodes. Timing of the TTL pulse was marked in the EEG data during recording, and used to construct 1200-ms epochs (including the 200-ms pretrial baseline) which were time-locked to the onset of standard and target tones. The average voltage in the first 200-ms baseline period was subtracted from the data for each electrode and trial. To remove artifacts caused by amplifier blocking, movement and any other non-physiological factors, any trials in either of the conditions with a voltage difference from baseline larger than ±1000 μV on any channel (including eye channels) were removed from further analysis. Over 98 percent of trials were retained after this procedure in each condition. This lenient threshold was chosen after also viewing all the analysis and figures with a second threshold after eye correction of ±500 μV. Since the results were not different with this more strict rejection threshold we decided to show the results using only the 1000 μV threshold and eye correction. This allows us to keep as many trials for power analysis as possible, to allow approximately equal numbers of rejected trials for both conditions, and to get a sense of the true level of noise introduced by biking on the ERP measurement. On average, artifact rejection left approximately equal numbers of trials per participant in the cycling outside (M_{targ} = 199; $range_{targ}$ = 186–205; SD_{targ} = 5.0632;

M_{stand} = 789; $range_{stand}$ = 761–804; SD_{stand} = 14.7083), and sitting inside conditions (M_{targ} = 201; $range_{targ}$ = 191–212; SD_{targ} = 4.7378; M_{stand} = 798; $range_{stand}$ = 788–806; SD_{stand} = 4.7065; SD = Standard Deviation) from which we computed the remaining analyses.

A regression-based eye-movement correction procedure was used to estimate and remove variance due to artifacts in the EEG due to blinks, as well as vertical and horizontal eye movements (Gratton et al., 1983). This technique identifies blinks with a template-based approach, then computes propagation factors such as regression coefficients, predicting the horizontal and vertical eye channel data from the signals at each electrode. This eye channel data is then subtracted from each channel, weighted by these propagation factors, allowing us to remove most variance in the EEG which can be predicted by eye movements. No further rejection or filtering was done on the data in order to include as many trials as possible for both conditions, as well as to investigate how minor sources of non-eye-related noise contribute to the power to measure ERP components during the outdoor cycling task.

2.6 Condition differences

When indoors, trials took place in a dimly lit sound and radio frequency attenuated chamber, with copper mesh covering the window. The only electrical devices in the chamber were an amplifier, speakers, keyboard, mouse, and monitor. The fan and DC lights were turned on, to allow proper ventilation and visual acuity of the fixation. The monitor runs on DC power from outside the chamber, the keyboard and mouse plugged into USB outside the chamber, and the speakers and amplifier were both powered from outside the chamber. Nothing was plugged into the internal power outlets. Any devices transmitting or receiving radio waves (i.e. cellphones) were either turned off or removed from the chamber for the duration of the experiment. The experiment was completed between the months of August and November.

When outdoors, participants wore a toque over the electrodes to prevent the electrolyte gel used with the EEG cap from drying out, goggles to avoid added blinking during the trials, and gloves, if desired due to the weather (Temperature range = −5.3–10.4 °C; Mean temperature = 2.04 °C). Each 6 min block would bring the participant approximately 650 m past the starting point, after which they would turn around, have the EEG impedance checked by a research assistant, and bike back.

3. Results

3.1 Data noise

In figure 1.2A raw data is depicted for a representative participant at the location of electrode Pz. To estimate the noise in the data on individual trials, we used two separate methods. First, we averaged the frequency power spectra over each EEG epoch in the Pz and Fz electrode locations. Each participant's data was sampled randomly for 504 of their artifact-removed standard trials. A fast Fourier transform (FFT) was then calculated by symmetrically padding the 600 time point epochs with zeros, making a 1024-point time series for each epoch, providing frequency bins with a resolution of 0.488 Hz. Only frequencies measuring up to 30 Hz were plotted because data were collected online with a low-pass filter of 30 Hz. Spectra for each participant were then calculated by averaging the 504 spectra from each participant, which were then combined into the grand-averaged spectra, demonstrated in Fig. 1.2B for the Pz and Fz channels. Shaded regions indicate the standard error of the mean across participants. Evident from the graph is an increase in beta oscillations (15–30 Hz) during the outside biking compared to inside condition at both Pz ($M_{\text{In-Out power}} = -0.3272$; $SD_{\text{power}} = 0.1633$; $p = 2.4468e{-}05$) and Fz ($M_{\text{In-Out power}} = -0.2433$; $SD_{\text{power}} = 0.1734$; $p = 5.0314e{-}04$) electrode locations, as tested using a two-tailed paired samples *t*-test. This difference was greatest in posterior locations, likely due to

muscle artifacts in the neck during biking. Also evident from the graphs is an increase in delta (1–4 Hz) frequencies during the outside condition at both Pz ($M_{\text{In-Out power}} = -0.1247$; $SD_{\text{power}} = 0.1233$; $p = .0049$) and Fz ($M_{\text{In-Out power}} = -0.1127$; $SD_{\text{power}} = 0.1104$; $p = .0046$).

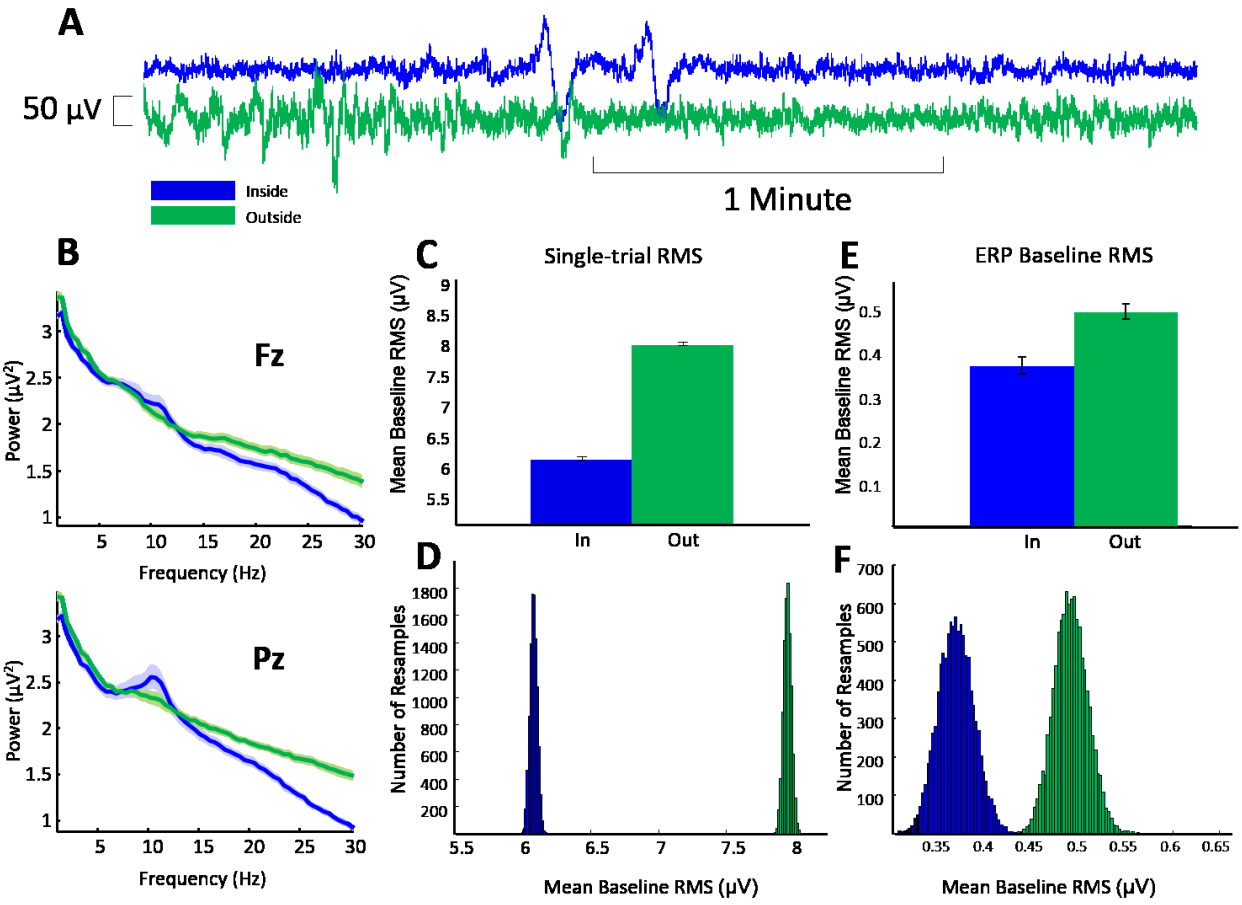

Figure 1. 2 Data noise levels
A: Raw EEG data (with online band-pass and notch filters) for a representative subject for several minutes within each condition, shown at the Pz electrode location. B: Single-trial EEG spectra from electrodes Fz and Pz, computed with zero-padded FFTs on 504 auditory standard trial epochs of each subject, averaged over trials, then subjects. Shaded regions represent the standard error of the mean. C: Bar graph of average single-trial root mean square (RMS) grand average values collected during a 200 ms baseline period prior to tone onset, for 10,000 permutations of 360 randomly chosen standard and target trials for each subject. RMS values are averaged over all electrodes within each trial, then averaged over trials, and then averaged over subjects. Error bars represent standard deviation of the permuted distributions. D: Histogram of these 10,000 permuted single-trial RMS values. E: Bar graph of average ERP baseline RMS values, calculated using 10,000 randomly selected permutations of 360 standard and target trials for each subject. RMS of the baseline period is computed for each permutation, and the data

averaged over trials. Error bars represent standard deviation of the permuted distributions. F: Histogram of these of these 10,000 permuted ERP baseline RMS values.

Both conditions showed the expected 1/frequency structure in the data, while the inside condition demonstrated the typical peak in the alpha frequency range between 8 and 12 Hz over posterior locations (Mathewson et al., 2012). However, data from the outdoor cycling condition did not appear to demonstrate this peak. The outside condition was shown through a two-tailed paired samples *t*-test to have marginally lower power in alpha oscillations compared to the inside condition ($M_{\text{In-Out power}} = 0.1209$; $SD_{\text{power}} = 0.2506$; $p = .1228$).

3.2 Single-trial noise

As an additional estimate of the noise on single-trial EEG epochs, we calculated the RMS value of a baseline period for each trial (de Vos & Debener, 2014). This baseline period consisted of the 100 time points (200 ms) prior to each tone's onset, to avoid including any interference of the evoked ERP activity in the measurement of RMS. RMS is equivalent to the average absolute voltage difference around the baseline, and therefore is a good estimate of EEG data single-trial noise. To estimate a distribution of RMS for each condition in our data, we used a permutation test that, without replacement, selects a different set of 360 epochs for each participant on each of 10,000 permutations before running second-order statistics (Laszlo et al., 2014; Mathewson et al., 2017). For each of these random selections and each condition, a grand average single-trial RMS was computed and recorded. A bar graph of the mean and standard deviation of grand average and single-trial RMS permutation distributions is shown in Figure 1.2C. Figure 1.2D shows a histogram of the grand-averaged single-trial RMS values calculated for each permutation, for each condition. Evident from these plots is a clear distinction between the single-trial noise between the two conditions. The outside condition ($M_{\text{RMS-}}$

$_{EEG}$ = 7.9512; $SD_{RMS\text{-}EEG}$ = 0.0291) clearly showed larger single-trial noise levels compared to the inside condition ($M_{RMS\text{-}EEG}$ = 6.0825; $SD_{RMS\text{-}EEG}$ = 0.0276; Wilcoxon rank sum test; $z = -122.4714$; $p < .0001$).

3.3 ERP baseline analysis

To test for noise that was not effectively averaged out over trials, we performed a similar analysis on noise levels within trial-averaged ERPs. To quantify the amount of noise in the participant average ERPs, we again used a permutation test of the RMS values in the baseline period. Complementary to the above single-trial analysis, this computation estimates the amount of phase-locked EEG noise in the data that is not averaged out over the trial with respect to onset of the tone. We randomly selected and averaged 360 standard trials without replacement from each participant's standard non-artifact trials. The RMS values obtained were then averaged over EEG channels to create a grand average for all participants. Once each participant's data were averaged together to compute second-order statistics, this made 10,000 permutations. The bar graph in Figure 1.2D depicts the means of these distributions, with error bars indicating the standard deviation of the distribution of permutation means. Figure 1.2E shows a histogram of the grand average RMS values calculated with these 10,000 permutations for each condition. Cycling outside ($M_{RMS\text{-}EEG}$ = 0.4904; $SD_{RMS\text{-}EEG}$ = 0.0181) produced a higher RMS value compared with the sitting inside condition ($M_{RMS\text{-}EEG}$ = 0.3685; $SD_{RMS\text{-}EEG}$ = 0.0190; Wilcoxon rank sum test; $z = -122.4709$; $p < .0001$).

3.4 ERP morphology and topography

Figure 1.3A depicts grand-averaged ERPs following target and standard tones from electrode Pz, calculated from each participant's corrected and artifact-free trials. The graph's shaded regions depict the standard error of the mean for each time point. Similar levels of error

are observed within each condition. Clearly, during outside cycling it is possible to measure ERPs with similar morphology and topography to those measured while sitting inside. Evident from the plots is the expected increase in amplitude for the P3 during target trials in posterior head locations (Pz), with a slightly greater P3 amplitude for targets in the inside condition.

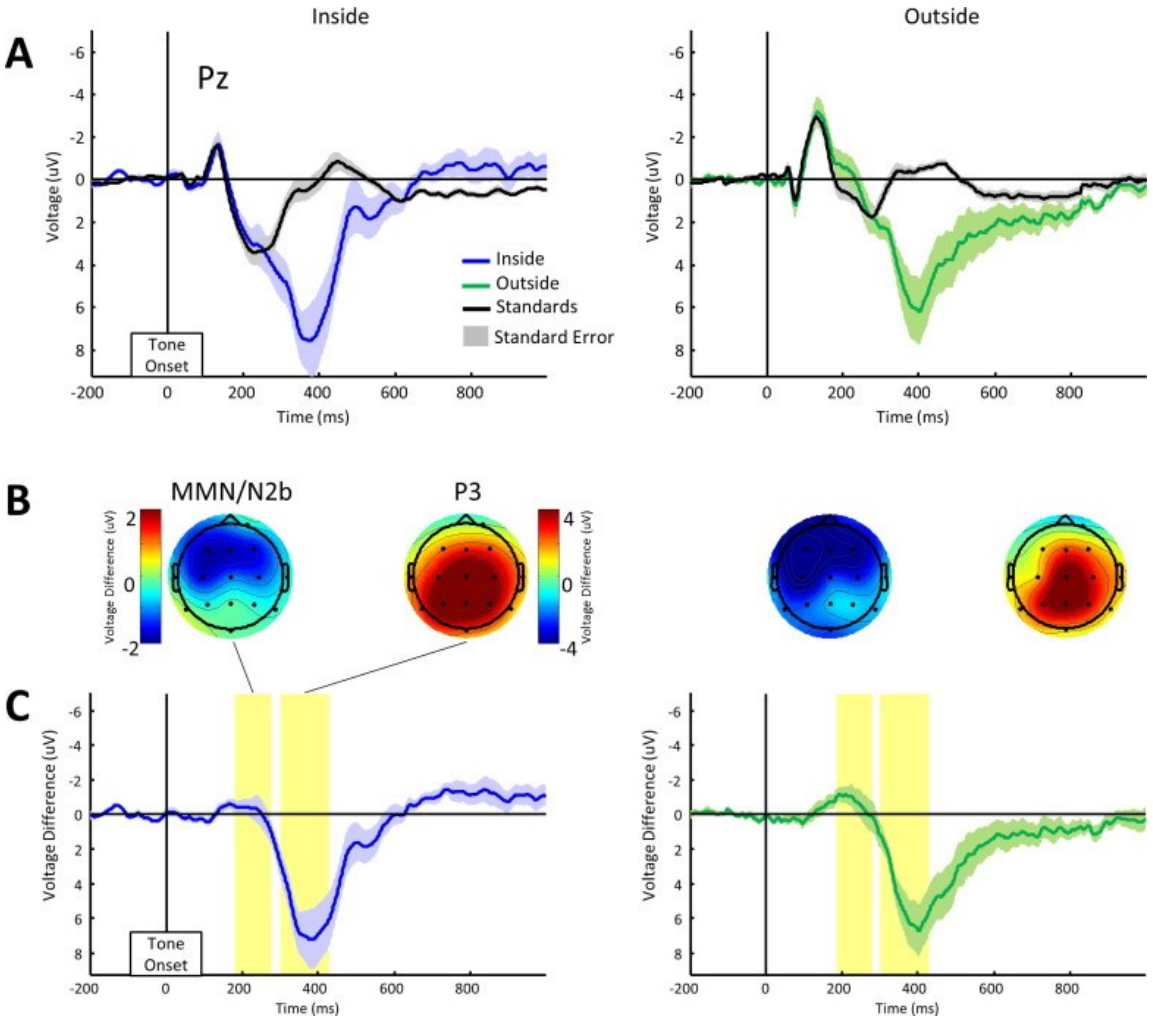

Figure 1. 3 ERP grand averages

A: Grand-averaged ERPs computed at electrode Pz for all artifact-removed trials, corrected for eye movements, for both target (color) and standard (black) and tones. Positive is plotted down, and shaded areas depict standard error of the mean. B: Scalp topographies of the grand-averaged ERP difference between target and standard tones in the MMN/N2b and P3 time windows (indicated in yellow), 175–275 ms and 300–430 ms after the tone, respectively. EEG data was re-referenced after recording to the average of the left and right ear lobe electrodes. C: Difference wave ERPs from electrode Pz for both conditions, with shaded regions representing within-subject standard error of the mean for this difference, with between-subjects differences removed (Loftus & Masson, 1994). Regions highlighted in yellow depict the time window for MMN/N2b and P3 analysis as well as topographic plots.

An expected P3 oddball difference was demonstrated with increased positive voltages between 300 and 430 ms following the rare target tones, compared to the frequent standard tones. This time window was then used for all further P3 analyses. Additionally evident in Figure 1.4A was a difference in the target-standard difference in the time window of the MMN/N2b, with more negative voltage between 175 and 275 ms following rare target tones compared to the frequent standard tones. This time window was then used for all further analysis of the MMN/N2b, using electrode Fz where this was maximal.

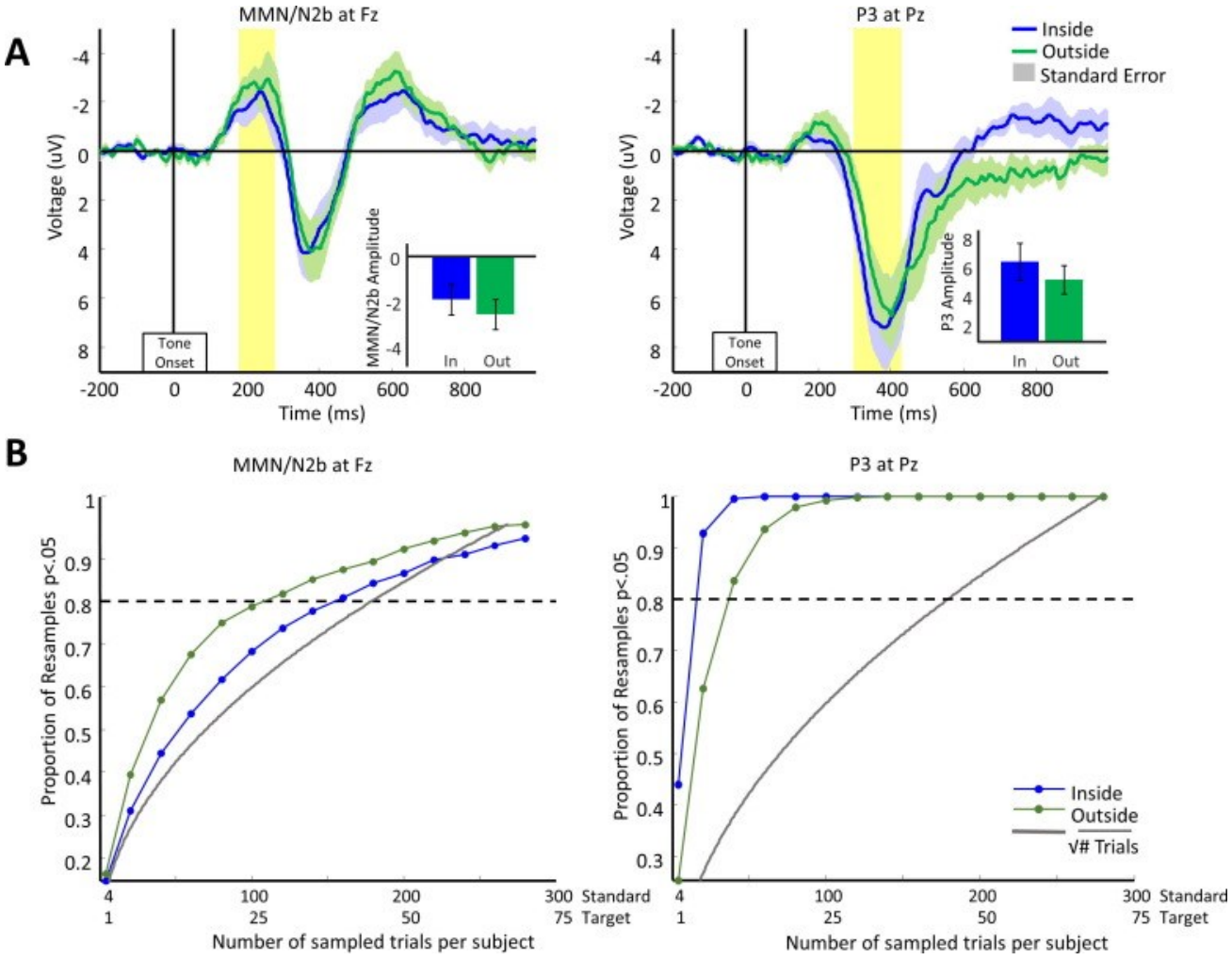

Figure 1. 4 Difference waves and ERP power analysis.
A: Difference waves indicating the average difference between target and standard trials for the two conditions are plotted for the Fz and Pz electrode locations. Yellow highlighted regions indicate main time windows compared, particularly the MMN/N2b at Fz (left) and the P3 at Pz (right). B: The results of a permutation test in which a number of trials selected within 10,000 permutations varied between 5 and 280, while keeping the 1:4 ratio of targets to standards. Randomly selected trials are averaged to calculate subject ERPs within each permutation for each number of trials. Differences in the P3 and MMN/N2b time window between standard and target trials is computed and compared using an across-subjects (paired samples) one-tailed *t* test (a = 0.05), before grand average statistics are computed. For each number of trials, the graph plots the proportions of the 10,000 permutations in which an uncorrected significant difference was obtained, for both conditions. The dashed horizontal line at 0.8 depicts the threshold to achieve 80% power to find an existing effect. The gray line represents a square root of the number of standard trials, scaled to a range between 0 and 1 on the vertical axis by dividing by the square root of the maximum number of trials.

Figure 1.3B illustrates topographies of these differences within the P3 and MMN/N2b windows. Topographies of the P3 time window show the expected posterior scalp distribution of activation for both conditions, while the MMN/N2b topographies reveal the expected distribution of activation toward the front of the head. Figure 1.3C plots the difference waves at Pz, which subtract the standard tone ERPs from their target tone ERPs for each subject. Shaded regions of this plot depict the within-participant standard error of the mean, with between-participant variation removed by the subtraction of standards from targets. This error estimate is therefore equivalent to that used in the *t*-test of this difference from zero (Loftus & Masson, 1994).

For both conditions there was a clear negative peak evident at approximately 220 ms at the Fz and even on the Pz electrode. A one-tailed, paired samples *t*-test comparing this MMN/N2b difference at electrode Fz averaged over the 175–275 ms time window centered around this peak revealed a significant MMN/N2b effect for the indoor condition ($M_{diff} = -1.9193$; $SD_{in} = 2.4026$; $t(11) = -2.7674$; $p = .0092$), as well as the outdoor cycling condition ($M_{diff} = -2.5988$; $SD_{out} = 2.3145$; $t(11) = -3.8897$; $p = .0013$). Additionally as expected, a clear positive peak was observed at around 380 ms at Pz. A one-tailed, paired samples *t* test compared this P3 difference at electrode Pz averaged over the 300–430 ms time window revealed Significant P3 effect in both the indoor sitting ($M_{diff} = 6.0319$; $SD_{in} = 4.4013$; $t(11) = 4.7474$; $p = .000301$) and outdoor cycling conditions ($M_{diff} = 4.7865$; $SD_{out} = 3.3884$; $t(11) = 4.8934$; $p = 2.3829e{-}04$).

3.5 ERP statistical power

Figure 1.4A plots difference waves for both of the conditions for electrodes Pz and Fz. As shown, there is no significant difference of the MMN/N2b between the two conditions at Fz. A two-tailed *t*-test between the inside sitting and outside cycling condition was performed to test for any condition differences between the targets-standards difference wave within the averaged

175–275 ms time-window, finding no significant difference ($M_{diff} = 0.6795$; $SD_{diff} = 1.8018$; $t(11) = 1.3064$; $p = .2181$).

To understand the different contribution to this effect between the MMN and N2b (Scanlon et al., 2017), we separated this window and differentially analyzed averages of an early time period for the MMN (100–200 ms) and a later time period for N2b (200–300 ms). No significant differences between conditions were found in the targets minus standards data when the two-tailed *t*-test was applied to either the MMN window (at Fz: $M_{diff} = 0.2770$; $SD_{in} = 0.9285$; $SD_{out} = 1.1425$; $SD_{diff} = 1.1643$; $t(11) = 0.8242$; $p = .4273$; at Pz: $M_{diff} = 0.2181$; $SD_{in} = 0.9587$; $SD_{out} = 1.2823$; $SD_{diff} = 1.6279$; $t(11) = 0.4641$; $p = .6516$) or the later N2b window (at Fz: $M_{diff} = 0.8028$; $SD_{in} = 2.6399$;$SD_{out} = 2.9497$; $SD_{diff} = 2.1544$; $t(11) = 1.2908$; $p = .2232$; at Pz: $M_{diff} = 0.7560$; $SD_{in} = 2.0251$; $SD_{out} = 2.3976$; $SD_{diff} = 1.8850$; $t(11) = 1.3894$; $p = .1922$). Both the MMN and N2b were likely elicited here; however the current design does not allow us to disentangle these components from one other. From here on, we will therefore focus on the time window of a combined MMN/N2b between 175 and 275 ms.

In Figure 1.4A, the difference wave for the P3 at Pz does not appear to show any large differences between conditions. However a two-tailed *t* test performed to test for a significant difference in the averaged P3 difference (targets – standards) between the two conditions revealed a significantly reduced P3 difference in the outdoor cycling compared to indoor condition ($M_{\text{in-out diff}} = 1.2454$; $SD_{diff} = 1.8072$; $t(11) = 2.3871$; $p = .0360$). Figure 1.3B shows topographies corresponding to these differences for the MMN/N2b and P3. It appears this difference is driven by a slightly earlier ramping up of the P3 in the inside condition. Following evidence of increased single-trial and trial-averaged noise in the outside cycling condition compared to the indoor condition, one may expect to observe lower statistical power in

the cycling condition. To test this prediction, we used a permutation procedure in which the 1:4 ratio of target to standard trials was held constant while varying the number of these trials contributing to the ERP average. Trial numbers increased from 1 target and 4 standard trial, by 20 standard trials, up to 300 standards and 75 target trials. We then randomly selected this number of trials from each participant's overall trials, with replacement, and averaged over subjects to obtain second-order statistics (e.g., grand averages). This random replacement procedure was performed separately for each biking condition and for both the MMN/N2b and P3 analyses. 10,000 permutations of this procedure were done for each number of trials. Note that this procedure is unable to consider possible changes in ERP morphology over time in the task due to attention or habituation, and assumes that these influences are observed consistently across conditions and stimuli (Scanlon et al., 2017).

For each permutation, the single trials selected were averaged together to create separate participant ERPs for standard and target tones. Differences between target and standard tones were then calculated at electrode Fz between 175 and 275 ms and electrode Pz between 300 and 430 ms in order to measure MMN/N2b and P3 average values, respectively. We then compared these participant-average ERP differences using a paired samples *t*-test ($df = 11$, one-tailed, $\alpha = 0.05$). Figure 1.4B plots the proportion of 10,000 permutations in which the p-value obtained passed the threshold of significance, as a function of the number of targets and standards selected for each permutation. It is evident from this plot that the MMN/N2b for the cycling outside condition reached significance for 80% permutations (80% power gray line) with fewer trials (30 target/120 standard trials) than the inside condition (40 target/160 standard trials). The effect is opposite in the P3 in which the P3 for the cycling condition reached significance for 80% of the

permutations with more trials (10 target/40 standard trials) than the inside condition trials (5 target/20 standard trials).

3.6 N1 and P2 amplitudes

In order to measure effects of biking outside on stimulus processing in general, figure 1.5A and B plot grand averaged ERPs comparing inside vs outside for each condition at the Fz and Pz electrode locations, respectively. A visual inspection of these plots reveals increased amplitude of the N1 component between 100 and 175 ms in the outside cycling condition for both electrodes Fz and Pz, within both target and standard trials. Two-tailed *t*-tests indicated a significantly larger average amplitude of the N1 for outside compared to inside conditions at electrode Fz for both standard ($M_{diff} = 1.8694$; $SD_{in} = 2.0195$; $SD_{out} = 1.5750$; $SD_{diff} = 1.2621$; $t(11) = 5.1309$; $p = 3.2783e{-}04$) and target ($M_{diff} = 1.9978$; $SD_{in} = 2.1191$; $SD_{out} = 2.3810$; $SD_{diff} = 1.6322$; $t(11) = 4.2401$; $p = 0014$) trials. Similar results were found for electrode Pz, indicating a significantly larger average N1 amplitude for the outside cycling condition, again within both standard ($M_{diff} = 1.5633$; $SD_{in} = 1.1053$; $SD_{out} = 1.0596$; $SD_{dif\,f} = 0.7939$; $t(11) = 6.8210$; $p = 2.8724e{-}05$) and target ($M_{diff} = 1.6707$; $SD_{in} = 1.4185$; $SD_{out} = 2.1360$; $SD_{diff} = 1.6819$; $t(11) = 3.4411$; $p = .0055$) trials. The topography of this difference is shown in figure 1.5C indicating a fronto-central distribution.

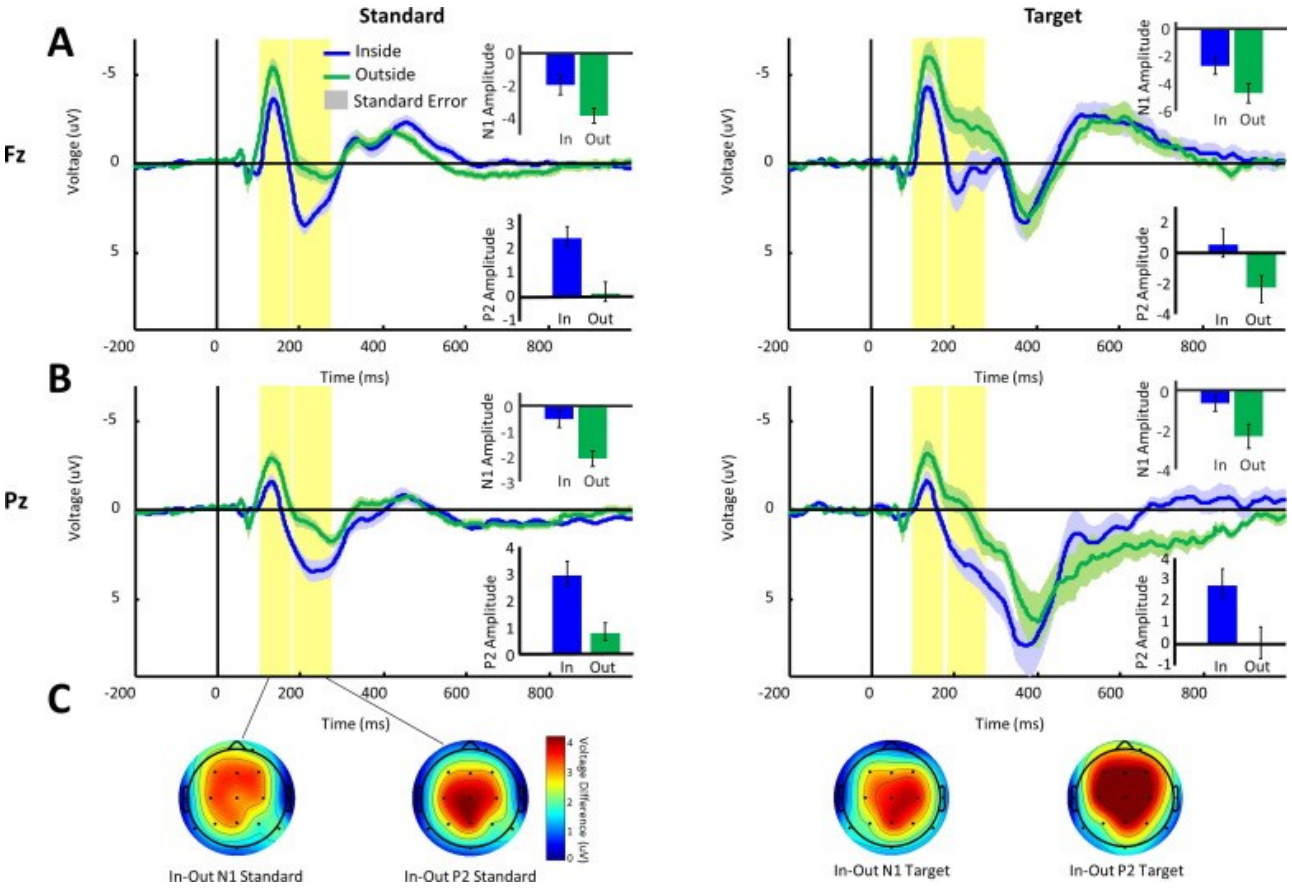

Figure 1. 5 Grand average ERPs.
A: Grand-averaged ERPs for the Fz electrode location, plotted separately to compare targets and standards between conditions. Shaded regions depict the standard error of the mean. Inset bar-graphs show the mean and standard-error across participants in the P2 window. B: Grand-averaged ERPs for the Pz electrode location, plotted separately to compare targets and standards between conditions. Shaded regions depict the standard error of the mean. C: Topographies of the N1 and P2 time window plotted for both inside and outside conditions.

Visual inspection of figure 1.5A and B also reveals decreased amplitude of the P2 component averaged between 175 and 275 ms, within both targets and standards of the Fz and Pz electrodes. Two-tailed *t*-tests revealed a significantly reduced P2 for the outdoor cycling condition at electrode Fz, mutually for standard ($M_{diff} = 2.3359$; $SD_{in} = 1.3812$; $SD_{out} = 1.4272$; $SD_{diff} = 1.3955$; $t(11) = 5.7986$; $p = 1.1953e{-}04$) and target trials ($M_{diff} = 3.0154$; $SD_{in} = 3.2177$; $SD_{out} = 3.0679$; $SD_{diff} = 2.4739$; $t(11) = 4.2223$; $p = .0014$). This effect was also shown in the Pz electrode, with a significantly reduced P2 component for the outdoor cycling condition within

both standard (M_{diff} = 2.1640; SD_{in} = 1.6686; SD_{out} = 1.1310; SD_{diff} = 1.2633; t(11) = 5.9338; p = 9.8189e−05) and target (M_{diff} = 2.7335; SD_{in} = 2.3643; SD_{out} = 2.5763; SD_{diff} = 1.9813; t(11) = 4.7792; p = 5.7211e−04) trials. The topography of this difference is shown in figure 1.5C indicating a slightly more anterior fronto-central distribution.

4. Discussion

Here we assembled all the necessary components of an ERP experiment into a portable backpack and were able to acquire research quality ERP data in an auditory oddball taskwhile users were riding a bicycle outdoors. We took advantage of recent advances in miniaturization of stimulus presentation devices (Kuziek et al., 2017) by using a Raspberry Pi computer to present the auditory oddball task in headphones and to mark the EEG data for stimulus onsets. We then used a tablet computer to acquire marked EEG data from a Brain Products v-AMP 16-channel amplifier as the EEG system. Based on previous research on the noise levels of various electrode types (Mathewson et al., 2017), we used actively amplified electrodes with electrolyte gel. In this experiment, we had participants aim to not move their head side to side, and to avoid excessive eye movements. In future research we aim to minimize the need for these constraints further and allow for free viewing of the scene while biking. In past research on ERPs during video game play this has still allowed for reliable ERP measurement (Maclin et al., 2011; Mathewson et al., 2012).

As expected, we found that biking outside produced a great deal more noise in the EEG compared to sitting in the lab. This can be seen in Figure 1.2 as increased RMS in the baseline period of the EEG for both single trial data and the trial averaged ERP for each subject. For single trial data this increase in noise is about double the increase in RMS noise observed by individual pedaling inside the lab on a stationary bike compared to not pedaling (Scanlon et al.,

2017). We attribute this additional noise to head and eye movements, and additional stimuli outside on the trail. The biking related increase in RMS noise we observed in the trial averaged ERP data (Figure 1.2E) is of similar magnitude as that found inside the lab in the previous study (Scanlon et al., 2017), suggesting that a great deal of this increased noise is not stimulus locked and is mitigated by trial averaging. Interestingly, when we considered the power spectra of this pre-stimulus noise, the results differ from that observed in Scanlon et al. (2017) previous indoor biking study. While we observed the same increase in high frequency (beta band) noise when biking outside compared to sitting, we also observed an increase in low frequency noise in the delta (1–4 Hz) range, as well as a very curious decrease in the peak of alpha normally observed in human EEG data. This decrease in the normally very prominent alpha peak indicates that the brain's electrical activity when outside in a realistic setting is very different from the classic observation of a large alpha peak observed for almost a century (Berger, 1929). Given the understanding of alpha power as a measure of a pulsating inhibition in the brain (Mathewson et al., 2012), we suggest that this decrease in alpha observed outside is related to the bombardment of our senses of the multitude of visual, auditory, and other sensory information.

That we were able to measure P3 response to oddball stimuli when participants were riding outside on a bike, which were similar in magnitude to those measured inside the lab, is an important advance. Previously we had shown that in a video game inside the lab it was possible to measure research quality P3 response (Maclin et al., 2011). It has also been shown that reliable P3 response can be measured while individuals were walking outside (Debener et al., 2012; de Vos et al., 2014a,b) as well as while biking outside (Zink et al., 2016). This is the first study to our knowledge that reliably compares the P3 observed between outside cycling and indoor laboratory conditions. As seen in figure 1.3, the MMN/N2b and the P3 measured had

similar topographies and morphologies inside the lab sitting compared to the same individuals outside the lab riding a bike.

In our analysis of the power of the ERP analysis as a function of the number of resampled trials used, we observed a moderate modulation of the ability to measure significant P3 and MMN/N2b effects. The MMN/N2b showed increased power, curiously, in the outside condition, with 50 fewer standard and 12 fewer target trials needed to allow for significant results on more than 80% of the resamples. For the P3, power to measure reliable differences between targets and standards we diminished in the outside condition, such that above 25 standard and 6 target trials more per person were needed. Our results indicate that to measure a reliable P3 outside with 100% power, around 125 artifact free standard and target trials would be needed, much less than then 1000 trials we recorded in this study.

As expected, a significantly reduced P3 was demonstrated while participants were cycling outside. This is in agreement with previous studies which have indicated that a lower amplitude P3 will be demonstrated when one's cognitive resources are being divided between a main task and concurrent task (Kramer & Strayer, 1988; Polich, 1987; Polich & Kok, 1995; Wicken et al., 1983), as well as with previous mobile EEG studies which showed a reduced P3 while cycling (Zink et al., 2016) and walking (Debener et al. 2012; de Vos et al., 2014a,b).

The most interesting and unexpected finding of our results was something that we did not predict. However, there was a large difference in the magnitude of early ERP components observed when we compared directly the ERPs evoked by stimuli types when they were heard inside the lab compared to outside the lab on a bike. From around 100–300 ms, there is a large difference in the ERP such that the N1 peak is larger outside, and afterwards the P2 peak is almost non-existent. These differences have a fronto-central topography on the head. These

changes in stimulus processing also do not seem to carry forward into differences in oddball detection, given the lack of differences in the P3 outside vs inside. Furthermore, when Scanlon et al. (2017) compared stationary biking in the lab vs. no movement, they did not find any modulations in the N1/P2, indicating that this effect is not due to the movement of biking itself.

The P2 has been associated with memory performance, working memory and semantic processing during tasks which are contextually based (Dunn et al., 1998; Federmeier & Kutas, 2002; Lefebvre et al., 2005), while the N1-P2 complex is thought to reflect pre-attentive sound processing in the auditory cortex (Näätänen & Picton, 1987). The components of the N1-P2 complex, which include the P1, N1 and P2 appear to reflect several processes that overlap temporally and originate within or near the primary auditory cortex (Näätänen & Picton, 1987; Wolpaw and Penry, 1975; Wood & Wolpaw, 1982). In particular, the auditory P2 component also appears to reflect the subjective difficulty involved in stimulus discrimination, as the P2 as well as the N1-P2 complex have both been reliably found to increase in amplitude following discrimination training (Atienza et al., 2002; Hayes et al., 2003; Reinke et al., 2003; Trainor et al., 2003; Tremblay et al., 1997, 2002, 2001). The P2 is also believed to reflect an aspect of perceptual processing and top-down cognition, and has been hypothesized to represent a process of inhibiting the perception of repetitive stimuli which has been deemed unimportant to the task (Freunberger et al., 2007; Luck & Hillyard, 1994). Additionally, the P2 has been proposed to be related to a process of suppressing irrelevant stimuli to allow discrimination between stimuli (Getzmann et al., 2016; Kim et al., 2008; Potts, 2004; Potts et al., 1996). The most relevant example of this was shown by Getzmann et al. (2016), demonstrating decreases in auditory P2 amplitude during speech discrimination while the participant ignored distracting background speech in a ‘cocktail party’ task, compared to a condition with no background stimuli.

We speculate that the modulation in the N1 and P2 we observed here is due to changes in discrimination difficulty and stimulus filtering outside. Our bike path was alongside a 50 km/h road, which creates a great deal of auditory and visual noise unrelated to the task. The peak of the auditory spectra for sounds of traffic overlap with the 1000 and 1500 Hz stimuli used in the current study. Additionally, our task differed from most previous studies of the auditory N1 and P2, in that our background noises were cars passing by at relatively high speeds. While being irrelevant to the task, these stimuli may still be highly salient as they represent a real-life possible hazard to the individual, which may help to explain why this exact pattern of results has not been seen in previous similar studies. In follow up research in the lab we are testing these predictions by playing various background noise and visual noise while participants perform auditory and visual oddball tasks. It is possible that the differences in the N1, P2 and P3 we observe here are related to the differences in RMS noise from artifacts in the bike condition, which we remove only the largest of due to our very lenient rejection thresholds. We are however confident in the quality of the data in the bike condition considering the similarity of the ERP with that obtained on the same subjects while sitting still on a chair inside the lab. If artifacts decreased the P3 and P2 outside on the bike, it is also likely that they would decrease all the other components as well. This was not the case however, as the N1 was shown to increase, while other components were unchanged. In follow up studies inside the lab we have since replicated these N1 and P2 effects using recordings of traffic sounds from outside. Inside the lab we use stricter artifact rejection criteria and require participants to sit still on a chair, therefore we do not believe the N1 and P2 differences are due to motion artifacts.

Another unexpected finding was in the power analysis of the MMN, in which the outside condition appeared to reach 80% significant permutations with a smaller number of trials than

the inside condition(Figure 1.4B), despite having a larger amount of noise by all other measures as well as no differences in mean amplitude. While it is difficult to speculate as to why this may have been, we believe that this may be due to noise from a few individual subjects. The standard deviation of the average MMN targets-standards difference was slightly higher for the inside condition (SD = 2.40) than the outside condition (SD = 2.31). The inside condition also had a wider range of values ($Range_{inside}$ = −7.3142 to 0.9951; $Range_{outside}$ = −7.6030 to −0.5067), three of which were greater than zero, while none of these values exceeded zero in the outside condition.

In this study we had participants ride as slow as comfortable to minimize noise from movement and to allow for sufficient recording time on the short trail we were having them ride on. Therefore, we don't believe that any of our effects on ERP's and data noise were due to effects of exercise on the brain. In a previous study inside the lab on stationary bikes (Scanlon et al., 2017), we did not observe these same modulations in the amplitude of the N1 and P2 when participants were pedaling a bike at a similar slow speed compared to sitting still on the bike. For the same reasons we don't believe that the modulations in the N1 and P2 we observed are due to increases in noise due to movement, respiration or perspiration, given the slow speed of biking and the very similar noise levels compared to studies of indoor biking. We believe that any effects of acute exercise on brain processing would require a much higher intensity of biking (see Pontifex & Hillman, 2007; Yagi et al., 1999; Grego et al., 2004; Bullock et al., 2017). In follow up research we plan to push individuals to faster biking paces and investigate changes in acute behavioural effects, ERP measurement ability, and measured noise in the data.

Cycling was used in this study for several methodological reasons. Firstly, for both the present study and the previous study with stationary cycling (Scanlon et al., 2017), as well as for our

current set-up which includes wires connecting the electrodes and amplifier, cycling allowed a method to record EEG data during movement while minimizing the artifacts introduced into the EEG data. For example, when individuals walk or run, their head often moves up and down as they step, allowing wire movements and artifacts, while cycling often allows one to move forward in a relatively smooth straight-forward movement. The second reason is that cycling is a common activity which requires balance, steering control, and attention to one's environment to be done correctly, making this a rich and unique activity to be explored experimentally. A simple oddball task was used to assess attentional allocation differences between sitting still inside and cycling outside in this study, which allowed us to infer that cycling at a slow and subaerobic pace outside is enough to alter the attentional resources allocated to the oddball task.

The limitations of our experimental setup continue to be in the bulk of equipment needed in the backpack. We have been using a large tablet computer to acquire the EEG data. To complement the Raspberry Pi used for stimulus presentation, we have now started testing the use of a similar miniature computer (Latte Panda) that runs windows OS and can be used to record EEG data with brain vision recorder software (Brain Products GmBH, 2014). Further, our EEG amplifier itself is quite bulky, with electrode leads plugged in directly. Recent advances in both research grade EEG portable systems (Debener et al., 2015; Zink et al., 2016), would further improve the portability of such a system. It is also not known how well the active electrodes that we used in this study preform in movement situations, and some research has shown that data of similar quality can be measured with electrodes with no active amplification (Debener et al., 2012; de Vos and Debener, 2014; Zink et al., 2016). Finally, consumer grade EEG hardware is becoming increasingly sophisticated, and very affordable Bluetooth EEG systems have been shown to measure research quality EEG and ERP data (Krigolson et al., 2017; Hashemi et al.,

2016). We are also testing how these systems can be integrated into our experimental setup to further increase portability and minimize obtrusiveness of the equipment.

The ultimate goal of this research program will be to measure ERP's to event that are naturally occurring out in the world, in order to gain a deeper understanding of how the brain works in everyday situations. This will require video capture and coding to identify moments in the EEG data when events of interest occur in the world. We have taken steps in this direction in the lab by testing the effectiveness of using virtual reality (VR) for stimulus presentation in ERP experiments. Further, we have begun filming our outdoor bike EEG sessions, and yoking the video recording to the EEG recording. We aim to start by using confederate actors to stimulate real life events (pedestrians, signals, obstructions, sounds), and move to video coding of real-world biking data.

4.1 Conclusion

In sum, here we have shown the ability to package an experimental EEG setup into a backpack and have individuals ride bicycles outside a path while engaged in an auditory oddball task. We reliably measured ERPs and can estimate the number of trials needed to measure reliable P3 responses outside on a bike. As expected, we found that while the P3 response was modulated by biking outside compared to sitting in the lab. However there was also a large modulation in the N1/P2 response to both standards and targets. We suggest that this modulation may be an effect of increased auditory filtering needed to focus on the task while ignoring the traffic sounds and sights.

Chapter 2: The ecological cocktail party: Measuring brain activity while filtering background noise

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Abstract

Most experiments using EEG recordings take place in highly isolated and restricted environments, limiting their applicability to real-life scenarios. New technologies for mobile EEG are changing this by allowing EEG recording to take place outside of the laboratory. However, before results from experiments performed outside the laboratory can be fully understood, the effects of ecological stimuli on brain activity during cognitive tasks must be examined. In this experiment, participants performed an auditory oddball task while also listening to concurrent background noises of silence, white noise and outdoor ecological sounds, as well as a condition in which the tones themselves were at a low volume. We found a significantly increased N1 and decreased P2 when participants performed the task with outdoor sounds and white noise in the background, with the largest differences in the outdoor sound condition. No behavioural differences were found. This lead to the conclusion that these components indicate a process of sensory filtering of background sounds, and that ecologically valid sounds require more filtering than synthetic sounds.

1. Introduction

Historically, experiments in cognitive neuroscience tend to require participants to experience highly isolated conditions during experiments, for two main reasons. The first is to control any effects that the environment may have on normal brain activity. The second is due to equipment limitations that make recording outside of the laboratory difficult and prone to large degrees of data noise. However since these equipment limitations have often made it difficult or impossible to test brain activity in different environments, the effects of ecologically valid environmental influences on brain activity have little been studied. New technologies are beginning to change this, with new mobile EEG technologies that can be carried almost anywhere (Debener, Minow, Emkes, Gandras, & de Vos, 2012; de Vos, Gandras, & Debener, 2014; Zink, Hunyadi, Van Huffel, and de Vos 2016). At this point, few studies have attempted to determine what effect natural environmental noise may have on brain activity. The present study was conducted to simulate some types of natural sound environments in order to determine the effect of environmental sounds may have on brain activity and the ERP.

Several studies have used mobile EEG to perform experiments in real-life environments. Debener et al. (2012) used a wireless EEG system while participants performed an auditory oddball task either while sitting indoors or walking outdoors. They were able to show that P3 amplitude was significantly larger when generated while sitting indoors than while walking outdoors. With a similar mobile EEG system, de Vos et al. (2014) instructed participants to perform a three-stimulus auditory oddball task during both outdoor sitting and walking conditions. Again, P3 amplitude was significantly larger while participants were seated. Zink et al. (2016) had participants performing an auditory oddball task during mobile cycling, stationary pedaling and sitting in a natural outdoor environment. The authors found no difference in P3

amplitude between the stationary cycling and sitting conditions, but demonstrated a near-significantly reduced P3 amplitude while participants were cycling. Similar to this, Scanlon, Sieben, Holyk, & Mathewson, (2017a) had participants both sitting and pedalling on a stationary bicycle inside the lab and found no P3 differences during the auditory oddball task. Scanlon, Townsend, Cormier, Kuziek & Mathewson (2017b) had participants performing an auditory oddball task both while cycling outside and while sitting inside. Again, the authors found a significantly reduced P3 during the mobile task of cycling. However they also found a significantly decreased P2 and increased N1 while participants had been cycling outside. Taken together, these studies indicate that while divided attention appears to have an effect on the P3, there is no evidence that one's environment would affect this component. However, the increased N1 and decreased P2 while participants cycled outside may warrant a further investigation.

As this previous study was primarily exploratory, there are several possible reasons for these changes in the N1 and P2 components of the ERP while participants had been cycling outside (Scanlon, et al., 2017b). In the outdoor condition, participants were also cycling, as opposed to sitting in the indoor condition. This meant that they were experiencing a physical (however sub-aerobic) mobile activity, visual optic flow, as well as auditory stimuli that they did not experience while sitting inside the laboratory. Additionally, Scanlon et al. (2017b) found that alpha power was decreased while participants cycled outside, and previous work by Brandt, Jansen & Carbonari (1991) has shown that alpha power may be positively correlated with visual N1 and P2 amplitudes. However, most literature concerning the auditory N1 and P2 components point to these components being mostly affected by auditory factors, especially for a task in the auditory modality (Näätänen & Picton, 1987).

The N1-P2 complex appears to reflect pre-attentive sound processing in the auditory cortex (Näätänen & Picton, 1987). The P1, N1 and P2 components which make up this complex have been shown to reflect several nearly simultaneous processes originating within or near the primary auditory cortex (Näätänen & Picton, 1987; Wolpaw and Penry, 1975; Wood & Wolpaw, 1982). The auditory N1 is a negative-going waveform with three subcomponents, which peak approximately between 75 and 150 ms after stimulus onset (Luck, 2014). The N1 wave appears to be sensitive to attention, and is modulated by how well an attended stimulus can be distinguished from other stimuli by physical cues such as pitch or location (Näätänen, 1982, 1992). The P2 component, on the other hand, is a positive-going waveform which occurs approximately 150-275 ms after stimulus onset as the second positive component of the ERP (Dunn, Dunn, Languis & Andrews, 1998). P2 is believed to represent a top-down, higher-order aspect of perceptual processing, which is also modulated by attention (Luck & Hillyard, 1994; Freunberger, Klimesch, Doppelmayr & Höller, 2007; Hackley, Woldorff, & Hillyard, 1990). Therefore, it appears that this change in the N1 and P2 components relates to some auditory aspect of top down perceptual processing and attention that is altered when participants performed the same task in a rich and noisy environment (Scanlon, et al., 2017b).

Perhaps some aspect of an outdoor environment changes the attentional and sensory processes required to perform an auditory task. This could be due to the overlapping sounds, as one filters unimportant background stimuli to focus on their current task. Conversely, the reason could also be as simple as the possibility that the same headphone task sounded subjectively quieter in an open environment. In the current study, we intend to investigate these possibilities by having participants perform the same headphone auditory oddball task as in previous studies (Scanlon et al., 2017a; Scanlon et al., 2017b) with the following conditions: background outdoor

traffic sounds, background white noise, silent background, and silent background with quieter tones. Evidence from the literature leads us to deduce that the effect within the N1 and P2 in our previous study was due to a process of filtering out extraneous ambient noise, while focusing in on the relevant task. Therefore we hypothesize that we will be able to most effectively replicate the increase in N1 and decrease in P2 when outdoor sounds and white noise are played in the background.

2. Methods

2.1 Participants

A total of fourteen members of the university community participated in the experiment (Mean age=21.6; Age range=18-26; Sex=5 female). Six participants were members or associated members of The Mathewson Lab at the University of Alberta. All participants were either compensated $10/hr or received course credit for participating in the experiment. Participants all had normal or corrected-to-normal vision with no history of neurological problems. The experimental procedures were approved by the Internal Research Ethics Board of the University of Alberta and gave informed consent prior to participating.

2.2 Materials

In all conditions, participants were seated in a radio frequency attenuated chamber in front of a 1920 x 1080 pixel ViewPixx/EEG LED monitor running at 120 Hz with simulated-backlight rastering. A fixation cross was presented using a windows 7 PC running Matlab with the Psychophysics toolbox. Video output was via an Asus Striker GTX760 and audio output was through an Asus Xonar DSX sound card. The participants pressed a button with their right index finger when they heard the high oddball tone. Responses from the button press were marked in

the EEG data by the Raspberry Pi 2 model B computer.

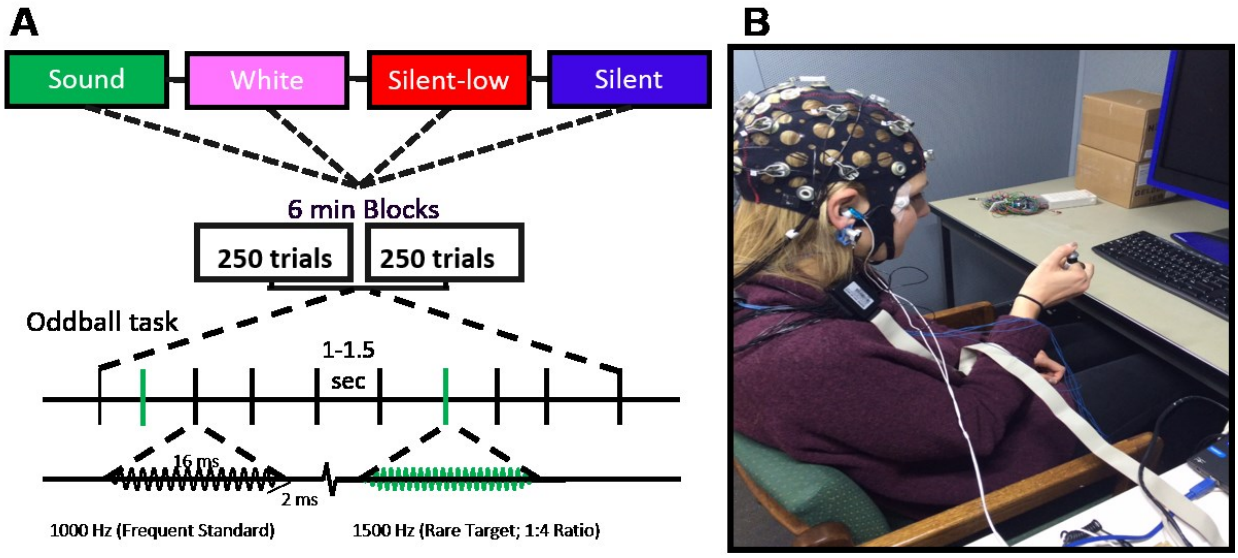

Figure 2. 1 EEG apparatus and procedure.
A: During each of the noise conditions, participants performed two 6-minute blocks of an auditory oddball task, with self-paced breaks in between. Within the task, 80% of the tones were frequent low-pitched tones (1000 Hz), and 20% were rare high-pitched tones (1500 Hz). Each tones was played for 16 ms with a ramp-up and down of 2 ms. Tones were played 1-1.5 seconds apart. B: The task was performed in a Faraday cage with the participant wearing an EEG cap and responding to target tones with a hand-held button connected to the Raspberry Pi.

2.3 Procedure

Each participant completed an auditory oddball task in four conditions: *silent*, *outside sounds*, *white noise*, and *silent-low*. For the oddball task, a pair of Sony MDR-E10LP headphones played one of two different frequency tones (either 1500 or 1000 Hz; sampled at 44.1 kHz; two channel; 16-ms duration; 2-ms linear ramp up and down; 65 Db). A pair of Logitech Z130 speakers played the outdoor sounds and white noise clip.

Condition order was counterbalanced across participants and they completed eight 6 minute blocks of 250 trials for a total of 2000 trials. Each trial had a 1/5 likelihood of being a target trial. Each block began with a 10-second countdown to ensure the oddball task only took

place when the participant was ready and when the necessary sounds were playing. Each trial also began with a pre-tone interval between 1000 and 1500ms, followed by the tone onset. The next trial began immediately after the tone offset, with participants responding to targets during the following pre-tone interval.

A Raspberry Pi 2 model B computer, which was running version 3.18 of the Raspbian Wheezy operating system, using version 0.24.7 of OpenSesame software (Mathôt, Schreij, & Theeuwes, 2012), was used both to run the oddball task and to mark the EEG for ERP averaging (Kuziek, Shein, and Mathewson, 2017). Audio output was via a 900 MHz quad-core ARM Cortex-A7 CPU connected through a 3.5 mm audio connector. Coincident in time with sound onset, 8-bit TTL pulses were sent to the amplifier by a parallel port connected to the General Purpose Input/Output (GPIO) pins to mark the data for ERP averaging. A start button was affixed to the Raspberry Pi to simplify the beginning of a trial. The participant's task was to press the button with their right hand when the rare tone was heard while keeping their eyes on a fixation cross.

2.4 Conditions

In the *silent* condition the participants were asked to perform the oddball task with no background noise. In the *outside sounds* condition, a 6 minute recording of sounds taken next to a noisy roadway was played in the background, with a maximum volume of 84 dB (Min 55 dB; tones played at 65 dB). The sounds were recorded on an iPhone 5, voice memos app from the same location the previous bike study took place (bike path along Saskatchewan Dr. NW, between 116 St and 111 St) in Dec 2015. In the *white noise* condition an even band of frequencies was played in the background at a volume of 54 dB for 6 minutes. In the *silent-low*

condition, no sounds were played in the background, and the oddball task itself was played at a decreased volume of 54 dB.

2.5 EEG Recording

Based on Mathewson, Harrison, & Kizuk's (2015) previous lab work directly comparing overall quality (noise levels, statistical power etc.) of: Active- Low impedance wet electrodes (Active Wet), Passive-Low impedance wet electrodes (Passive Wet), and Active-Dry electrodes (Active Dry), Active Wet electrodes (BrainProducts actiCAP) were selected for the study, as they previously were found to afford clean and good quality signals. Ag/AgCl pin electrodes were used and arranged in 10-20 positions (Fp2, F3, Fz, F4, T7, C3, Cz, C4, T8, P7, P3, Pz, P4, P8, and Oz). Additionally, a ground electrode, embedded in the cap at position Fpz, and two reference electrodes, clipped to the left and right ear, were used. SuperVisc electrolyte gel and mild abrading of the skin with the blunted syringe tip were used to lower impedances of all the electrodes. Gel application and aforementioned techniques continued until impedances were lowered to < 10 kΩ, measured using an impedance measurement box (BrainProducts) and until data quality appeared clean and reduced of noise. In addition to the 15 EEG sensors, 2 reference electrodes, and the ground electrode, the vertical and horizontal bipolar electrooculogram was recorded from passive Ag/AgCl easycap disk electrodes affixed above and below the left eye, and 1 cm lateral from the outer canthus of each eye. NuPrep preparation gel was applied to the applicable areas of the face, followed by wiping of the skin using an antibacterial sanitizing wipe, both used to lower the impedance of these EOG electrodes based on visual inspection of the data. These bipolar channels were recorded using the AUX ports of the V-amp amplifier, using a pair of BIP2AUX converters, and a separate ground electrode affixed to the central forehead.

EEG was recorded with a Brain Products V-amp 16- channel amplifier. Data were digitized at 500 Hz with a resolution of 24 bits. Data were filtered with an online bandpass with cutoffs of 0.1 and 30 Hz, along with a notch filter at 60 Hz. Data was recorded using a Microsoft Surface Pro 3 running Brain Vision Recorder, and powered along with the Raspberry Pi by an Anker Astro Pro2 20000 mAh Multi-Voltage External Battery. The mentioned technology was connected to the Surface Pro 3 using a Vantec 4-Port USB 3.0 Hub.

Trials took place in a dimly lit sound and radio frequency attenuated chamber, with copper mesh covering the window. The fan and lights were turned on, to allow proper ventilation and visual acuity of the fixation. The monitor runs on DC power from outside the chamber, the keyboard and mouse plugged into USB outside the chamber, and the speakers and amplifier were both powered from outside the chamber. Nothing was plugged into the internal power outlets. Any devices transmitting or receiving radio waves (i.e., cellphones) were removed from the chamber for the duration of the experiment.

2.5. EEG analysis

EEG analyses were computed using MATLAB 2012b with EEGLAB (Delorme & Makeig, 2004), as well as custom scripts. After recording, EEG data was re-referenced to the average of the left and right ear lobe electrodes. Timing of the TTL pulse was marked in the EEG data during recording, and used to construct 1200-ms epochs (including the 200-ms pretrial baseline) which were time-locked to the onset of standard and target tones. The average voltage in the first 200-ms baseline period was subtracted from the data for each electrode and trial. To remove artifacts caused by movement, amplifier blocking, and any other non-physiological factors, any trials in either of the conditions with a voltage difference from baseline larger than ±1000 μV on any channel (including eye channels) were removed from further analysis.

Following eye correction, a second threshold was applied to remove any trials with a voltage difference from baseline of ±500 μV. Over 98 percent of trials were retained after this procedure in each condition. On average, artifact rejection left approximately equal numbers of trials per participant in the sound (M_{targ} = 99.9286; $range_{targ}$ = 99-100; SD_{targ}= 0.26726; M_{stand} = 398; $range_{stand}$ = 386-400; SD_{stand} = 3.7622), white noise (M_{targ} = 99.5; $range_{targ}$ = 97-100; SD_{targ} = 1.0919; M_{stand} = 397.1429; $range_{stand}$ = 382-400; SD_{stand} = 5.6821), silent-low (M_{targ} = 99.7143; $range_{targ}$ = 97-100; SD_{targ} = 0.82542; M_{stand} = 397.6429; $range_{stand}$ = 378-400; SD_{stand} = 6.0461), and silent (M_{targ} = 99.5714; $range_{targ}$ = 96-100; SD_{targ} = 1.1579; M_{stand} = 398; $range_{stand}$ = 381-400; SD_{stand} = 5.0536; SD = Standard Deviation) from which we computed the remaining analyses.

A regression-based eye-movement correction procedure was used to estimate and remove variance due to artifacts in the EEG due to blinks, as well as vertical and horizontal eye movements (Gratton et al., 1983). This technique identifies blinks with a template-based approach, then computes propagation factors such as regression coefficients, predicting the horizontal and vertical eye channel data from the signals at each electrode. This eye channel data is then subtracted from each channel, weighted by these propagation factors, allowing us to remove most variance in the EEG which can be predicted by eye movements. No further rejection or filtering was done on the data in order to include as many trials as possible for both conditions, as well as to investigate how minor sources of non-eye-related noise contribute to the power to measure ERP components during the outdoor cycling task.

3. Results

3.1 ERP morphology and topography

Figure 2.2A depicts grand average ERPs calculated from each participant's artifact-removed and corrected target and standard tones at electrode Pz. Shaded regions represent the standard error of the mean for each time point. Evident from the plots is the expected increase in P3 amplitude during target trials in the central posterior topographical regions (Pz; Figure 2.2B). This expected oddball task difference in the P3 is shown with increased positive voltage between 300 and 430 ms following the rare target tones, compared the frequent standard tones. We continued to use this time window for all further analysis of the P3. Figure 2.4A plots the target-standard difference at electrode Fz. Evident from the plot is a target-standard difference in the MMN/N2b time window, with an increase in negative voltage between 175 and 275 ms following the rare target tones compared to frequent standard tones. Also evident in figure 2.2B is that this difference appears to be visibly maximal at fronto-central electrodes. Therefore, this time window at electrode Fz was used for further analysis of the MMN/N2b.

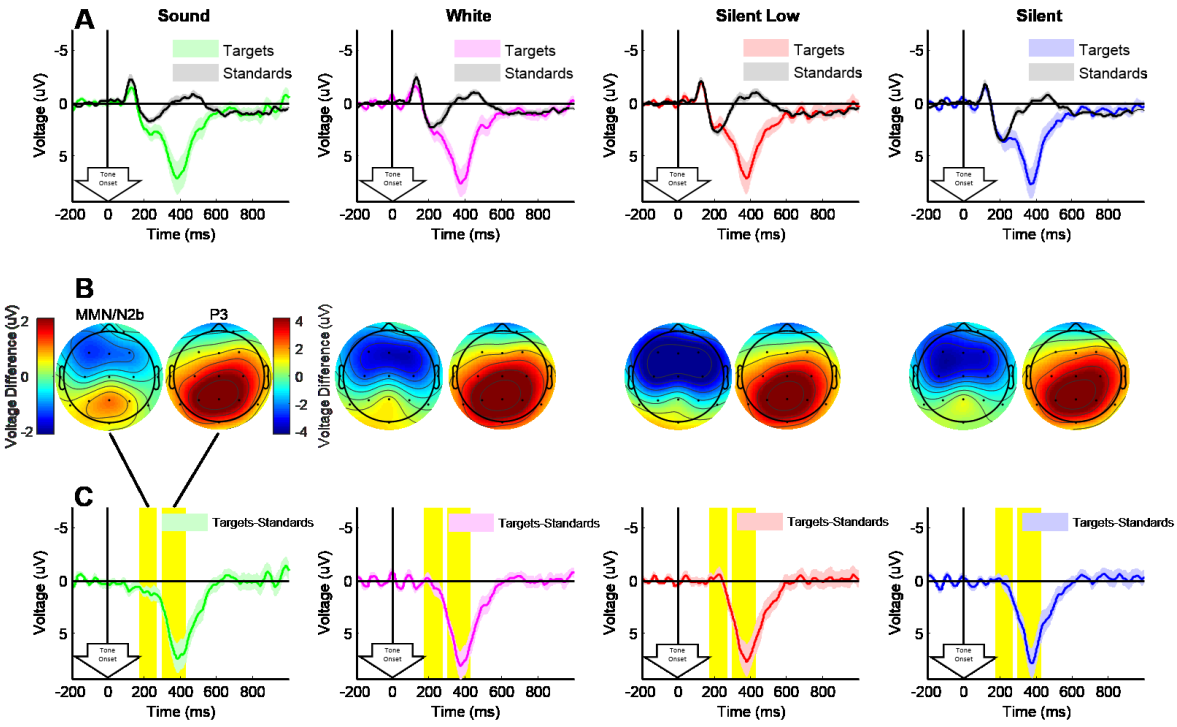

Figure 2. 2 Grand average ERPs.
Grand average ERPs. A: Grand-average ERPs computed at electrode Pz for all eye movement corrected and artefact-removed trials, for both target (colour) and standard (black) tones. B: Scalp topographies for grand-average ERP difference between target and standard tones in the MMN/N2b and P3 time windows (highlighted in yellow), 175-275 ms and 300-430 ms after the tones, respectively. C: ERP difference wave from electrode Pz for both, with shaded regions repreenting within-subject standard error of the mean for mean for this difference, with between-subjects differences removed (Loftus & Masson, 1994). Yellow highlighted regions depict the time window for the MMN/N2b and P3 analysis as well as topographical plots.

Figure 2.2B depicts topographies of the target-standard differences within the MMN/N2b and P3 time windows. The MMN/N2b time window topography shows the expected activation distribution toward the front of the scalp for all four conditions, while the P3 topographies demonstrate the expected posterior scalp activation distributions. Figure 2.3C depicts the ERP difference waves at electrode Pz, which are created through the subtraction of the standard tone ERPs from the target tone ERPs for each subject. Shaded regions depict the within-participant standard error of the mean, with variation between participants removed by the target - standard

subtraction. This error estimation is therefore an equal demonstration of that used in the t-test of the target-standard difference from zero (Loftus & Masson, 1994).

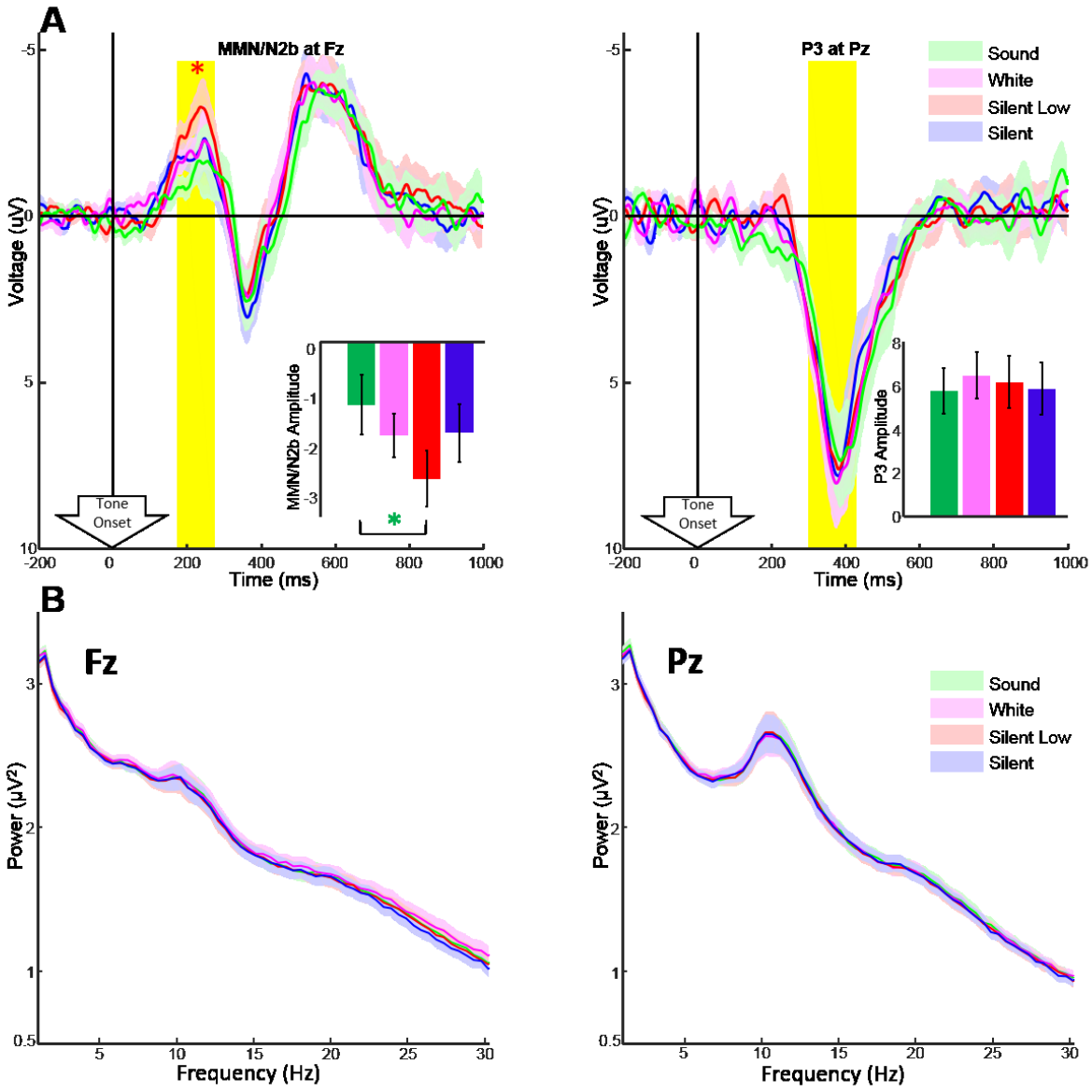

Figure 2. 3 Difference waves and spectral analysis.

A: Difference waves indicating the average difference between target and standard trials for all four conditions are plotted for the Fz and Pz electrode locations. Yellow highlighted regions depict the main time windows compared, particularly the MMN/N2b at Fz (left) and the P3 at Pz (right). Inset bar graph indicate the mean and standard error across participants for the highlighted time window in each plot, for each condition. B: Single-trial EEG spectra from electrodes Fz and Pz. This was calculated with zero-padded FFTs on 290 auditory standard trial epochs for each subject, averaged over trials, then subjects. Shaded regions indicate the standard error of the mean. Red asterisks denote significant differences, while green asterisks denote a marginal difference.

All conditions showed a clear negative peak at approximately 230 ms at the Fz electrode (Figure 2.3A). To test for a significant MMN/N2b effect, we ran a one-tailed, paired samples *t*-test comparing the MMN/N2b at electrode Fz averaged over the 175-275 ms time window centered around this peak to zero. The test revealed a significant MMN/N2b effect in all four conditions (*Outdoor sounds*: M_{diff}= -1.2718; SD_{diff}= 2.2244; $t(13)$ = -2.1393; p= 0.0260; *White*: M_{diff}= -1.8893; SD_{diff}= 1.6441; $t(13)$ = -4.2998; p= 4.3183e-04; *Silent-low*: M_{diff}= -2.7604; SD_{diff}= 2.1091; $t(13)$ = -4.8971; p= 1.4581e-04; *Silent*: M_{diff}= -1.8346; SD_{diff}= 2.1841; $t(13)$ = -3.1429; p= 0.0039). Additionally, figure 2.3B revealed a clear positive peak as expected at approximately 380 ms at electrode Pz. To test for a P3 effect, a one-tailed paired samples t-test was used to compare this P3 difference averaged over the 300-430 ms time window at the Pz electrode to zero. This test revealed a significant P3 effect in the *outdoor sounds* (M_{diff}= 5.7391; SD_{diff}= 3.9481; $t(13)$ = 5.4390; p= 5.6661e-05), *white noise* (M_{diff}= 6.4586; SD_{diff}= 3.9557; $t(13)$ = 6.1091; p= 1.8625e-05), *silent-low* (M_{diff}= 6.1518; SD_{diff}= 4.4448; $t(13)$ = 5.1786; p= 8.8798e-05), and *silent* (M_{diff}= 5.8368; SD_{diff}= 4.4633; $t(13)$ = 4.8931; p= 1.4685e-04) conditions.

Figure 2.3A depicts difference waves plotted for all four conditions at the Fz and Pz electrodes. Evident from the plots is no significant differences in P3 target-standard difference between any of the four conditions at Pz. To test for group differences in the P3 difference at

electrode Pz, a repeated measures one-way ANOVA was used, revealing no significant differences ($F(3,13) = 0.713$, $p = 0.5503$). Also evident from the Figure 2.3A plots is a larger MMN/N2b amplitude standard-target difference for the *silent-low* condition at electrode Fz. The same test was used to test for groups differences within the MMN/N2b time window at electrode Fz, revealing significant group differences ($F(3,13) = 3.845$, $p = 0.0167$). To investigate this difference, six two-way paired and Bonferroni corrected ($\alpha = 0.0083$) t-tests were used, revealing that the difference was driven by a larger MMN/N2b amplitude in the *silent-low* condition compared to the *outside sounds* and *silent* conditions. The target-standard difference within the MMN/N2b time window at Fz for the *silent-low* condition was found to be marginally higher than *silent* (Mdiff= -0.9258; SDdiff= 1.2440; $t(13) = -2.7845$; $p=0.0155$) condition. No other differences were found for the MMN/N2b.

Because there is some possibility that the MMN and N2b differentially contribute to the MMN/N2b effect (Scanlon et al., 2017), we separated this time window in order to analyze averages of the early MMN time window (100-200 ms) and the later N2b time window (200-300 ms). We found no significant group differences when the repeated measures one-way ANOVA was applied to the MMN (at Fz: $F(3,13) = 1.397$, $p = 0.2583$; at Pz: $F(3,13) = 1.608$, $p = 0.2032$) or the N2b time window (at Fz: $F(3,13) = 2.268$, $p = 0.0958$; at Pz: $F(3,13) = 0.889$, $p = 0.4555$). It is possible that both the MMN and N2b were elicited within this time window, however the current design does not allow us to disentangle these components from each other. Therefore this paper from here on will focus on the combined time window of the MMN/N2b between 175 and 275 ms.

3.2 N1 and P2 Amplitudes

In order to observe the effects of the four different sound conditions on general stimulus processing, grand averaged ERPs were separated into standards and targets for each condition at the Fz and Pz electrodes and plotted in figure 2.4B and C. A visual inspection of the plots in figure 2.4B indicates increased amplitude in the N1 component (100-175 ms) for the *outside sound*, *white noise* and *silent-low* conditions for the standards and targets at Fz. To test for significant differences for the N1 time window, a one-way repeated measures ANOVA tests were used, revealing significant group differences for the N1 at Fz within standard ($F(3,13) = 11.607$, $p < 0.0001$) and target ($F(3,13) = 3.668$, $p = 0.0202$) trials. Within standard trials, six pair-wise Bonferroni corrected ($\alpha = 0.0083$) t-tests were used to determine the cause of group effects, demonstrating that the difference was driven by a difference between the silent condition and all three of the sound-altered conditions. The silent condition was found to have a significantly smaller amplitude N1 compared to the *outside sound* (Mdiff= -1.6826; SDdiff=1.0293; t(13) = -6.1164; *p*=3.6818e-05), *white noise* (Mdiff= -1.3187; SDdiff=1.1154; t(13) = -4.4236; *p*=0.0006872) and *silent-low* (Mdiff= -0.9005; SDdiff=0.9573; t(13) = -3.5193; *p*=0.003772) conditions. Within target trials again we used six pair-wise Bonferroni corrected ($\alpha = 0.0083$) t-tests to determine the cause of group effects. Within target trials at Fz, a marginally significant difference at N1 was found in which the *outside sound* condition was significantly larger than the *silent* condition (Mdiff= -1.0925; SDdiff=1.3163; t(13) = -3.1055; *p*=0.008357).

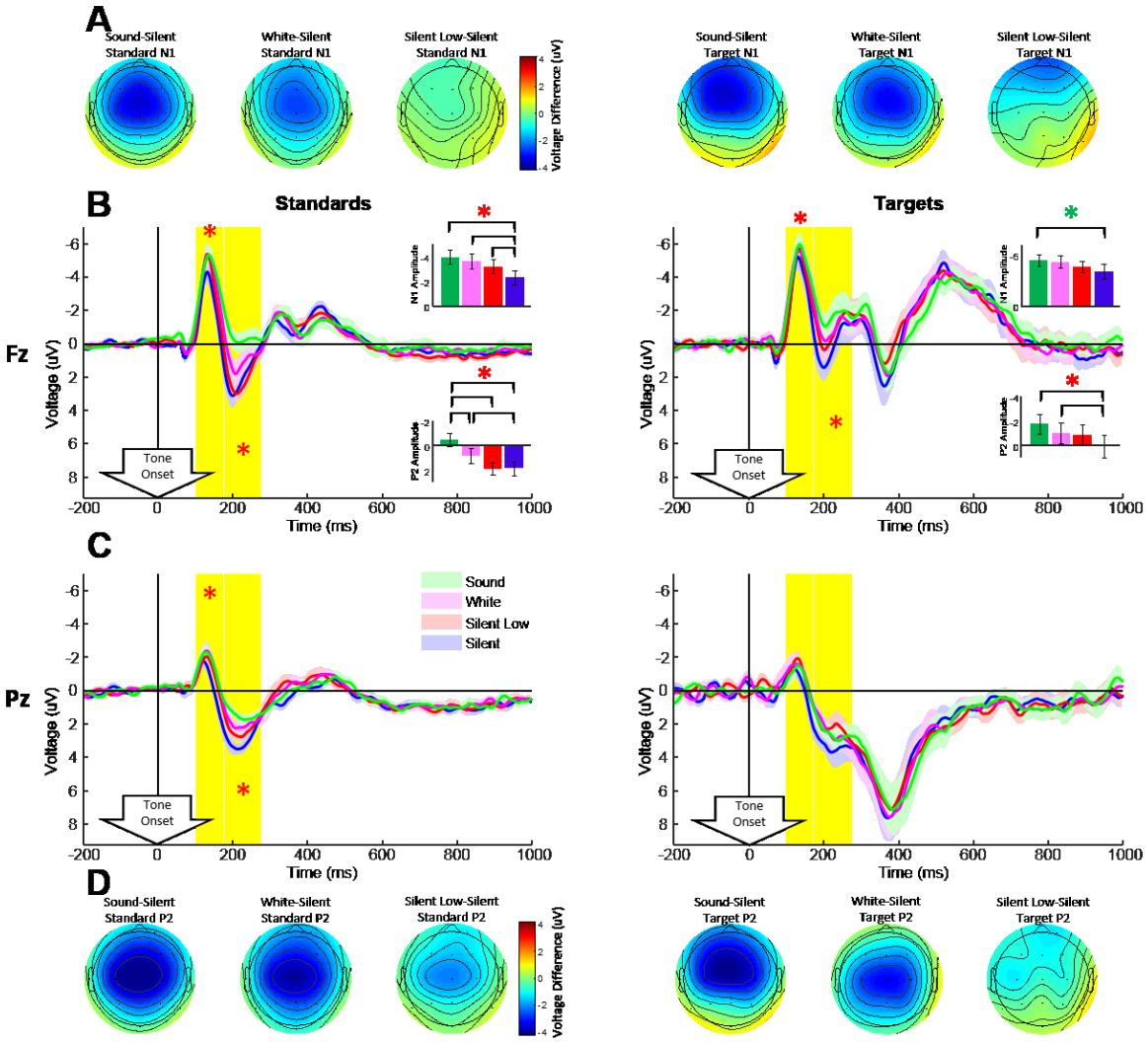

Figure 2. 4 Grand average ERPs
A: Topographies for the N1 time window comparing each condition to the silent background condition. B: Grand average ERPs collected at the Fz electrode location, plotted separately to compare within standards and targets between conditions. Shaded regions indicate the standard error of the mean. Inset bar graphs show the mean and standard error across participants in the N1 and P2 time windows. C: Grand average ERPs collected at the Pz electrode location, plotted separately to compare within standards and targets between conditions. D: Topographies for the P2 time window comparing each condition to the silent background condition. Red asterisks denote significant differences, while green asterisks denote a marginal difference.

Visual inspection of figure 2.4C appears to indicate similar differences in the N1 time window between the silent and other noise conditions within standard and target trials at electrode Pz. One-way repeated measures ANOVA tests were carried out for the N1 time window at Pz, indicating significant group differences within standard trials ($F(3,13) = 7.008$, $p = 0.0007$) but not target trials ($F(3,13) = 0.816$, $p = 0.4927$). Six pair-wise Bonferroni corrected ($\alpha = 0.0083$) t-tests were again used to determine significant differences between conditions, indicating that the silent condition had a significantly lower amplitude than the *outside sound* (Mdiff=-0.9995; SDdiff=0.8145; t(13) =-4.5913; p=0.0005057) and *white noise* (Mdiff=-0.9309; SDdiff=0.7218; t(13) =-4.8255; p=0.0003313) conditions. In summary, the N1 amplitude for standard trials was increased for all of the sound-altered conditions at both Fz and Pz, with only a marginal N1 increase in the *outside sounds* condition for target trials at Fz.

Visual inspection of figure 2.4B and C at the P2 time window (175-275 ms), reveals an increased positive voltage for the *silent* condition compared to the sound, *white noise* and sometimes the *silent-low* condition. To test for significant differences in the P2 time window at Fz, a one-way repeated measures ANOVA was performed, revealing significant group differences for both standard ($F(3,13) = 23.474$, $p < 0.0001$) and target ($F(3,13) = 7.552$, $p = 0.0004$) trials. Within standard trials at Fz, we used six pair-wise Bonferroni corrected ($\alpha = 0.0083$) t-tests to determine the cause of group effects, finding significant differences between several conditions. The P2 amplitude during the sound condition was significantly lower than the *white noise* (Mdiff=-1.3327; SDdiff=1.0333; t(13) =-4.826; p=0.0003310), *silent-low* (Mdiff=-2.3615; SDdiff=1.3437; t(13) =-6.5758; p=1.7807e-05) and *silent* (Mdiff=-2.348; SDdiff=1.2094; t(13) =-7.2639; p=6.3273e-06) conditions. Additionally, the standard P2 amplitude for the *white noise* condition was significantly lower than in the *silent* condition

(Mdiff=-1.0152; SDdiff=1.1034; t(13) =-3.4426; *p*=0.004370). Another set of six Bonferroni corrected ($\alpha = 0.0083$) paired t-tests were performed to determine the cause of the group effects for the P2 at Fz in target trials, revealing that this effect was driven by the *silent* condition having a significantly higher P2 amplitude than the *outside sound* (Mdiff=-1.7852; SDdiff=1.558; t(13) =-4.2872; *p*=0.0008840) and *white noise* (Mdiff=-1.0699; SDdiff=1.122; t(13) =-3.5678; *p*=0.003437) conditions.

Visual inspection of figure 2.4C appears to indicate differences between the sound condition and other conditions in the P2 (175-275 ms) time window within standard and target trials at electrode Pz. We again tested for this difference using a one-way repeated measures ANOVA, revealing significant group differences in standard ($F(3,13) = 11.930$, $p < 0.0001$) and marginally significant group differences in target ($F(3,13) = 2.789$, $p = 0.0532$) trials. Six pair-wise Bonferroni corrected ($\alpha = 0.0083$) t-tests were used to determine the cause of group effects in the standard trials, indicating significantly lower P2 amplitude in the *outside sound* condition when compared to the *silent* (Mdiff=-1.5403; SDdiff=0.7874; t(13) =-7.3194; *p*=5.8368e-06) and *silent-low* (Mdiff=-0.8871; SDdiff=0.8520; t(13) =-3.8959; *p*=0.001841) conditions. Additionally, the *white noise* condition was found to have significantly lower P2 amplitude compared to the *silent* (Mdiff=-1.0077; SDdiff=0.9255; t(13) =-4.0741; *p*=0.001316) condition. Another set of six pair-wise Bonferroni corrected ($\alpha = 0.0083$) t-tests were performed to determine the cause of group differences in the target trials at Pz, revealing the *silent* condition to have a significantly larger P2 amplitude than the *silent-low* (Mdiff=-1.0658; SDdiff=1.1668; t(13) =-3.4178; *p*=0.004583) condition. In summary, the P2 amplitude was significantly reduced for the *outside sounds* and *white noise* conditions compared to the *silent* condition for both standards at both Fz and Pz, as well as targets at Fz.

3.3 Spectral differences

Figure 2.3B shows the grand average spectra for the Fz and Pz electrodes. This plot was made from a random sample of 370 of each participant's artefact-removed standard trials. These trials were then used to calculate a fast Fourier transform (FFT) through a procedure of symmetrically padding the 600 time point series with zeros, making a 1,024-point time series for each epoch, providing .488 Hz frequency bins. Because the data were collected with an online low-pass filter of 30 Hz, only frequencies measuring up to 30 Hz were plotted. We then calculated the spectra for each participant by calculating the average of the 370 spectra for each participant, and then combining these into a grand average spectra. Shaded regions indicate the standard error of the mean across participants. Evident from the plots, all four conditions show the expected 1/frequency structure in the data. Also evident are no significant differences in any frequency. To test for differences in alpha power, a one-way repeated measures ANOVA was performed in both the Fz and Pz electrode locations, indicating no significant group differences for either the Fz ($F(3,13) = 0.318$, $p = 0.8124$) or Pz ($F(3,13) = 0.025$, $p = 0.9946$) electrodes.

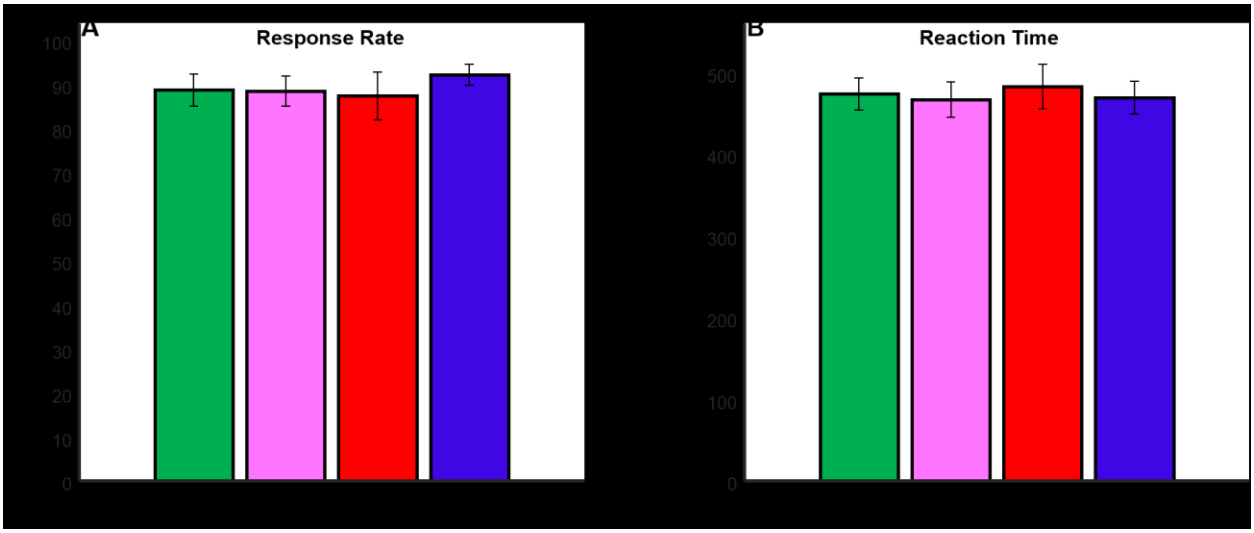

Figure 2. 5 Behavioural analysis.

A: Bar graph depicting mean and standard error for the percentage of targets that received a response within 2 seconds after tone onset across participants for both conditions. B: Bar graph depicting the mean and standard error for the average response time (with missed responses removed) across participants for each condition.

3.4 Behavioural differences

A bar graph of the response rate and reaction time is depicted in figure 2.5A and B. To test for differences in response rate and average reaction time to targets in each condition, one-way repeat-measures ANOVA tests were performed, revealing no significant group differences in the response rate ($F(3,13) = 0.913$, $p = 0.4434$) or mean response time ($F(3,13) = 1.229$, $p = 0.3122$).

4. Discussion

In this study we compared ERPs during an oddball task in four conditions: with background traffic sounds, background white noise, silent background with quiet tones, and silent background. We found that we were able to replicate the main findings of a previous study that used an oddball task outside by only playing recorded outdoor sounds in the background of the same task. In particular, when we played a recording of *outdoor sounds* in the background while participants performed a headphone auditory oddball task, the N1 was increased and the P2 was decreased compared to the *silent* condition, which is the same result found when the task was performed during outdoor cycling compared to inside in silence. This indicates that these sounds had an effect on the sensory processing involved with the auditory task. The present paper was also able to look at reaction time and response rate, finding no behavioural differences between the conditions. Additionally, the *white noise* condition had a similar effect to a lesser extent, indicating that a simple, unchanging background sound can have a similar effect on sensory processes. Finally, the *silent-low* condition, in which the tones themselves were played

at a quieter volume also appeared to have an effect, but only at the N1, indicating that a quiet task volume may also have some effect on these sensory processes. While we cannot say for certain that no other factors played a part in the N1-P2 effect found in the first study (Scanlon et al., 2017b), we can determine that background noises were at least sufficient to replicate this effect.

4.1 Alpha power

We investigated changes in alpha power for the differing sound conditions because previous studies have indicated that alpha power can influence N1 and P2 amplitudes (Brandt, Jansen & Carbonari, 1991; Jansen, & Brandt, 1991). However, in this study, no differences in alpha power were found between conditions, demonstrating that the effects within the N1 and P2 were independent of alpha power.

4.2 N1 and P2 components

The auditory N1 appears to reflect several functions, including an attentional function of sensory acceptance and rejection, which appears to amplify auditory perception of interesting, pleasant or important stimuli while attenuating the perception of uninteresting, unpleasant or unimportant stimuli (Näätänen & Picton, 1987; Roder et al., 1999). The N1 has been referred to as an early, rapid selection of competing auditory 'channels' or auditory inputs, defined by differing pitch or location cues (Hansen & Hillyard, 1988). For example, the N1 tends to be increased when a sensory stimulus is located where one was already attending, and decreased when the same stimulus appears anywhere else, (Teder-Sälejärvi, et al. 1998). This is believed to allow enhanced processing of the stimuli of interest, and the effect is increased when the individuals performing the task are blind (Roder et al., 1999). The N1 component tends to have shorter latency and larger amplitude when the attended and unattended sounds are easily

distinguishable by physical cues such as their pitch or location (Näätänen, 1982, 1992). This component has been shown to have increased amplitude as a function of increased attentional allocation to a specific input channel, as well as more accurate behavioural target detection for targets in that channel (Hink, Voorhis, Hillyard, & Smith, 1977). Functionally, the N1 amplitude and latency is believed to represent the amount of sensory information moving through an early mechanism of channel selection (Hillyard. Hink, Schwent, & Picton, 1973), further processing of information from the attended channel (Näätänen, 1982; Okita, 1981) as well as how well the eliciting stimulus and cue characteristics match within the attended input channel (Näätänen, 1992). In this study, it appears that the N1 increased when participants had to pay more attention and 'tune in' in order to perform the task properly in less than ideal conditions, and therefore was increased when *outdoor sounds* and *white noise* were played in the background, as well in the *silent-low* condition when the tones were simply quieter.

While the N1 has been shown to increase with increased attentiveness, the P2 has been shown to decrease to attended stimuli (Crowley & Colrain, 2004). The P2 has been found to reflect stimulus evaluation and classification as well as attentional allocation (Potts, 2004). For example, this component has been shown to decrease in response to speech sounds in a cocktail party task, while individuals had to pay attention to certain speech cues while ignoring simultaneous irrelevant speech sounds (Getzman, Golob & Wascher, 2016). This may be related to a mechanism of how effectively stimuli are able to be discriminated, as several studies have shown that the auditory P2 increases in amplitude after discrimination training (Atienza, Cantero, Dominguez-Marin, 2002; Hayes, Warrier, Nicol, Zecker, Kraus, 2003; Reinke, He, Wang, Alain, 2003; Trainor, Shahin, Roberts, 2003; Tong, Melara & Rao, 2009; Tremblay, Kraus, Carrell & McGee, 1997; Tremblay & Kraus, 2003) as well as with simple exposure to the stimulus

(Sheehan, McArthur & Bishop, 2005). In our study, playing a conflicting sound in the background may have decreased the participant's ability to discriminate the tones from background sounds in the traffic sounds and white noise conditions, causing a decrease in the P2. This may also explain why there was no P2 effect in the quiet tones condition, as the lower volume may have increased attention to the task, without decreasing the ability to discriminate the tones.

It appears that not only are both the N1 and P2 components affected by changes in one's sensory environment, they appear to serve separate functions and be differentially affected by changes to the task. Looking again at the plot of grand average ERPs to the standard tones in figure 2.4B, the N1 appears to be altered from default value (e.g. amplitude in the silent condition) by any change that may alter one's attention to the task. In other words, as both of the background noise conditions and the *silent-low* condition would require the participant to 'tune-in' to the oddball tones in order to perform the task properly, all of these conditions caused an increase in the N1 component compared to the silent condition, with none of these conditions significantly differing from each other. Conversely, the P2 appears to only respond to background sounds during the task, as only the *outdoor sounds* and *white noise* conditions had significantly smaller P2 amplitude than the *silent* condition. Further, this effect appears to be especially strong for salient and/or 'eventful' background stimuli, as the *outdoor sounds* had a significantly smaller P2 amplitude than the *white noise* condition. As no behavioural differences were found, it appears that the N1 and P2 represent two separate but related processes that allow individuals to both hone-in on a relevant task, while tuning-out any extraneous and distracting sound in order to perform the task sufficiently in a noisy environment.

4.3 Future Directions

With this new knowledge about the functions of the N1 and P2 components, we intend to investigate further into how these components relate to the way humans perform auditory and visual tasks in ecologically valid environments. This includes studies on the visual ERP when the task is performed with a visually noisy background, as well as cross modal studies in which an auditory task is used in a visually noisy environment, and vice versa. As well we plan to perform further outdoor studies in which auditory and visual tasks are performed in environments with differing auditory and visual noise. The main goal is to examine exactly how the human brain is able to compensate and perform tasks effectively in the face of distracting stimuli.

4.4 Conclusion

In this study, we replicated the effects found in a previous outdoor ERP study by only replicating the sounds from the previous task. We found evidence that the N1 and P2, while functionally related, appear to perform two distinct mechanisms during stimulus discrimination in ecologically valid conditions. It appears that the N1 increases with attentiveness as one tunes in to a particular channel of auditory input, while the P2 decreases with attention and as the auditory channel becomes more difficult to discriminate. This effect appears to be part of a mechanism that allows one to selectively attend to auditory tasks in noisy sound environments.

Chapter 3: Cognition in Real-World Contexts: The Visual P2 in Visually Complex Environments

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Abstract

Recent advances in electroencephalogram (EEG) equipment and analysis have allowed cognitive neuroscience research to extend beyond artificially simplified lab environments and begin studying the human brain in complex, real-world contexts. Previous work in our lab has indicated that event-related potentials (ERPs) show marked decreases in P2 component amplitude both when auditory oddball tasks are performed outside when cycling next to a busy street and when participants are inside the laboratory immersed in complex auditory environments, such as recorded sounds of traffic. These results have led to a hypothesis that the P2 component may be involved in filtering overlapping stimuli in complex environments. To determine if this P2 effect is multimodal, we evaluated the P2 component during a visual oddball task with dynamic visual backgrounds of varying complexity. We found significantly reduced P2 amplitude when a visual oddball task was completed with traffic in the visual background, compared to a less complex visual static. This modulation of the P2 was found in response to both target and non-target stimuli. Neither reaction times nor other ERP components varied between these two conditions, indicating that these results cannot be explained by task difficulty alone. These results support our hypothesis that the P2 component plays a role in filtering of complex environmental stimuli, and suggest that our brains process information differently in real-world contexts than in isolated laboratory conditions.

1. Introduction

To understand the mental and neural processes that underlie human cognition, cognitive neuroscience has relied heavily on neuroimaging and electrophysiological data techniques. While both of these techniques have provided a vast amount of information to researchers, most of what we know from this field has come from experiments conducted in highly isolated, artificially simplified environments. Continual advances in electroencephalogram (EEG) technology are now allowing cognitive neuroscience to extend beyond the laboratory environment and to understand how our brains process and interact with information in complex, real-word contexts (Aspinall, Mavros, Coyne, & Roe, 2015; De Vos & Debener, 2014).

An EEG is a commonly used electrophysiological technique that records brain activity by placing multiple electrodes across the scalp and recording the resultant voltage over time. The EEG signal (measured in microvolts) is the result of the summated and synchronous activity of large groups of cortical neurons, creating large dipoles that are measured by the electrodes on the scalp (see Luck, Woodman, & Vogel, 2000). Changes in the EEG signal, such as frequency and amplitude, may be analyzed in individual epochs (recording periods) to gain meaningful information about the change in brain activity in relation to an event or cognitive state. A commonly studied phenomenon in EEG research is the event-related potential (ERP) which has been used to evaluate attention and cognition extensively throughout the last several decades (Kappenman & Luck, 2011; Luck et al., 2000).

Event-related potentials (ERPs) are a continuous series of changes in the polarity of recorded brain activity in response to a visual, auditory, or tactile stimulus, and are impacted both by endogenous factors, such as attention, and exogenous environmental factors (Blackwood & Muir, 1990; Sur & Sinha, 2009). By time-locking EEG data from each electrode to the

stimulus onset, and averaging the signal across multiple trials, a recognizable series of positive and negative-going waveforms appear which together form the ERP. The recorded ERP is the result of simultaneous activation of a large group of pyramidal neurons in response to a stimulus, and can be divided into different peaks that, although not equivalent to, are approximately correlated with underlying ERP components (see Kappenman and Luck, 2011 for a review of this distinction). These individual ERP components may be analyzed individually or in relation to each other, and are generally understood to represent a specific psychological or neural process (Kappenman & Luck, 2011).

A commonly used paradigm to study the ERP is the oddball task, which requires participants to respond to a rare, target stimulus and to ignore the standard, frequent stimulus. ERP components in response to attended and unattended stimuli begin to differ coincident in time with when sensory information is just reaching sensory processing areas of the brain: this, and other research, has provided evidence that top-down cognitive processes such as attention can modulate sensory processing (Hillyard & Münte, 1984; Luck et al., 2000; Mangun & Hillyard, 1988). ERP amplitude is generally used as a functional measure of how a component responds to various manipulations – whereas the location of the recorded activity provides the pattern of activation (Friedman, Cycowicz, & Gaeta, 2001).

The P3 component, the most-studied ERP component with respect to attention, is larger in amplitude in response to infrequent and task-relevant stimuli, such as the target stimuli in an oddball task (Donchin & Coles, 1988; Potts, 2004). The P3 is thought to have a role in renewing the representation of one's current environment with the representation held in one's working memory, and has been considered to reflect "contextual updating" with high dependency on levels of attention and arousal (Donchin & Coles, 1988; Polich & Kok, 1995). The mismatch

negativity (MMN), first described by Näätänen, Tervaniemi, Sussman, Paavilainen, and Winkler (2001) appears as part of the ERP in response to rare, or "surprising" target stimuli within a sequence independent of participant attention (Pazo-Alvarez, Cadaveira, & Amenedo, 2003; Stefanics, Kremláček, & Czigler, 2014). Though most research points to a frontal localization of the visual MMN, there is contradicting evidence throughout the literature on the specifics of the visual MMN (see Pazo-Alvarez et al., 2003 for a review). Compared to other components of the ERP, less is known about the P2 component and its role in attention and sensory processing.

The P2 is associated with working memory, memory performance and semantic processing in contextually based tasks (Dunn, Dunn, Languis, & Andrews, 1998; Federmeier & Kutas, 2002; Lefebvre, Marchand, Eskes, & Connolly, 2005). Both the auditory and visual P2 are thought to reflect an aspect of top-down cognition and perceptual processing, and the visual P2 is hypothesized to represent an increased inhibitory process that is used to repress a repetitive stimuli when it is determined to be irrelevant (Freunberger, Klimesch, Doppelmayr, & Höller, 2007; Luck & Hillyard, 1994). In auditory oddball tasks, the P2 component has been reported to have increased amplitude for the standard stimulus, referred to as the non-target response, or "nontarget positivity" (Crowley & Colrain, 2004; Novak, Ritter, & Vaughan, 1992; Potts, Liotti, Tucker, & Posner, 1996), though these results are less consistent in the visual domain.

A review of the literature indicates that late-components of the ERP, such as the P3 and the P2, are modulated by the attentional and cognitive demands of a task. In dual task paradigms, increased primary task difficulty leads to increased P3 amplitude elicited by the primary task, and reduced P3 amplitude elicited by the secondary task (Kramer, Schneider, Fisk, & Donchin, 1986; Kramer et al., 1986; McCarthy & Donchin, 1981). In contrast to the P3, the more attention that a person generally pays to a stimulus, the smaller the P2 amplitude is (see Crowley and

Colrain, 2004 for a review). Very little research has been done to determine how task difficulty affects the P2 component, but at least one study has reported that increased difficulty in discriminating between standard and target stimuli leads to an increased P2 amplitude (Kim, Kim, Yoon, & Jung, 2008). This result suggests that the P2 component may reflect a neural process involved in evaluation of task relevance.

Studying cognition in real-world environments has been the goal of several studies in our lab (Scanlon, Townsend, Cormier, & Mathewson, in preparation; Scanlon, Sieben, Holyk, & Mathewson, 2017). One such study compared ERPs in response to an auditory oddball task when participants cycled next to a street with traffic or completed the task inside while pedalling on a stationary bike or sitting still (Scanlon, et al., in preparation). Interestingly, reduced P2 amplitude in response to both target and standard stimuli was found when participants were outside, but not when the task was completed inside. A previous study in our lab showed that sub-aerobic stationary biking does not result in a P2 change, meaning that these differences were not a result of the motor effects of biking (Scanlon et al., 2017a). One possible explanation for these results is that background sounds, such as traffic, are filtered from task-relevant stimuli when participants are immersed in complex auditory environments, and that this attentional engaging process is responsible for the reduced P2 amplitude. In a subsequent study aimed at addressing this possibility, participants completed an auditory oddball task inside the lab either in silence or with sounds (white noise or traffic) playing in the background (Scanlon, Cormier, Townsend, & Mathewson, *In preparation-a*). The results of this study showed significantly reduced P2 amplitude in sound conditions, as opposed to silent conditions. The successful replication of the P2 effects seen outside lends support to the hypothesis that the P2 is involved in sensory filtering in the auditory domain. However, it is not known if this effect occurs in the visual domain.

Previous research in our lab has indicated that the auditory P2 component might be involved in task-relevant filtering of complex auditory environments. As the P2 has been shown to have similar functions in the auditory and visual domains, we hypothesized that this filtering is multimodal and observable in the visual domain in addition to the previously studied auditory domain. To test this, we evaluated the P2 component inside a standard laboratory environment during a visual oddball task with dynamic visual backgrounds of varying complexity. Either a first-person video of cycling through traffic, or a video of visual noise played as a background to a visual oddball task. We hypothesized that the ecological visual complexity of the Video condition would lead to decreased P2 component amplitude compared to the less complex Noise condition.

2. Methods

2.1 Participants

Twenty-one participants completed the experiment (Mean age = 20.8; Age range = 18-25; 13 = female). One participant was a member of the Attention, Perception, and Performance (APP) Lab. Seventeen participants were undergraduate students at the University of Alberta who volunteered their participation for course credits. Three participants were neither members of the APP lab nor undergraduate students, and were compensated $10 / hour for their participation. Two participants were removed due to technical errors during the experimental recording. The experimental procedures were approved by the Internal Research Ethics Board of the University of Alberta and all participants gave informed consent prior to participating in the experiment.

2.2 Materials

In both conditions, participants were seated in a radio frequency attenuated chamber, 57 cm away from a 1920 x 1080 pixel ViewPixx/EEG LED monitor running at 120 Hz with

simulated-backlight rastering. Stimuli were presented using a Windows 7 PC running Matlab with the Psychophysics toolbox (Brainard, 1997). Video output was via an Asus Striker GTX760, and responses to stimuli were recorded with a keyboard button press and time-locked to EEG data. The backgrounds to the oddball task in both conditions were taken, with permission, from the internet.

2.3 EEG Recording

Active Wet electrodes (BrainProducts antiCAP) were used for this experiment based on previous work by Mathewson, Harrison, and Kizuk (2016) and Oliveira et al. (2016) which showed that between Active-Low impedance wet electrodes (Active Wet), Passive-Low impedance wet electrodes (Passive Wet), and Active-Dry electrodes (Active Dry), Active Wet electrodes provided a better quality signal. Ag/AgCl pin electrodes were arranged in 10-20 positions (Fp2, F3, Fz, F4, T7, C3, Cz, C4, T8, P7, P3, Pz, P4, P8, and Oz). In addition, a ground electrode, embedded in the cap at position Fpz, and two reference electrodes, clipped to the left and right ear, were used. SuperVisc electrolyte gel and mild abrading of the skin using a blunted syringe tip were used to lower impedances of all the electrodes. These techniques were used until impedances were lowered to < 10 kΩ, measured with an impedance measurement box (BrainProducts), and until visual inspection of the data appeared clean and reduced of noise. Online EEG recording was referenced to the electrode clipped onto the left earlobe. Afterwards, offline data were re-referenced to the arithmetically derived average of the left and right ear lobe electrodes.

In addition to the 15 EEG sensors, two reference electrodes, and the ground electrode, the vertical and horizontal bipolar electrooculogram (EOG) were recorded from passive Ag/AgCl easycap disk electrodes affixed above and below the left eye, and 1 cm lateral from the

outer canthus of each eye. First, NuPrep preparation gel was applied to the applicable areas of the face, followed by wiping of the skin using an antibacterial sanitizing wipe, both used to lower the impedance of these EOG electrodes based on visual inspection of the data. These bipolar channels were recorded using the AUX ports of the V-amp amplifier, using a pair of BIP2AUX converters, and a separate ground electrode affixed to the central forehead.

EEG data were recorded with a Brain Products V-amp 16-channel amplifier and digitized at 500 Hz with a resolution of 24 bits. Data was filtered with an online bandpass with cut-offs of 0.1 and 30 Hz, along with a notch filter at 60 Hz. Recording was conducted in a dimly lit, sound and radio frequency attenuated chamber free from electromagnetic instruments, with copper mesh covering the window. The fan and lights were turned on to allow proper ventilation and visual acuity. The monitor runs on DC power from outside the chamber, the keyboard and mouse are plugged into USB outside the chamber, and the amplifier is powered from outside the chamber. Nothing was plugged into the internal power outlets and any devices transmitting or receiving radio waves (i.e., cellphones) were removed from the chamber for the duration of the experiment.

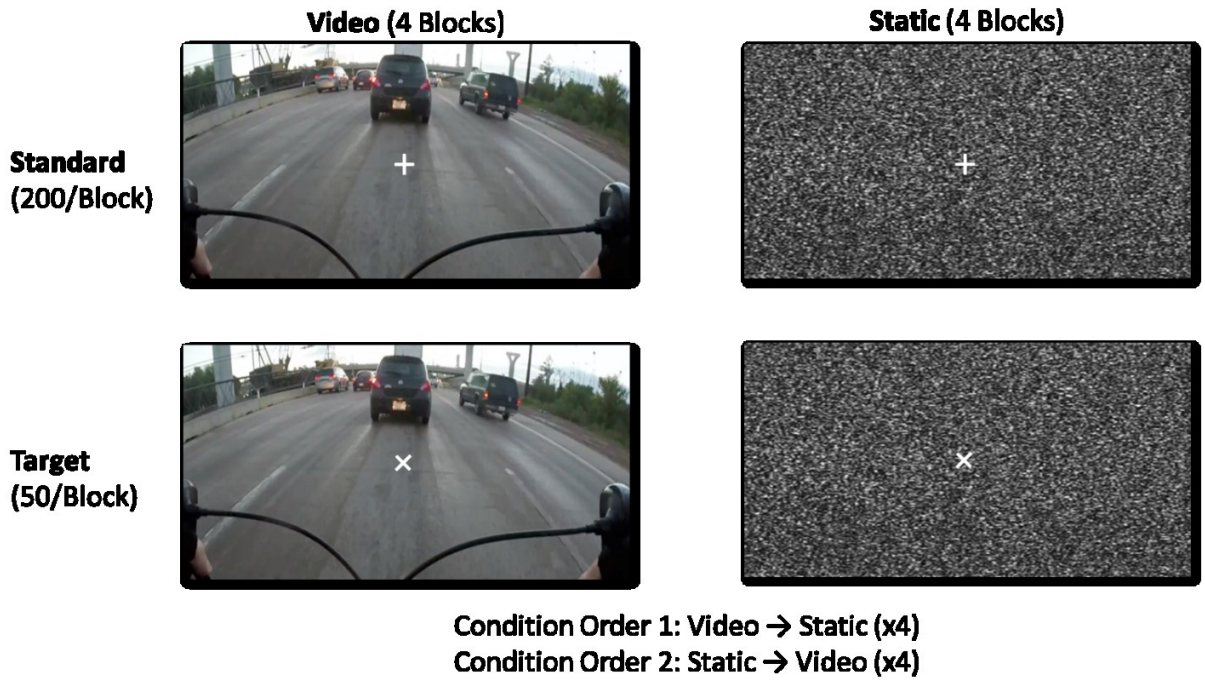

Figure 3. 1 Experimental design.
Participants completed a visual oddball task in which 20% of the 250 trials were targets (×) and 80% were standards (+) with an interstimulus interval of 1-1.5 seconds. The task of the participant was to respond as quickly as possible to the target (×) stimuli via a keyboard button push. Reaction time was recorded and time-locked to EEG data. Each participant completed four blocks of each condition, totalling eight blocks. During the Video condition (left), a full-colour video of cycling through traffic served as the background to the oddball task. The Noise condition (right) used a video of visual noise in black and white pixels as the background to the oddball task. Adjacent blocks alternated between conditions, with the condition order counterbalanced across participants.

2.4 Procedure

Figure 3.1 demonstrates the general experimental procedure. Participants completed a visual oddball task in order to record their ERPs in response to standard (frequent) and target (infrequent) stimuli. Two conditions were used in this experiment: a Video condition, in which the background to the oddball task was a video of cycling through traffic, and a Noise condition, in which the background was a video of visual "noise". Each participant completed four blocks of each condition, totaling eight alternating blocks. Each block consisted of 250 trials comprised

of 50 target stimuli and 200 standard stimuli. Condition order was counterbalanced across participants.

In this visual oddball task, participants focused on a fixation cross in the center of the screen and began each block when they indicated they were ready via pressing a button on the keyboard in front of them. Once the block began, the fixation cross disappeared and stimuli were presented in its place. Standard stimuli appeared as a white "+" and target stimuli appeared as a white"×". Stimuli were presented in random order with each stimulus remaining on the screen for 66 ms and with a random time interval of between 1–1.5 seconds between stimuli presentation.

The task of the participant was to indicate the presence of a target stimulus as quickly as possible by pressing the space bar on the keyboard in front of them with their right hand. After each block, participants were instructed to take a self-timed break before beginning the next block. All stimuli presentations, as well as responses, were time-locked to the EEG data.

2.5 Conditions

This experiment used two conditions that varied across one parameter: visual background to a visual oddball task. In the Video condition, a video of cycling through street traffic served as the background to the oddball task. The full-colour video was recorded from a fixated camera on the front of a bicycle, and was aimed to give participants a first-person perspective of navigating through traffic. In the Noise condition, the background consisted of visual "noise" made up of a dynamic pattern of greyscaled pixels, akin to the static seen in analog television when there is no transmission signal. Both videos were presented at 30 fps. All stimuli were the same colour, shape, and size across conditions. Participants were instructed to complete the task in the same way for both conditions. Neither video had any audio component.

2.6 EEG Analysis

Analysis was completed using EEGLAB (Delorme & Makeig, 2004) and custom MatLab scripts. First, epochs of 1000-ms time-locked to the stimulus onset were constructed, with the average voltage over the first 200-ms baseline period subtracted from the data for each electrode and trial. In order to remove artifacts due to non-physiologic factors, any trials in each of the two conditions with a voltage difference from baseline greater than +/-1000 μV at any electrode were eliminated from further analysis. We used a regression based eye-movement correction procedure that computes propagation factors as regression coefficients in order to predict the vertical and horizontal eye channel data at each electrode in order to remove as much artificial variance due to eye movements and/or blinks as possible (Gratton, Coles, & Donchin, 1983). Using this method allowed subtraction of eye channel data from each EEG channel, weighted by these propagation factors, thus removing most variance in the EEG predicted by eye movements. ERPs were analyzed across trial-averages, by averaging together the ERPs in each condition, separated by target and standard stimuli at each electrode. Differences in mean ERP amplitudes were evaluated by using within-subjects (paired) t-tests.

3. Results

3.1 ERPs

The P3 component (400-600 ms after stimulus onset) was analyzed at electrode Pz in both conditions. The grand averaged ERP recorded from electrode Pz was calculated from each participant's artifact-free trials. As expected, a P3 oddball task difference was evident in both conditions (Figure 3.2). Response to target and standard stimuli in the Video and Noise conditions are indicated in Figure 3.2. A simple one-tailed t-test (α=.05) of the difference between stimuli (targets-standards) against zero revealed that there was a significant increase in

P3 amplitude in response to the target stimuli in the Video condition (Figure 3.2; M_{diff}=10.5151 SD_{diff}=3.8541; t(18)=11.8925; p=2.9163e-10). A simple one-tailed t-test also showed a significant P3 effect in the Noise condition (Figure 3.2; M_{diff}=10.2419; SD_{diff}=3.6877; t(18)=12.1059; p=2.1901e-10). There was no difference in P3 amplitude between conditions (Figure 3.2; M_{diff}=0.2732; SD_{diff}=2.3418; t(18)=0.5085; p=0.6172). Evident in the topographies of the P3 difference (targets-standards) during both the Noise and the Video conditions is the characteristic posterior scalp localization of the P3 component (Figure 3.2).

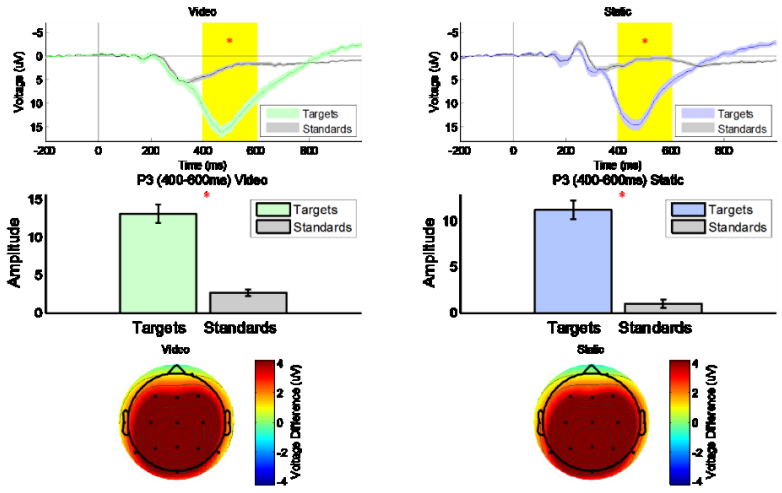

Figure 3. 2 P3 component response separated by condition.

Asterisks (*) indicate statistical significance. A, Grand averaged ERPs calculated at electrode Pz in response to standard (+) and target (×) stimuli for all artifact-free trials after eye movement corrections during Video (left) and Static (right) conditions. The P3 time window (400-600 ms) is indicated in yellow. Shaded areas indicate standard error of the mean, positive voltage is plotted down. P3 effects were found using a within-subjects t-test comparing stimuli difference in each condition against a null difference (α=.05). B, Mean P3 amplitude in response to standard and target stimuli in the Video (left) and Static (right) conditions. Standard error is indicated on each bar. C, Scalp topographies of the P3 component. Topographies are calculated from the recorded voltage difference between target and standard (targets-standards) stimuli in the P3 window not including the reference or eye channels. A posterior P3 effect is evident in both the Video (left) and Static (right) conditions.

The period of 325-400 ms after stimulus onset was analyzed to look for the visual MMN at electrode Fz for both conditions (Figure 3.4). A simple one-tailed t-test of the difference between stimuli (targets-standards) against a null difference (α=.05) showed that there was no significant MMN present for either the Video condition (Figure 3.4; M_{diff}=.7481; SD_{diff}=3.1020; $t(18)$=1.0513; p=.84647) or the Noise condition (Figure 3.4; M_{diff}=-.2332; SD_{diff}=3.2205; $t(18)$=-.3156; p=0.37798). Additionally, there was no difference in MMN between the two conditions (Figure 3.4; M_{diff}=0.9813; SD_{diff}=2.7441; $t(18)$=1.5588; p=.1365).

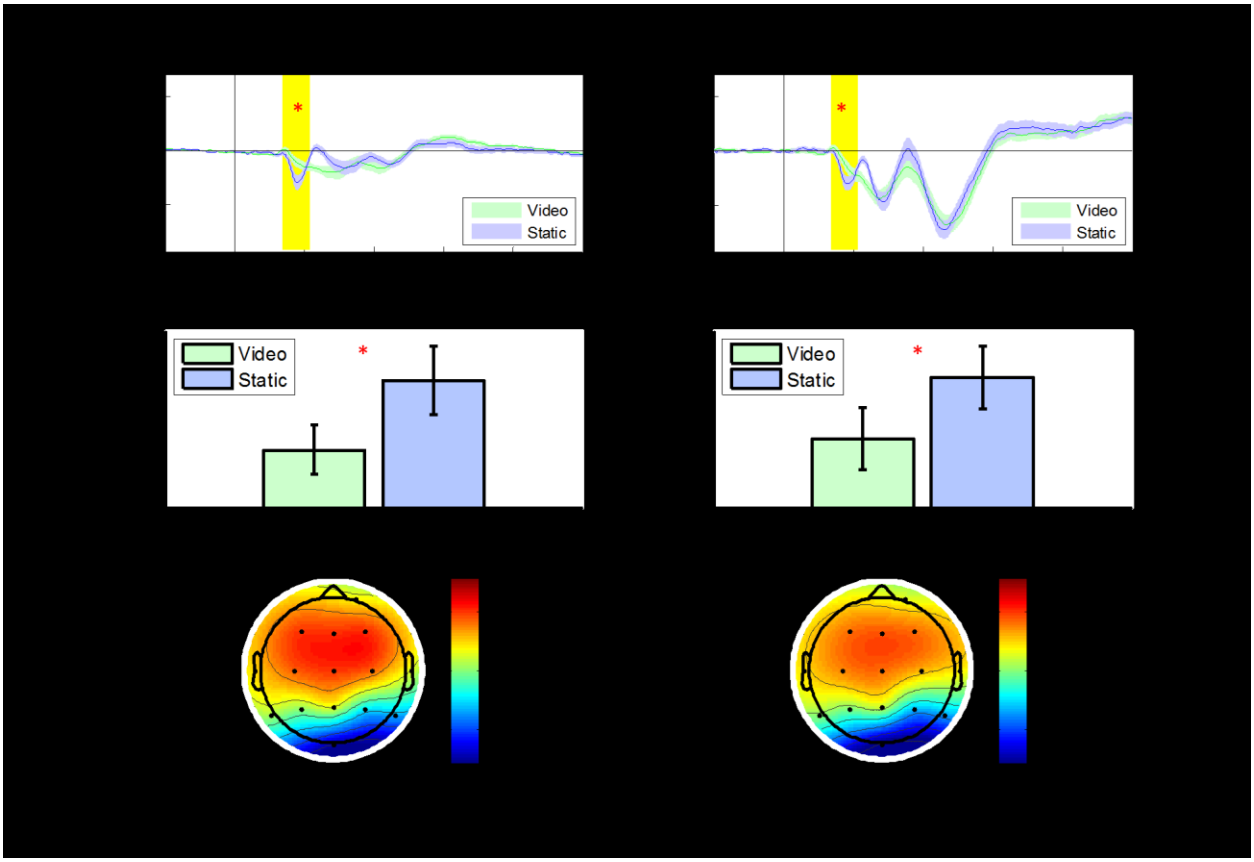

Figure 3. 3 P2 effect between conditions.

Asterisks (*) indicate statistical significance. A, Grand average ERPs calculated at electrode Fz comparing Video and Noise conditions in response to standard (+) stimuli (left) and target (×) stimuli (right) for all artifact-free trials after eye movement corrections. The P2 time window (140-210 ms) is indicated in yellow. Shaded areas indicate standard error of the mean, positive voltage is plotted down. Reduced P2 amplitude during the video condition was found by completing a within-subjects one-tailed t-test (α=.05). B, Mean P2 amplitude in the P2 window comparing Video and Noise conditions in response to standard stimuli (left) and target stimuli (right). Standard error is indicated on each bar. C, Scalp topographies of the P2 effect. Topographies are calculated from the recorded voltage difference between Noise and Video conditions (Noise-Video) in response to target (left) and standard (right) stimuli during the P2 window, not including the reference or eye channels. A fronto-central difference between conditions is evident in response to both stimuli.

The P2 component (140-210 ms after stimulus onset) was analyzed at electrode Fz for both conditions (Figure 3.3). Simple one-tailed t-tests showed that target stimuli elicited a significant P2 response in both the Noise condition (Figure 3.3; *M*=1.9305; *SD*=2.0327; *t*(18)=4.1397; p=3.0768e-4) and the Video (Figure 3.3; *M*=1.0229; *SD*=2.0286; *t*(18)=2.1979; p=.0206). The P2 was also significant in response to the standard stimuli in the Noise condition (Figure 3.3; *M*=1.8593; *SD*=2.1746; *t*(18)=3.7269; p=7.7165e-4) and the Video condition (Figure 3.3; *M*=0.8405; *SD*=1.5821; *t*(18)=2.3158; p=0.0163).

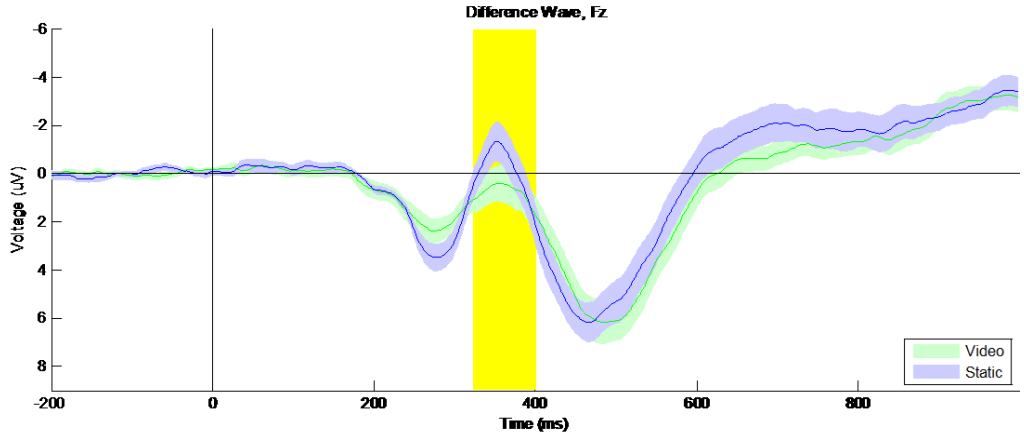

Figure 3. 4 Difference wave at electrode Fz.

Difference of the average response between target and standard stimuli (targets-standards) for each condition at electrode Fz. The MMN time window (325-400 ms) is indicated in yellow. Shaded areas indicate standard error of the mean, positive voltage is plotted down. The MMN was calculated in the MMN time window using a within-subjects t-test comparing stimuli difference (targets-standards) in each condition against a null difference (α=.05). Neither condition elicited a significant MMN.

As hypothesized, there was a reliable P2 difference between conditions: there was significantly reduced P2 amplitude at electrode Fz in the Video condition compared to the Noise condition in response to both types of stimuli (Figure 3.3). A one-tailed t-test of the P2 in response to target stimuli showed that the P2 had significantly reduced amplitude in the Video condition compared to the Noise condition (Figure 3.3; M_{diff}=0.9076; SD_{diff}=1.6090; t(18)=2.4588; p=.0121). This result was also present in response to standard stimuli (Figure 3.3; M_{diff}=1.0188; SD_{diff}=1.0084; t(18)=4.4039; p=1.7126e-4). Topographical maps of this observed P2 effect (Noise-Video) showed fronto-central topographical distribution in response to both standard and target stimuli (Figure 3.3).

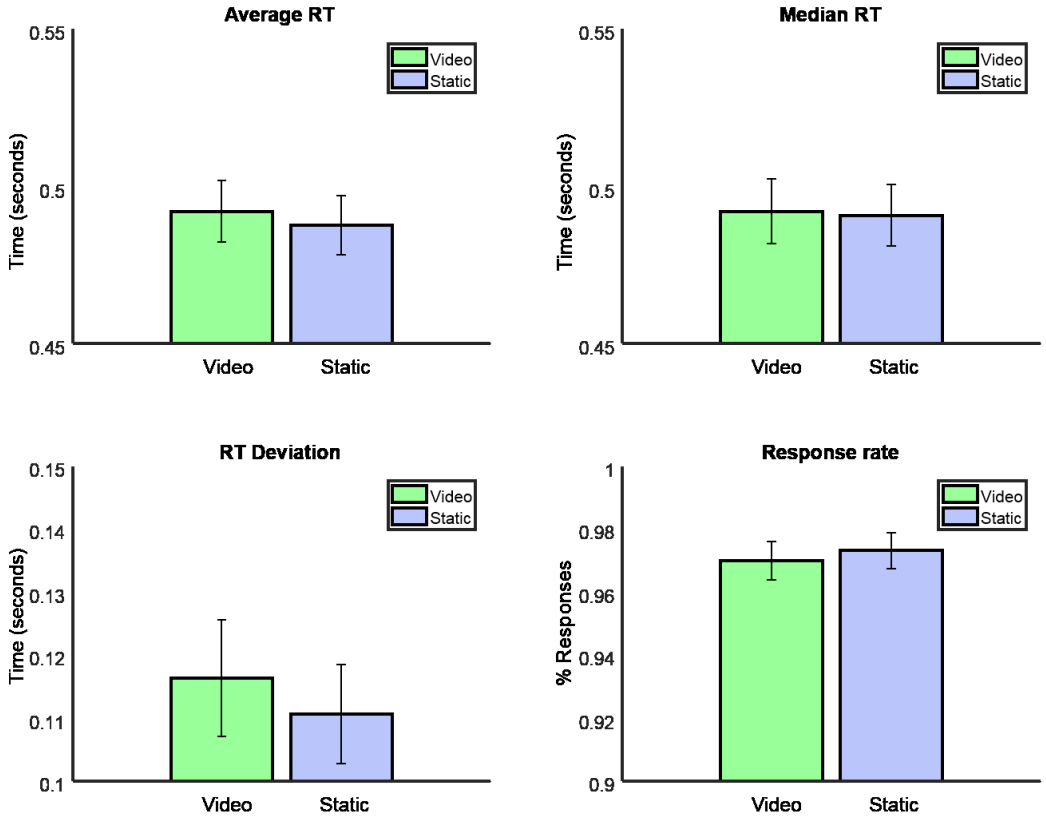

Figure 3. 5 Reaction times to target stimuli.
Reaction times were recorded via a button press, which was time-locked to stimulus onset and EEG data. Differences were found using a within-subjects t-test comparing between conditions measures (α=.05). Asterisks (*) indicate statistical significance. A, Average reaction time (in seconds) to target (×) stimuli in the Video and Noise conditions did not significantly differ from one another. B, Median reaction time (in seconds) did not significantly differ between Video and Noise conditions. C, Response time deviation was larger in the Video condition than in the Noise condition. D, Response rate was higher during the Noise condition than during the Video condition. Standard error is indicated on each bar.

3.2 Reaction Times

A two-tailed paired samples t-test was used to determine if the conditions differed in average or median reaction time, reaction time deviation and response rate. Neither the average reaction time (Figure 3.5; M_{diff}=0.0308; SD_{diff}=0.0159; $t(18)$=1.2094; p=0.2421) nor the median reaction time (Figure 3.5; M_{diff}=0.0546; SD_{diff}=0.0140; $t(18)$=0.4001; p=0.6938) showed any

significant difference between conditions. The response rate had no significant difference between conditions (Figure 3.5; M_{diff}=-0.0433; SD_{diff}=0.0304; $t(18)$=-0.4516; p=0.6569), and there was no difference in reaction time deviation (Figure 3.5; M_{diff}=0.0255; SD_{diff}=0.0288; $t(16)$=0.8681; p=0.3968), indicating that target stimuli did not elicit any differences in behaviour between the two conditions.

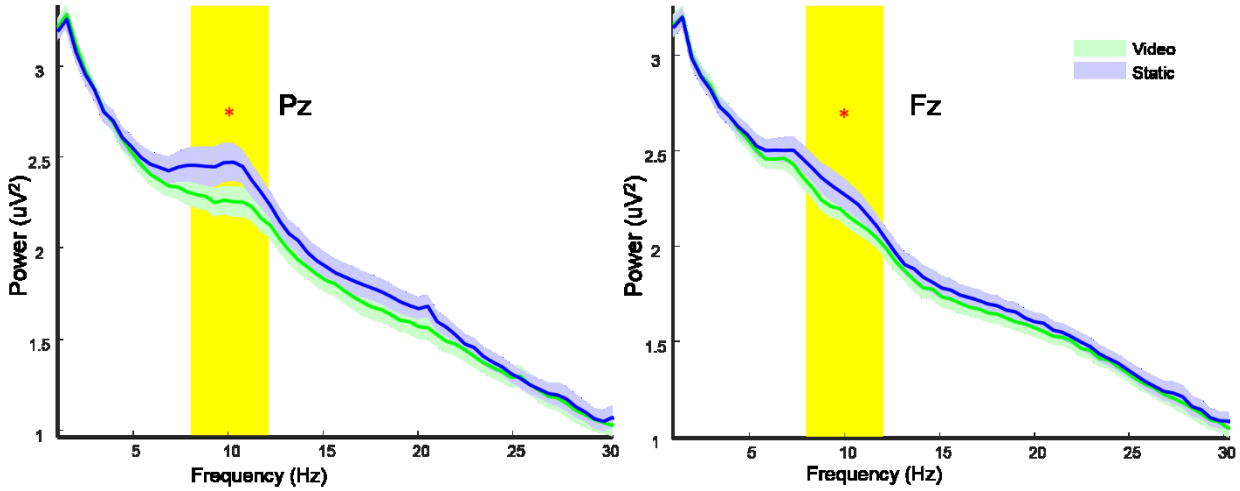

Figure 3. 6 Spectral plots.
Single-trial EEG spectra from electrodes Fz and Pz, computed with zero-padded FFTs on 465 auditory standard trial epochs of each subject, averaged over trials, then subjects. Shaded regions represent the standard error of the mean. Asterisks denote a significant difference.

3.3 Spectral analysis

To analyze any differences in oscillations during the task, we took an average of the frequency spectra over each standard trial epoch in both the Pz and Fz electrode locations. The data from each participant was randomly sampled for 465 of their artefact-removed standard trials. A fast Fourier transform (FFT) was then calculated through a procedure of symmetrically zero-padding the 600 time point series, making a 1,024-point time series, which allowed for frequency bins of .488 Hz. As the data were collected with an online low-pass filter of 30 Hz, only frequencies up to 30 Hz were plotted. We then calculated the average of the 465 spectra for each participant, and then combined these into a grand average spectra, shown in figure 3.5.

Apparent from the graphs is a greater amount of alpha (8-12 Hz) power in the Noise condition at both the Fz and Pz electrode. A paired samples two-tailed t-test was performed on the alpha range at both the Fz and Pz electrode locations, revealing significantly higher alpha power in the Noise condition at both Fz (M_{diff}=-0.088292; SD_{diff}=0.079095; t(18)= -4.8658; p=0.00012424) and Pz (M_{diff}=-0.17177; SD_{diff}=0.12647; t(18)= -5.9202; p=1.3276e-05).

4. Discussion

The current study aimed to investigate effects of visually complex environments on the P2 component of the ERP. To address this, we used a visual oddball task on top of two different visual backgrounds: visual Noise and first-person navigation through traffic (Figure 3.1). The use of an oddball task to study the P2 was useful for multiple reasons. Firstly, oddball tasks elicit a very reliable and characteristic set of ERP results in response to the rare target stimuli, which allowed us to confirm that our task was effective. If an oddball task is effective, it should cause significantly increased P3 amplitudes in response to the target stimuli when compared to standard stimuli (Polich et al., 1997). In both the Noise and video conditions, a reliable P3 effect was observed, indicating that both conditions were effective oddball tasks (Figure 3.2). Secondly, oddball tasks were used in both of our previous studies which first found an environmental modulation of the P2 component (Scanlon et al., 2017b). The choice to keep the task paradigm consistent in the current study reduced the chance of introducing other potentially modulating variables that could make it difficult to compare the results across modalities.

Previous results from our lab show that the P2 component is significantly smaller when participants complete an oddball task while cycling next to a street with traffic than while inside a lab environment (Scanlon et al., 2017b). Given that the participants were completing the same task in both conditions, and that a previous study in our lab showed that sub-aerobic stationary

biking does not result in a P2 change, these results cannot be explained by task differences or motor effects of biking (Scanlon et al., 2017a). Instead, it is more likely the result of the difference in auditory and/or visual environments between the two conditions. Using audio recordings of traffic from the same street as the previous study, we were able to replicate this P2 effect inside the lab, leading to the hypothesis that the P2 component may represent a form of task-relevant filtering in the auditory domain.

The current results build on those from our previous two studies, and suggest that this task-relevant filtering is observable in the visual domain in addition to the previously studied auditory domain. In both conditions, participants were exposed to dynamic visual backgrounds during the visual oddball task, but with the Video condition being of higher complexity than the Noise condition. Therefore, while both conditions likely require some extent of sensory filtering, they were designed such that the Video condition would engage this process to a higher extent. As hypothesized, the P2 component was significantly reduced when participants completed the visual oddball task with a video of traffic in the background compared to completion of the same task with visual Noise in the background (Figure 3.3). In line with our previous studies, this effect was found for both target and standard stimuli (Figure 3.3). This suggests that the mental process underlying this modulation was engaged while participants processed both types of stimuli during the Video condition, therefore the P2 effect was dependent on the visual background, and not due to stimulus differences. The topographical difference in the P2 window between the Noise and Video conditions shows that this P2 effect expresses frontal localization in response to standard and target stimuli, with a slightly more centrally extending difference to target stimuli (Figure 3.3). Taken as a whole, these results support our hypothesis that the

proposed task-relevant filtering is multimodal and present when participants are viewing both standard and target stimuli in visually complex environments.

Both conditions successfully produced a P2 and a P3 component in response to target and standard stimuli, but no significant MMN was elicited in either condition (Figure 3.4). The MMN occurs independently of attention, and seems to reflect a form of deviance detection in which the brain recognizes statistical regularities and responds to unlikely or rare/target stimuli (Näätänen et al., 2001; Stefanics et al., 2014). It is difficult to say why neither of these conditions elicited a significant MMN. If the participants were unable to differentiate between the standard and target stimuli, then we would not expect to have observed the P3 oddball response as we did in both conditions. However, given the high standard deviation found in the MMN time window, it is possible that high participant variability is responsible for the non-significant MMN.

4.1 P2 Modulation

P2 modulation can sometimes be explained by differences in task difficulty between the conditions. However, research on the influence of task difficulty on the P2 component during visual oddball tasks shows that the P2 amplitude increases with increasing task difficulty (Kim et al., 2008). Our results, which demonstrate a significantly decreased P2 in the Video condition, are opposite to that which we would expect to see if the complexity of the video had made the task significantly more difficult for participants. There were no significant differences in mean reaction times between the conditions, providing further evidence against task difficulty being solely responsible for the observed P2 modulation (Figure 3.5).

Given the P2 is thought to be involved in inhibiting repetitive stimuli that have been deemed irrelevant (Freunberger et al., 2007), it may seem surprising that the P2 would be decreased in the Video condition where there were large amounts of complex background

stimuli. However, even though an increased P2 may reflect increased inhibition of stimuli that our brain has deemed unimportant and repetitive, the complex outside environment is not repetitive, and our brains therefore may not process it as "irrelevant" information. Navigating through traffic on a bicycle, as was the visual environment in our Video condition, is full of complex, meaningful information that our brains are receiving. Seeing a car come towards you on the road while cycling between two vehicles is conceptually very different from seeing visual Noise or other artificially created stimuli, which are typically used in ERP studies. Therefore, one possible explanation of these results is that our brains may process this information in different ways, perhaps engaging these inhibitory processes to a lesser extent in environments such as those in the Video condition of our experiment.

Another possible, and perhaps concurrent explanation, is that more than just environmental background complexity and movement determines sensory-filtering of complex environments. It may be the case that dynamic and complex backgrounds containing meaningful information require task-relevant filtering to a higher extent, which leads to a reduced P2 amplitude. This idea fits well with the observed P2 responses in our Noise condition. Although the Noise condition uses a dynamic background made of many pixels, it is neither as complex nor as meaningful as the traffic in our Video condition. Perhaps the proposed filtering mechanism is engaged to a lesser extent in the Noise condition, and more so in the Video condition.

Alternatively, by combining these two explanations, it is possible that our brains inhibit or supress the visual background in the Noise condition, as suggested by Freunberger et al. (2007) more than in the Video condition, while simultaneously filtering the overlapping and meaningful information in the Video condition – the combination of which results in the

observed P2 difference. This explanation also fits with our results regarding alpha power, as alpha power was increased in the Noise condition, and has been known as a measure of pulsating inhibition of visual attention and processing in the brain (Mathewson et al., 2012). If we do indeed inhibit processing of the background stimuli more in the Noise compared to the Video condition, this may be shown in both measures of the P2 and alpha waves. Both explanations are based on the hypothesis that our brains process these two conditions differently because the Video condition contains meaningful information, the Static condition does not, and this difference leads to P2 modulation. This hypothesis remains to be tested.

Differentiating between selective attention and the sensory filtering we are proposing is best accomplished by comparing these results to those found in other studies of selective attention. Korsch, Frühholz, and Herrmann (2016) found significantly increased P2 amplitude during incongruent trials of a Flanker Conflict Task. The authors considered this P2 effect to be the result of stimulus evaluation: trying to determine which of the five stimuli on the screen is relevant. Stimulus evaluation, as required in this experiment, represents a form of selective attention. Similarly, Phillips and Takeda (2009) found that P2 amplitude is sensitive to the number of distractors in a task and is increased for efficient visual searches, suggesting that the P2 is involved in selective attention via feature suppression. We suggest that these forms of selective attention may be a different process than sensory filtering. Whereas in selective attention there is a need to differentiate between several separate objects, the proposed filtering would be relevant in complex environments in which the stimulus you need to pay attention to is immersed in other information, requiring the ability to filter out that complex background.

To the best of our knowledge, there have not been other studies testing the visual P2 in complex visual environments in a comparable way to that done in this experiment. Our results

show a decreased P2 amplitude in complex visual environments, which contrasts with previous studies of selective attention, as discussed above. Together, the contrasting results seem to suggest that filtering and selective attention may not be identical, but may instead be two related yet distinct mental processes. However, given the lack of previous literature on the topic, it is too early to say with certainty that these processes are entirely dissimilar, or modulate the P2 in dissimilar ways in the visual domain. Future research will need to be done to discriminate between selective attention and sensory filtering.

While our results in combination with previous findings by Scanlon et al. (2017b) indicate the proposed sensory filtering is multimodal, it remains to be determined if this is a cross-modal phenomenon. Thus, while the current results suggest that the P2 component effects seen while outside may be modulated, in part, by the visual environment, this cross-modal effect has not yet been tested. Future studies could address this by using an oddball task in one modality while simultaneously immersing participants in a complex environment in another modality. For example, having participants complete a visual oddball task with a classic and simple black background while they listen to recorded sounds of traffic. Evaluating any modulation of the P2 during such experiments could help to determine if the proposed sensory filtering operates in multiple modalities simultaneously in order to effectively perceive task-relevant stimuli.

In order to distinguish between selective attention mechanisms and sensory filtering, and determine any differential effects on the visual P2, new research should directly compare selective attention, such as through a visual search task, and filtering, perhaps through a similar experimental setup to the one used in the present study. Considering that current literature on selective attention in the visual domain seems to indicate an increased P2 component when

selective attention mechanisms are engaged (Korsch et al., 2016; Phillips & Takeda, 2009), yet the current results show an attenuated P2 component in complex environments, it would be interesting to directly compare and contrast the results of such a study. Although selective attention and sensory filtering may reflect separate mental processes, it seems unlikely that the two are orthogonally related. Future research directly comparing the two could help to clarify the relationship between these processes, and their modulation of the P2 component.

Understanding the functional difference between the way the Noise and Video conditions affect the P2 would be another interesting avenue of research. As suggested earlier, it may be that a combination of differential inhibition and/or stimulus filtering accounts for the observed P2 modulation in a way that depends on the meaning of background information. To test this hypothesis, we could pixelate and scramble the recording used in the video condition of the current experiment and play it as a background to a visual oddball task. The background would therefore be equally as visually complex as the original video, with just as many colours changing at the same frame rate, but it would not contain meaningful information in the same way as the original video. If the proposed filtering mechanism is differentially engaged when the stimulus of interest is overlaid on top of other meaningful information, then the intact video should have smaller P2 amplitude than the pixilated video. Likewise, if non-meaningful information is inhibited more than meaningful stimuli, in a way similar to that suggested by Freunberger et al. (2007) then the pixilated video should have higher P2 amplitude than the intact video.

4.2 Future Direction

In the continued effort to study cognition outside of laboratory environments and in more ecologically valid contexts, future research in our lab will take EEG recording back outside.

Until now, all of our experiments have focused on using urban sensory information during an oddball task through audio and visual traffic recordings, or cycling next to a busy street. We have yet to test the effect of more "natural" environments on ERPs during oddball tasks. Increasingly, there has been a trend in the literature to study the restorative effects of nature on cognition, with several studies pointing to increased cognitive performance and reduced need for top-down attention and cognition in natural environments (Berman, Jonides, & Kaplan, 2008; Bratman, Daily, Levy, & Gross, 2015). We plan to use an auditory oddball task, such as that used by Scanlon et al. (2017b), and compare ERPs, and specifically the P2 when participants bike next to a busy street, versus biking through a river valley. This will help to further our understanding of P2 modulation and sensory filtering, and further inform cognitive research by gathering information on ERP differences within different environmental contexts.

4.3 Conclusions

Most of what we understand about cognition has come from isolated and artificially simplified laboratory environments. In order to make valid and meaningful conclusions about the visual attention system and sensory processing, the complex environment in which people are immersed in their daily lives must be considered. Research such as the current study helps to inform researchers of the complex factors underlying cognition. With advances in EEG recording equipment and mobile EEG analysis, several labs, including ours, have begun taking EEG research outside of the lab and into more ecologically valid environments. Previous findings in our lab have shown distinct P2 reduction when an auditory oddball task is completed outside, next to a busy street, or when inside while listening recorded traffic in the background (Scanlon et al., 2017b; Scanlon et al., *In preparation-a*). We proposed that in order to perceive task-relevant information, other overlapping sensory information may need to be effectively

filtered, and that this process results in decreased P2 amplitude. Specifically, we hypothesized that using a complex visual background to a visual oddball task would result in similarly attenuated P2 amplitude.

Our results support the idea of a P2-related sensory filtering process in complex environments, and support our hypothesis that the proposed filtering process is multimodal, occurring in visual domain in addition to the previously studied auditory domain. These results have added to the body of knowledge surrounding the P2, which is still in early stages compared to other ERP components, providing some of the first knowledge of modulation of the visual P2 component in complex, ecologically valid visual environments. As a whole, the results of this study suggest that our brains process information differently in complex-real world contexts than in the artificially simplified environments typical of laboratory studies, and that the P2 component may play a role in filtering sensory information in complex visual environments.

Chapter 4: A ride in the park: Cycling in different outdoor environments affects the auditory N1

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Abstract

Mobile EEG allows the investigation of brain activity outside of the lab and in increasingly complex environments. In this study, EEG equipment was adapted for use and transportation in a backpack while cycling. Participants performed an auditory oddball task while cycling outside either in a quiet park or near a noisy roadway. In both conditions, we were able to accurately measure reliable event related potentials (ERP). The P3 was similar in topography, and morphology, with no differences in amplitude between conditions. When biking near the roadway, an increased N1 amplitude was observed when evoked by both standards and targets compared with biking in the quiet park. This may be due to attentional processes filtering the overlapping sounds between the tones used and similar environmental frequencies. No behavioural differences were found. This study established methods for mobile recording of ERP signals. Future directions include investigating auditory P2 in more rigorous studies outside of laboratory.

1. Introduction

Cognitive neuroscience often requires subjects to avoid any kind of natural light, sound and movement during recording. This is because all uncontrolled sensations have the possibility of introducing noise into the EEG signal (Schlögl, Anderer, Roberts, Pregenzer, & Pfurtscheller, 1999; White & Van Cott, 2010), and this noise can often be what determines the statistical power when analyzing EEG and ERP data (Luck, 2014). New technologies are beginning to make it easier to record laboratory-quality brain activity data outside of the lab while subjects are mobile (Kuziek, Sheinh, & Mathewson, 2017; Scanlon et al. 2017b; Debener et al., 2012). While the effects of movement on EEG data are beginning to be understood, few studies have attempted to investigate the effect that different environments may have on the way the brain functions. The present study was conducted in an attempt to go beyond the limitations of measuring EEG on a mobile participant, while also investigating the ways in which different environments may affect the ERP.

In mobile EEG literature, the oddball task is commonly used due to its high signal to noise ratio in the detection of the P3, as well as for the ability to infer changes in attentional resources due to a concurrent task (Polich, 1987; Polich & Kok., 1995). This robust pattern of activity is especially useful for brain-computer interface (BCI) technologies, which when effective, can use P3 amplitude to classify stimuli as targets or standards, and use this as a signal to control a computer. In EEG studies, the accuracy of a computer's ability to classify a set of oddball signals in a dataset can be used as a measure of data quality and noise. Debener et al. (2012) recorded brain activity using a small consumer passive electrode wireless EEG mounted to a typical laboratory electrode cap, and had participants perform an auditory oddball task while either walking outdoors or sitting indoors. The authors then analyzed the data using brain-

computer interface (BCI) single-trial P3 classification with linear discrimination, revealing high prediction accuracies in both outdoor (69%) and indoor (77%) conditions, with significantly higher classification accuracy in the indoor condition. Additionally, they demonstrated that the P3 was significantly larger when generated indoors while sitting than during outdoor walking. Using a similar wireless EEG system to Debener et al. (2012), de Vos et al. (2014) had participants perform a three-stimulus oddball paradigm during outdoor walking and outdoor sitting conditions. The authors found no significant differences in noise between the two conditions, however classification accuracy was significantly higher in the sitting (71%) than walking (64%) walking condition. Again, the P3 response to targets was significantly larger while participants were seated (de Vos et al., 2014), demonstrating a consistent effect of walking on attentional resources. Zink, Hunyadi, Van Huffel, and de Vos (2016) used a passive wireless mobile EEG system and asked participants to perform an auditory oddball paradigm during mobile cycling, stationary pedaling and sitting in a natural outdoor environment. The authors found no difference in RMS data noise or P3 amplitude between sitting and pedaling, but demonstrated a significant increase in noise and near-significant decrease in P3 amplitude while participants were cycling. Additionally, single trial BCI classification accuracies were significantly lower in the cycling (67.7%) condition than the pedaling (72.7%) and sitting (76.7%) conditions.

Several studies have investigated how EEG can be optimized for mobile tasks. De Vos and Debener (2014) recommended that new technologies for mobile EEG be lightweight, small, and able to avoid cable motion (ideally wireless). Similarly, Makeig et al. (2010) made several recommendations for the ideal mobile EEG system. These include small and lightweight EEG sensors to avoid hindering movement and removing the use of wires through the use of wireless

data recording and battery powered amplifiers. In accordance with these recommendations, Debener, Emkes, Gandras, de Vos and Bleichner (2015) demonstrated reliable P3 effects while using a cEEGrid electrode array, composed of a flexible sheet of electrodes, which were placed around the ear, and using a smartphone for stimulus presentation. The authors demonstrated that this system can yield a high test-retest reliability, as well as a high classification accuracy when data was collected in both morning (70.3%) and afternoon (70.9%) sessions. Another study by Bleichner et al. (2015) used a BCI speller, which uses the P3 signal to allow participants to spell words by focusing on individual letters in a matrix. The authors were able to use this system to obtain significant P3 effects during a spelling task, while making the device small enough to be concealed under a baseball cap. De Vos, Kroesen, Emkes, and Debener (2014) used a similar approach with a BCI speller task, and were able to demonstrate equivalent results between a wireless mobile amplifier and a wired laboratory EEG system.

In addition to ERPs, some studies have used oscillations measured during mobile EEG to answer novel questions about the body in motion. Storzer et al. (2016) recorded EEG in the motor cortex during walking and cycling tasks of comparable speed, to investigate cortical oscillations during these tasks. The authors showed, similar to Scanlon et al. (2017b) that both walking and cycling were associated with a decrease in the power of alpha (8-12 Hz) oscillations, with walking being associated with a significantly larger power decrease than cycling. Further, during the cycling condition they were able to demonstrate decreases in the power of high beta band (23-35 Hz) during initiation and execution of movements, with subsequent increases in this band during movement termination (Storzer et al., 2016). Another study by Jain, Gourab, Schindler-Ivens, and Schmit (2013) also used EEG to measure motor cortex oscillations, this time with an active and passive (low effort) pedaling stationary cycling

task. The authors demonstrated significantly more beta desynchronization during active compared to passive pedaling. These studies demonstrate the potential for measuring oscillations during mobile tasks, as well as the effects of cycling on alpha and beta band oscillations.

Recent studies in mobile EEG technology have demonstrated that this type of data collection is becoming a feasible way to ask questions which were previously out of reach for cognitive neuroscience research. For example, Scanlon et al. (2017a) looked at the effects of cycling on EEG data, and had participants perform an auditory oddball task before, during and after a sub-aerobic stationary cycling task. The authors found increased noise in the EEG data during the stationary cycling task, however despite this noise, ERP signals were reliably recorded, with no differences in the ERP components between any of the cycling conditions. In a follow-up to this study, Scanlon et al. (2017b) used compact technologies that could be fit inside a backpack, in order to have participants perform the auditory oddball task while cycling outside. Participants were asked to listen to the oddball task through headphones both while cycling outside and while sitting in the laboratory, responding with a mock-press button placed either on the handlebar of the bike or armrest of the chair. Baseline data noise was increased during the cycling condition, however the authors were successful in collecting laboratory quality ERPs in both conditions. Conversely to the stationary cycling study (Scanlon et al., 2017a) however, this study by Scanlon et al. (2017b) demonstrated P3 amplitude and alpha band oscillations to be significantly decreased while participants cycled outside, likely due to the sharing of attentional resources between the cycling and oddball task. This study also found an unexpected increase in the N1 component and decrease in the P2 component of the ERP, during both standard and target tones while participants were cycling outside. In a follow-up study, Scanlon et al. (In preparation-a) investigated this effect further by having participants perform

the same headphone auditory oddball task inside the lab with different sounds playing in the background of the task. The background sound conditions included a recording of a noisy outdoor roadway, white noise, silent background with low-volume tones and silence. The authors found that they were able to replicate the N1 and P2 effects most reliably while playing outdoor noises in the background, indicating that the effect may have been due to a filtering of background noises in order to perform the task. These studies indicate that bringing EEG into the real world opens up the possibility of answering new questions about the way the mind works in the real world.

Few previous studies have directly measured EEG in a fully outdoor and mobile context. The current study extends the findings of Scanlon, Townsend, Cormier, Kuziek, Mathewson, (2017b), and Scanlon, Townsend, Cormier, Kuziek, Mathewson, (In preparation-a), using similar methods and analysis. It is of particular interest to examine variations in ERP components between path cycling in quiet and noisy outdoor areas, as well as how these conditions differ in statistical power and noise. Each participant completed four 6-minute blocks in an auditory oddball task while both sub-aerobically cycling near a noisy roadway and in a quiet city park. Similar to Scanlon, et al. (2017b), active low-impedance electrodes were used. Levels of data noise and power spectra were analyzed, as well as ERP magnitude, morphology and topography for the P3, P2, N1 and MMN/N2b. Our first hypothesis is that even with the increased noise created during movement in both conditions, we will be able to accurately record ERPs in both the noisy and quiet cycling conditions, with enough accuracy to detect possible ERP differences between the conditions. Our second hypothesis is that due to increased ambient noise in the roadway condition, there will be an increased N1 and decreased P2 while participants cycle near the roadway.

2. Materials and Methods

2.1 Participants

10 people who were part of the university community participated in the experiment (mean age = 23.4; Age range= 20-31; 4 female). Each participant received an honorarium of $20. All participants had normal or corrected to normal vision with no history of neurological problems. Experimental procedures used were approved by the Internal Research Ethics Board of the University of Alberta.

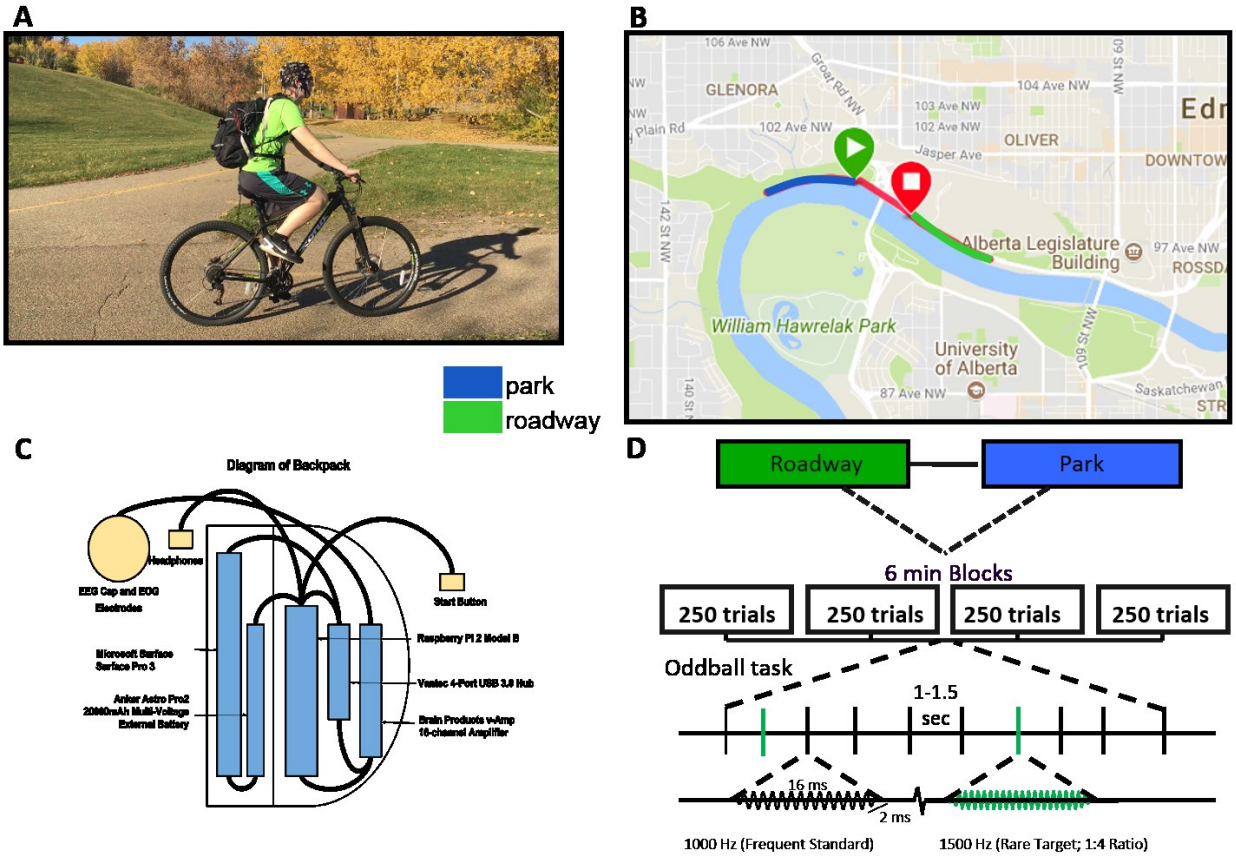

Figure 4. 1 Biking apparatus and procedure for mobile EEG.

A: The task was performed while cycling on a bicycle, with the participant wearing an EEG cap and backpack which contained the EEG equipment. B: A map of the cycling routes. C: Schematic layout of the contents of the mobile EEG backpack. The backpack had two pockets and contained the following: Anker Astro Pro2 20,000 mAh Multi-Voltage external battery or Tzumi Extreme PocketJuice 6000mAh battery, Raspberry Pi 2 model B, Microsoft Surface Pro 3, Vantec 4-Port USB 3.0 hub, Brain Products v-Amp 16 channel amplifier. D: During both cycling by the roadway and in the park, participants performed four 6 minute blocks of an auditory oddball task, with self-paced breaks in between. Within the oddball task, 20% of the tones were rare high-pitched tones (1500 Hz) and 80% were frequent low-pitched tones (1000 Hz). Each tone played for 16 ms with a 2 ms ramp-up and down. Tones were spaced 1-1.5 seconds apart.

2.2 Materials

Prior to the experiment, participants selected one of two bicycles (Kona Mahuna), which differed only in frame size (17 or 19 inches) based on the participant's height. Seat height was adjusted according to the participants' comfort level. Bicycle gears were set to the 2nd gear in both the front and back, in order to allow participants to pedal constantly and evenly throughout the trials at a sub-aerobic level. Data was collected using a Microsoft Surface Pro 3 running Brain Vision recorder (Brain Products), and powered by an Anker Astro Pro2 20000mAh Multi-Voltage External Battery or or Tzumi Extreme PocketJuice 6000mAh battery. Due to technical problems with the Anker astro battery, the Tzumi battery was used for 8 subjects. The various technologies mentioned were connected using a Vantec 4-Port USB 3.0 Hub.

To run the oddball task and mark the EEG data for ERP averaging, we used a Raspberry Pi 2 model B computer, running version 3.18 of the Raspian Wheezy operating system, using version 0.24.7 of the OpenSesame software (Mathôt, Schreij, & Theeuwes, 2012; see Kuziek, Sheinh, & Mathewson, 2017 for validation study). A 900 MHz quad-core ARM Cortex-A7 CPU was connected through a 3.5 audio connector for audio output. To mark the data for EEG averaging, 8-bit TTL pulses were sent to the amplifier through a parallel port connected to the

General Purpose Input/Output (GPIO) pins. A button connected to the Raspberry Pi was affixed to the handlebar of the bike, which was used both as a start button for each block, and a response button to the target tones. Participants wore a two-pocket backpack (Lululemon; Figure 1.1A-B) containing all of the stimulus generating and recording materials. In the *roadway* condition, participants rode along approximately 0.65 km of a shared use path next to River Valley Road in Edmonton, Canada (Figure 3.4.1C-D). During the park condition, participants rode along approximately 0.65 km of a shared use path in MacKinnon Ravine Park, also in Edmonton, Canada.

2.4 EEG Recording

Active wet electrodes were selected for EEG recording in this study based on previous studies by Laszlo et al. (2014) comparing active and passive amplification electrodes at differing levels of impedance, as well as by Oliviera et al. (2016) who compared active wet, passive wet and passive dry electrodes during a mobile task. Both of these studies demonstrated that active wet electrodes afford cleaner and better quality signals in non-ideal recording conditions. Fifteen Ag/AgCl pin electrodes were arranged in 10-20 positions (Fp2, F3, Fz, F4, T7, C3, Cz, C4, T8, P7, P3, Pz, P4, P8, and Oz). Additionally, a ground electrode was embedded in the cap at the Fpz position, along with two reference electrodes clipped to the right and left ears. To lower electrode impedance, SuperVisc electrolyte gel was used, followed by mild abrading of the skin with a blunted syringe tip. The aforementioned techniques and gel application continued until all the electrodes had impedance levels lower than 10 kΩ, as measured using an impedance measurement box (BrainProducts) and until the raw data appeared to be clean and free of excessive noise. In addition to the 15 EEG electrodes, two reference electrodes and one ground electrode, horizontal and vertical bipolar electrooculogram (EOG) was recorded through passive

Ag/AgCl easycap disk electrodes placed above and below the left eye, as well as 1 cm from the outer canthus of each eye. These passive electrodes were used for the EOG because the AUX ports of our amplifier do not support active electrodes and we did not see a benefit to giving up 4 EEG channels for active-wet EOG sensors. These EOG electrodes can nonetheless record reliable signals due to their placement on the face, where there is generally less hair to impede the signal. Any dirt and oils on the EOG electrode sites are removed using NuPrep preparation gel, followed by cleaning the skin with an antibacterial sanitizing wipe prior to electrode placement in order to reduce impedance levels of the EOG electrodes based on visual inspection of the raw data. These bipolar channels were recorded using a pair of BIP2AUX converters plugged into the AUX ports of the V-amp amplifier, along with a separate ground electrode placed on the central forehead. EEG and EOG was recorded using a V-amp 16 channel amplifier (Brain Products) through a laptop USB port. Data were digitized at 500 Hz with a 24 bit resolution. The data were filtered using an online bandpass with 0.1 and 30 Hz cutoffs, along with a 60 Hz notch filter. These narrow filters were recommended in the actiCap Xpress manual in order to increase signal quality and reliability in mobile settings (Brain Products, 2014).

2.5 EEG Analysis

Analyses of EEG data were completed using MATLAB 2016b with EEGLAB (Delorme & Makeig, 2004), with custom scripts. Following data recording, the EEG data was re-referenced to an average of the left and right ear lobe electrodes. TTL pulses time-locked to the onset of target and standard tones were marked in the EEG data during recording, and were then used to construct epochs 1200-ms long (including a 200-ms pretrial baseline). Average voltage in the first 200-ms baseline was subtracted from the data for each trial and each electrode. To remove artifacts caused by movement, amplifier blocking, and any other non-physiological

factors, any trials in either of the conditions with a voltage difference from baseline larger than ±1000 μV on any channel (including eye channels) were removed from further analysis. Following eye correction, a second threshold was applied to remove any trials with a voltage difference from baseline of ±200uV. Following this procedure, over 88% of trials were retained in each condition. Overall, artifact rejection left approximately equal trial numbers per participant in the park (M_{targ} = 183.1; $range_{targ}$ = 127-200; M_{stand} = 722.4; $range_{stand}$ = 457-800; SD = Standard Deviation) and roadway (M_{targ} = 178.6; $range_{targ}$ = 124-200; M_{stand} = 707.9; $range_{stand}$ = 498-800) conditions, which we then used for the remaining analysis.

A regression-based procedure was used to estimate and remove variance due to EEG artifacts caused by blinks, as well as horizontal and vertical eye movements (Gratton, Coles, & Donchin, 1983). This technique uses a template-based approach to identify blinks, then computes propagation factors such as regression coefficients, and predicts the vertical and horizontal eye channel data from each electrode's signal. Then, weighted by these propagation factors, this eye channel data is then subtracted from each channel, allowing us to remove most variance in the EEG data that can be predicted by movements from the eyes. In order to keep as many trials as possible for both conditions, no further filtering or rejection was done on the data.

Data collection was completed between the months of August and November. When outside, participants sometimes wore a toque over the EEG cap to prevent the electrolyte gel from drying out, goggles to prevent excessive eye blinking during the trials, and gloves, if desires due to the weather (Temperature range = -4 - 17°C; Mean temperature = 11°C). During each 6 minute block the participant would travel approximately 650 metres from the starting point, after which they would turn around, have the data visually inspected for noise and

electrode problems by a research assistant, and complete another 6 minute block going in the opposite direction.

3. Results

3.1 Data Noise

Figure 4.2A depicts raw data for a representative participant at the Pz electrode location. We used two separate methods to estimate the data noise on individual trials. First, we took an average of the spectra over each EEG epoch in the Fz and Pz electrode locations. Each participant's data was randomly sampled for 290 of their artefact-removed standard trials. A fast Fourier transform (FFT) was then calculated through a procedure of symmetrically padding the 600 time point epochs with zeros, making for each epoch a 1,024-point time series, which provided frequency bins of .488 Hz. Because the data were collected online with a low-pass filter of 30Hz, only frequencies measuring up to 30 Hz were plotted. We then calculated the spectra for each participant by computing the average of the 290 spectra for each participant, and then combining these into the grand average spectra, as shown in figure 4.2B for the Fz and Pz channels. Shaded regions depict the standard error of the mean across participants. Evident in the plots, both conditions depict the expected 1/frequency structure in the data. Also evident is a significant increase in beta oscillations (15-30Hz) at the Fz electrode location (M_{diff}=0.06410; SD_{diff}=0.07322; t(9)= 2.7685; p=0.02181) during the park compared to the roadway condition, as tested with a two-tailed paired samples *t*-test.

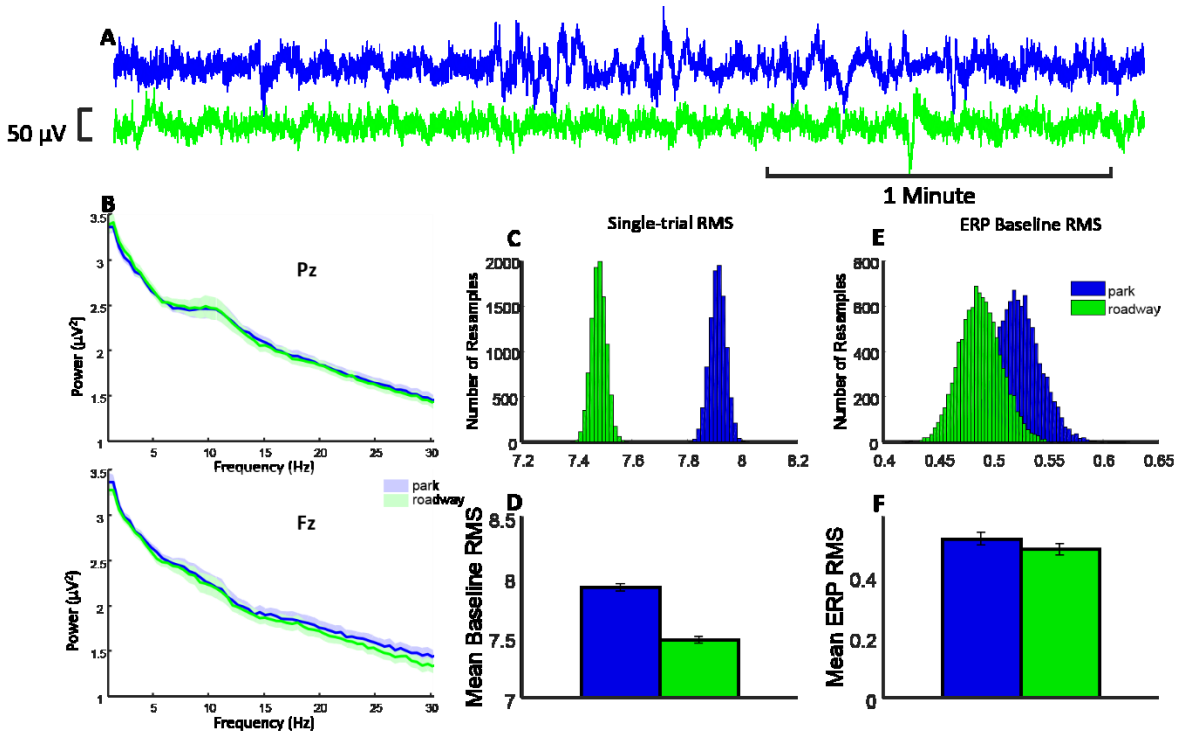

Figure 4. 2 Data noise levels
A: Raw EEG data (with online band-pass and notch filters) for several minutes for a representative subject and for each condition, shown at the Pz electrode location. B: Single-trial EEG spectra from electrodes Pz and Fz, calculated with zero-padded FFTs on 290 auditory standard trial epochs for each subject, averaged over trials, then subjects. Shaded regions depict the standard error of the mean. C: Histogram of average single-trial root mean square (RMS) grand average values collected during a 200 ms baseline period before tone onset, for 10,000 permutations of 290 randomly chosen standard trials for each subject. RMS values are averaged first over all electrodes within each trial, then over trials, then over subjects. D: Bar graph of these 10,000 permuted single-trial RMS values. Error bars depict standard deviation of the permuted distributions. E: Histogram of average ERP baseline RMS values, computed using 10,000 randomly selected permutations of 290 standard trials for each subject. For each permutation RMS of the baseline period is computed and the data is averaged over trials. F: Bar graph of these 10,000 permuted ERP baseline RMS values. Error bars depict standard deviation of the permuted distributions.

3.2 Single-Trial Noise

As an additional estimate of the single-trial EEG noise, we computed the RMS value for a baseline period of each standard trial (de Vos & Debener, 2014). To avoid any interference from the evoked ERP activity while measuring RMS, the baseline period consisted of the 200 ms

(100 time points) prior to each tone's onset. RMS is a good estimate of single trial noise in EEG data, as it is equivalent to the average absolute voltage difference around the baseline. To estimate an RMS distribution for each subject in the dataset, we used a permutation test that selects a different set of 290 epochs without replacement for each participant on each of 10,000 permutations before running second order statistics (Laszlo et al., 2014; Mathewson et al., 2017). For each condition and each permutation, a grand average single-trial RMS was calculated and recorded. Figure 4.2C depicts a histogram of these grand averaged single-trial RMS values computed for each permutation and each condition. Below this is a bar graph of the mean and standard deviation of the grand average distributions of RMS permutations. These plots demonstrate a clear distinction in single-trial noise for the two conditions. The park condition ($M_{RMS\text{-}EEG}$ = 7.9102; $SD_{RMS\text{-}EEG}$ = 0.028773) clearly demonstrated larger single-trial noise levels compared to the roadway condition ($M_{RMS\text{-}EEG}$ = 7.4784; $SD_{RMS\text{-}EEG}$ = 0.027161; Wilcoxon rank sum test; $z = 122.4714$ $p < 0.0001$).

3.3 ERP Baseline Analysis

We ran a similar permutation analysis to test for noise that was not effectively averaged out across trials on noise levels within trial averaged ERPs. We again used a permutation test of the baseline RMS values to quantify the amount of noise in the participant average ERPs. This analysis is complementary to the above single-trial analysis, as the computation estimates the amount of phase-locked EEG data noise which is not averaged out over the trial with respect to tone onset. The computation randomly selected and averaged 290 of each participant's standard artefact-removed trials without replacement. The obtained RMS values were then averaged over EEG electrode channels to create a grand average of all participants. This made 10,000 permutations after averaging each participant's data together to compute second-order statistics.

Figure 4.2F shows a bar graph of the means of these distributions, with error bars to indicate the standard deviation of the permutation mean distributions. The histogram in figure 4.2E depicts the grand average RMS values calculated from these 10,000 permutations in each condition. The park condition ($M_{RMS\text{-}EEG}$ = 0.52212; $SD_{RMS\text{-}EEG}$ = 0.020648) had a higher RMS value compared to the roadway conditions ($M_{RMS\text{-}EEG}$ = 0.48812; $SD_{RMS\text{-}EEG}$ = 0.019298; Wilcoxon rank sum test; z = 94.6177 p < 0.0001).

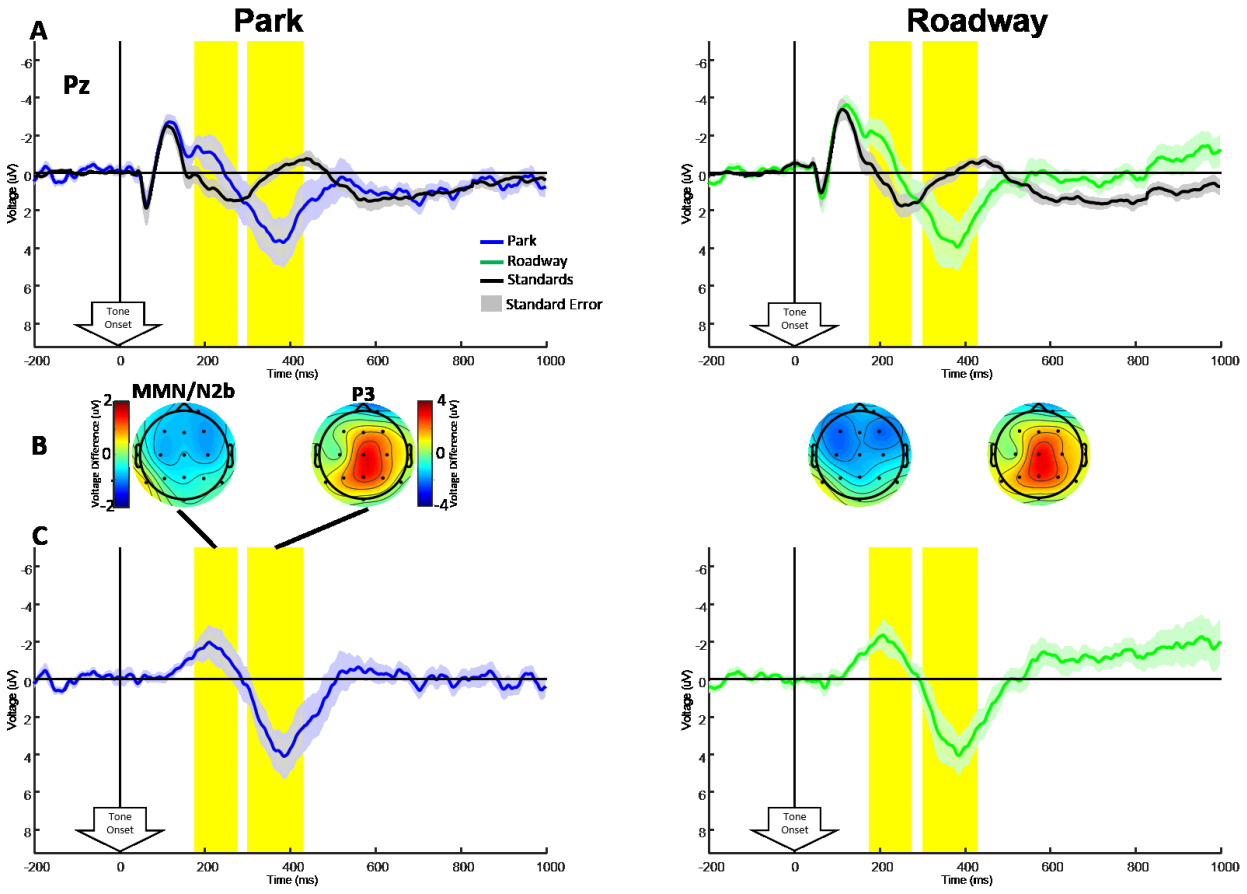

Figure 4. 3 ERP grand averages.

A: Grand-average ERPs computed at electrode Pz for all artefact-removed and eye movement corrected trials, for both standard (black) and target (colour) tones. B: Scalp topographies for grand-average ERP difference between standard and target tones in the MMN/N2b and P3 time windows (indicated in yellow), 175-275 ms and 300-430 ms after the tone, respectively. C: ERP difference wave from electrode Pz for both conditions, with shaded regions depicting within-subject standard error of the mean for this difference, with between-subjects differences removed (Loftus & Masson, 1994). Yellow highlighted regions represent the time window for the MMN/N2b and P3 analysis as well as topographic plots.

3.4 ERP Morphology and Topography

Grand average ERPs calculated from each participant's corrected and artefact-removed standard and target tones at electrode Pz are depicted in figure 4.3A. Similar error levels can be observed within the two conditions. Evident from the plots is the expected P3 amplitude increase during target trials in the posterior topographical locations (Pz; figure 4.3B). The expected oddball difference in the P3 is shown with an increased positive voltage between 300 and 430 ms following the infrequent target tones, compared with the common standard tones. We used this time window for all further analysis of the P3. Additionally evident in the Figure 4.4A plots is a target-standard difference in the MMN/N2b time window, with increased negative voltage from 175-275 ms following infrequent targets tones compared to common standard tones. This time window was used for any further MMN/N2b analysis, using the Fz electrode, as the effect is visibly maximal in frontal regions (figure 4.3B).

Figure 4.3B shows topographies of these target-standard differences within the MMN/N2b and P3 time windows. The MMN/N2b time window topography demonstrates the expected frontal scalp activation distribution for both conditions, while the P3 topographies reveal the expected activation distribution toward the back of the head. Figure 4.3C plots the ERP difference waves at electrode Pz, which are created by subtracting the standard tone ERPs from target tone ERPs for each subject. This estimation of error is therefore an equal

demonstration of that used in the t-test of the target-standard difference from zero (Loftus & Masson, 1994).

Both conditions demonstrated a clear negative peak at approximately 230 ms at the Fz electrode. To test for the MMN/N2b effect, we ran a one-tailed, paired samples *t*-test comparing the MMN/N2b averaged over the 175-275 ms time window centered around this peak at electrode Fz to zero. This test revealed a significant MMN/N2b effect for both the park condition (M_{diff}=-2.4188; SD_{park}=2.3427; $t(9)$ =-3.2649; p=0.0048811) and roadway condition (M_{diff}=-2.2506; $SD_{traffic}$=1.9142; $t(9)$ =-3.718; p=0.0023928). Additionally, a clear positive peak was observed as expected at approximately 380 ms at electrode Pz. A one-tailed paired samples t-test was used to compare this P3 difference averaged over the 300-430ms time window at electrode Pz to zero revealed a significant P3 effect in both the park (M_{diff}=2.8799; SD_{park}=3.37; $t(9)$ =2.7024; p=0.012148) and roadway (M_{diff}=2.8932; $SD_{roadway}$=3.3644; $t(9)$ =2.7194; p=0.011815) conditions.

3.5 ERP Statistical Power

Figure 4.4A shows differences waves plotted for both conditions at electrodes Pz and Fz. Evident from the graphs is no significant MMN/N2b or P3 differences between the two conditions at Fz and Pz, respectively. A two-tailed t-test between the park and roadway conditions was performed to test for differences in the targets-standards P3 difference between conditions at electrode Pz, finding no significant difference (M_{diff}=-0.013282; SD_{diff}=1.5997; $t(9)$ =-0.026255; p=0.97963). The same test was performed to test for any differences between conditions in targets-standards difference waves within the averaged 175-275 ms time-window at electrode Fz, and found no significant differences (M_{diff}=-0.16821; SD_{diff}=1.3555; $t(9)$ =-0.39241; p=0.70389).

As there is a possibility that the MMN and N2b contribute differentially to the MMN/N2b effect (Scanlon et al., 2017), we separated this window in order to analyze averages of the early MMN time period (100-200 ms) and the later N2b time period (200-300 ms). We found no significant differences between conditions in the targets-standards difference when the t-test was applied to either the MMN (at Fz: M_{diff}=0.021454; SD_{diff}=0.80884; $t(9)$ =0.083877; p=0.93499; at Pz: M_{diff}=0.21574; SD_{diff}=0.75063; $t(9)$ =0.90885; p=0.38712) or N2b time window (at Pz: M_{diff}=0.19951; SD_{diff}=1.487; $t(9)$ =0.42427; p=0.68133; at Fz: M_{diff}=-0.2088; SD_{diff}=1.4541; $t(9)$ =-0.45407; p=0.66053). It is likely that both the MMN and N2b were elicited within this time window, however with the current design we were unable to disentangle these components from each other. Therefore from here on, we will focus on the combined MMN/N2b time window between 175 and 275 ms.

Following the evidence of increased trial-averaged and single-trial noise during the park conditions, one may expect this to result in lower statistical power in the park condition. In order to test this prediction, a permutation procedure was used in which the 4:1 ratio of standard to target trials was kept constant while increasing the number of these trials that are able to contribute to the ERP average. Number of trials increased from 4 standard and 1 target trial, by 20 standard trials, up to 280 standard and 70 target trials. We then chose a random selection of this number of trials from each participant's data with replacement, and averaged over subjects to obtain grand averages. This random replacement procedure was used for both the MMN/N2b analysis at Fz and P3 analysis at Pz, and separately for each condition. For each number of trials, 10,000 permutations of this procedure was done. Note that this procedure cannot be used to examine changes in ERP morphology over time on the task due to habituation or attention, and

assumes that these influences would be observed equally across conditions and stimuli (Scanlon et al., 2017).

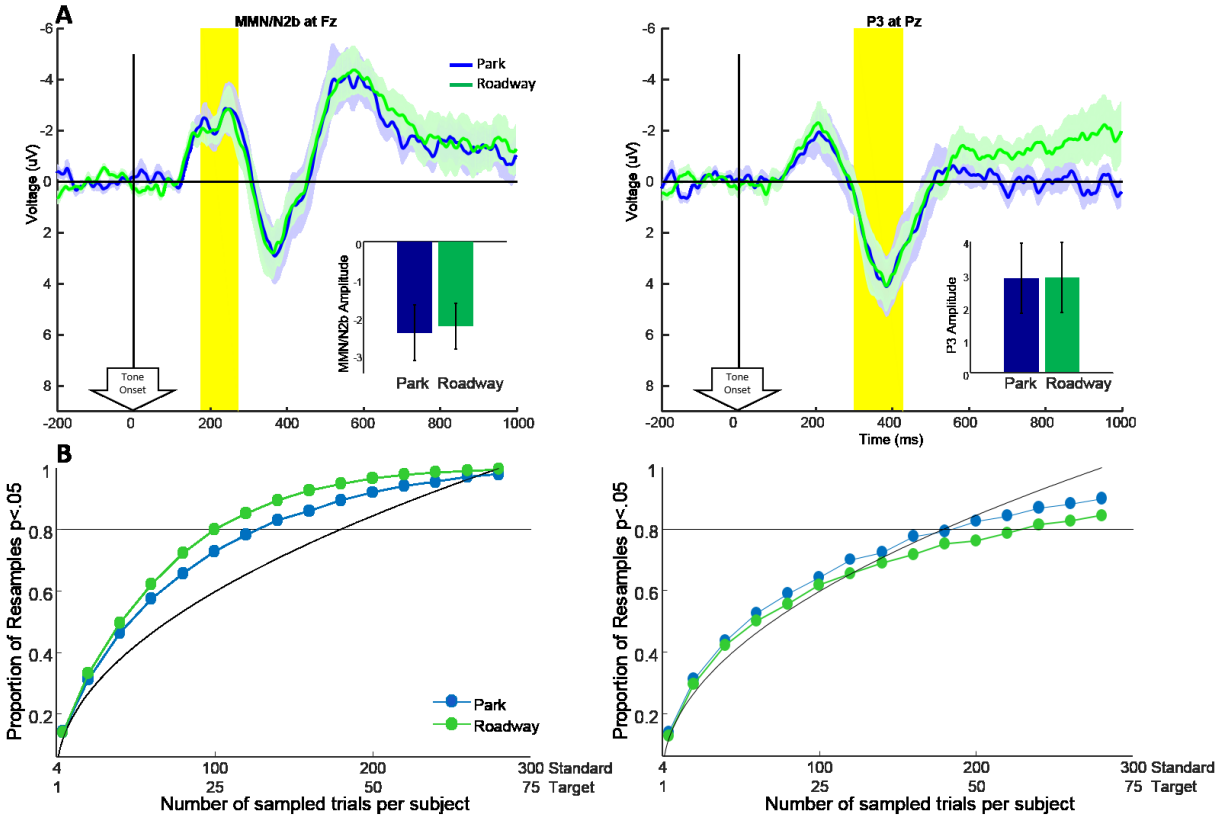

Figure 4. 4 Difference waves and ERP power analysis.
A: Difference waves indicating the average difference between standard and target trials for the two conditions are plotted for electrode locations Fz and Pz. Yellow highlighted regions depict the main time windows compared, particularly the MMN/N2b at Fz (left) and the P3 at Pz (right). B: The result of a permutation test in which a number of trials selected within 10,000 permutations varied between 5 and 280, while keeping the 4:1 ratio of standards to targets. Within each permutation, trials are selected randomly and averaged to compute subject ERPs. Differences in the MMN/N2b and P3 time windows between target and standard trials is computed and compared using an across-subjects (paired samples) one-tailed t test (a = 0.05), before grand average statistics are computed. For each number of trials and each condition, the graph plots the proportions of the 10,000 permutations in which an uncorrected significant difference was obtained. The dashed horizontal line at 0.8 indicates the threshold to achieve 80% power to find an existing effect. The gray line represents a square root of the number of standard trials, scaled to a range between 0 and 1 on the vertical axis by dividing by the square root of the maximum number of trials.

The selected single trials for each permutation were averaged together to create separate participant ERPs for target and standard tones. Target-standard differences were computed between 175 and 275 ms at electrode Fz and between 300 and 430 ms at electrode Pz in order to measure average MMN/N2b and P3 values, respectively. We then used a one tailed paired samples t-test (df = 9, α=0.05). Figure 4.4B demonstrates plots of the proportion of the 10,000 permutations in which the obtained p-value was passed the significance threshold as a function of the number of standards and targets selected in each permutation. Evident from this plot, the MMN/N2b for roadway condition required fewer trials (120 standard/30 target trials) to reach significance in 80% of permutations (gray line depicts 80% power) than the park condition (140 standard/35 target trials). The opposite effect is shown for the P3, in which the park condition appears to require fewer trials (200 standard/50 target trials) than the roadway condition (240 standard/60 target trials) to reach 80% permutation significance.

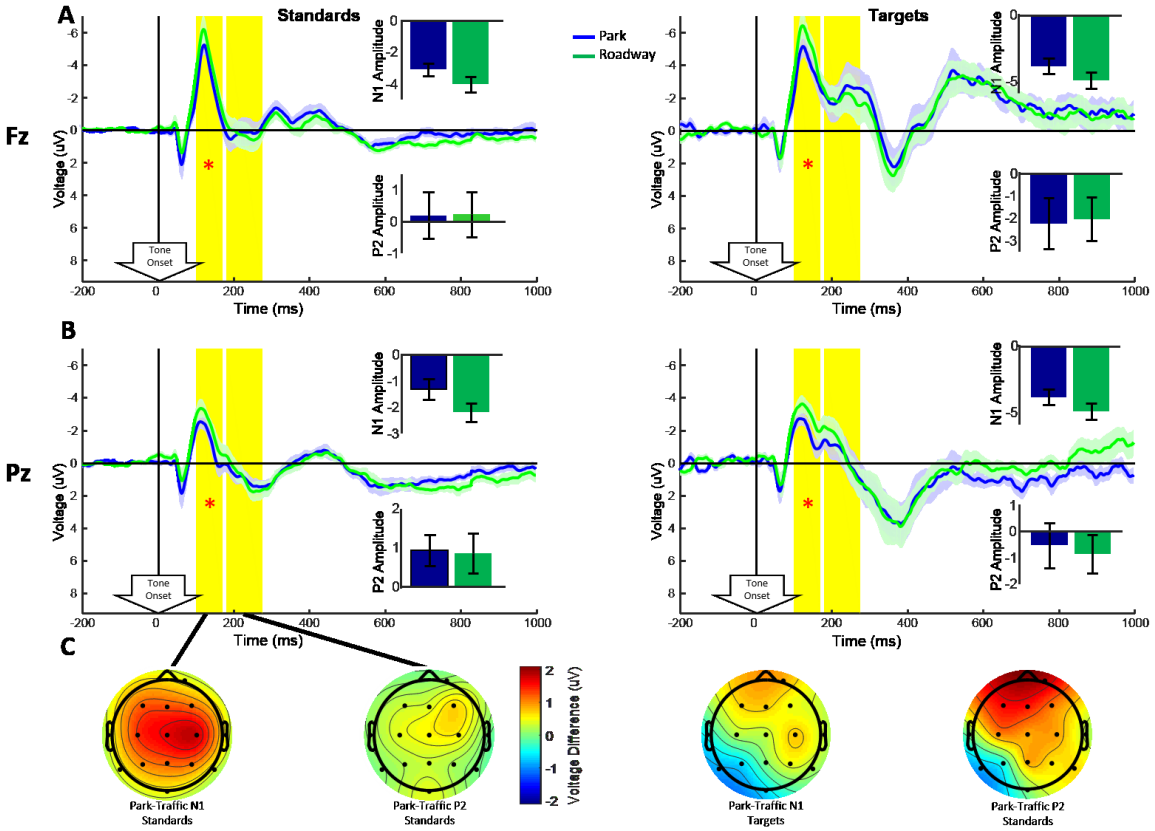

Figure 4. 5 Grand average ERPs
A: Grand average ERPs collected at the Fz electrode location, plotted separately to compare standards and targets between conditions. Shaded regions indicate the standard error of the mean. Inset bar graphs show the mean and standard error across participants in the N1 and P2 time windows. B: Grand average ERPs for the Pz electrode location, plotted separately to compare standards and targets between conditions. Inset bar graphs depict mean and standard error across participants in the N1 and P2 time windows. C. Topographies of the N1 and P2 time window plotted for the park-roadway condition differences.

3.6 N1 and P2 Amplitudes

In order to observe the effects of two different environments on general stimulus processing, grand averaged ERPs with a comparison of park vs. roadway at the Fz and Pz electrode locations are plotted in figure 3.5A and B, respectively. A visual inspection of these plots shows increased amplitude in the N1 component (100-175 ms) in the roadway condition, both in targets and standards and within electrodes Fz and Pz. Two-tailed paired t-tests of these

differences indicated significantly larger N1 amplitude during the roadway compared to the park condition at Fz (standards: M_{diff}=0.92109; SD_{diff}=1.1408; $t(9)$ =2.5533; p=0.031024; targets: M_{diff}=1.0752; SD_{diff}=1.433; $t(9)$ =2.3727; p=0.041723) and Pz (standards: M_{diff}=0.87623; SD_{diff}=1.0001; $t(9)$ =2.7706; p=0.021733; targets: M_{diff}=1.0437; SD_{diff}=1.1443; t(9) =2.8844; p=0.018049). Figure 3.5C plots topographies of this differences, indicating a frontocentral distribution.

Additionally, as previous studies have shown increased background noise to decrease the amplitude of the P2 component between 175 and 275 ms, one may expect to observe a similar effect in which the roadway condition shows a lower P2 amplitude. However, evident from the plots in figure 4.5A and B, no difference in P2 amplitude exists between the two conditions. Two-tailed paired samples t-tests revealed no significant P2 amplitude differences between conditions within both targets and standards at electrodes Fz (standards: M_{diff}=-0.024896; SD_{diff}=0.90966; $t(9)$ =-0.086546; p=0.93293; targets: M_{diff}=-0.1931; SD_{diff}=1.7528; $t(9)$ =-0.34838; p=0.73556) and Pz (standards: M_{diff}=0.075133; SD_{diff}=0.83215; $t(9)$ =0.28552; p=0.78171; targets: M_{diff}=0.33211; SD_{diff}=1.8257; $t(9)$ =0.57523; p=0.57923).

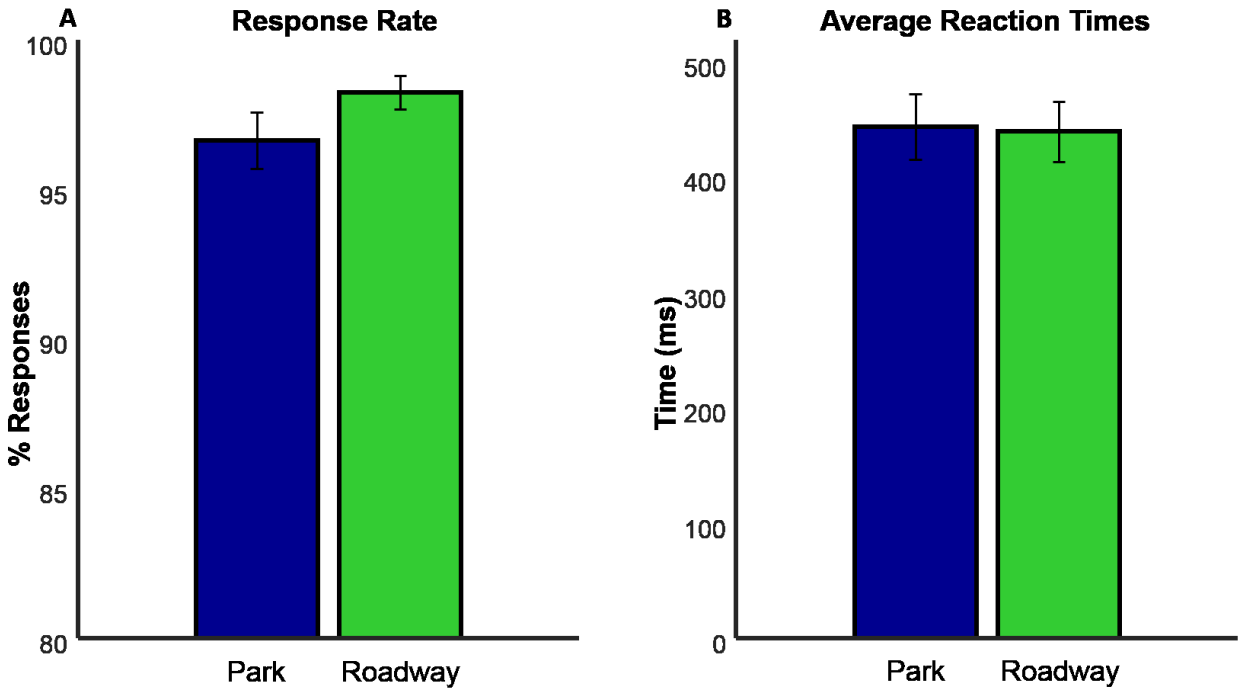

Figure 4. 6 Behavioural analysis.
A: Bar graph depicting mean and standard error for the percentage of targets that received a response within 2 seconds after the tone onset across participants for both conditions. B: Bar graph depicting the mean and standard error for the average time taken to respond (with missed responses removed) across participants for each condition.

3.7 Behavioural analysis

In order to assess behavioural effects in this task, we tested for condition differences in response rate and average reaction time to the target stimuli in the task, depicted in figure 4.6. A two-tailed paired samples t-test indicated a marginal difference in response rate between the two conditions, with participants responding to a higher percentage of targets in the roadway than park condition (M_{diff}=-1.6; SD_{diff}=2.4922; t(9) =-2.0302; p=0.07291). The same test was used to test for differences in average reaction time, finding no differences between conditions (M_{diff}=4.1037; SD_{diff}=26.2207; t(9) =0.4949; p=0.6325).

3.8 Combined experimental analyses

Figure 4.7A, B and C shows three bar graphs of N1 amplitude, P2 amplitude and alpha power, respectively, compared across 5 experiments which all used the oddball task (Scanlon et al., 2017a; Scanlon et al., 2017b; Scanlon et al., In preparation-a; Scanlon et al., *In preparation-b*; Scanlon et al., *In preparation-c*). Four of these experiments used the same auditory oddball task, while the fifth used a visual oddball task, and is therefore only included on the plot of alpha power. The '3 stage bike' experiment mentioned is a previous study in which participants performed an auditory oddball task on a stationary bicycle (Scanlon et al., 2017a). While performing the task, participants were asked to sit still (pre), pedal sub-aerobically (bike) and sit still again (post). Figure 4.7A shows the N1 amplitudes to standard tones in 11 conditions from four experiments using the same auditory oddball task. Evident from the graph is that experimental conditions in which the participant performed the task in non-ideal auditory conditions (e.g. with background noise or low volume; shades of green and yellow) show generally larger N1 amplitudes than when the task was performed in ideal situations (silent background, normal volume; shades of grey). Figure 4.7B depicts the P2 amplitudes to standard tones in 11 conditions from four experiments using the same auditory oddball task. The graph shows that experimental conditions in which the participant performed the task with background noise (shades of green) have generally lower P2 amplitude than those in which the task was performed in silence (shades of grey and yellow). Figure 4.7C demonstrates the alpha power for standard tones in 13 conditions within five experiments using either auditory or visual oddball tasks. Evident from the plot is that experimental conditions in which the participant viewed a visually rich stimuli had generally lower alpha power than those conditions in which the participant viewed a blank screen during the experiment.

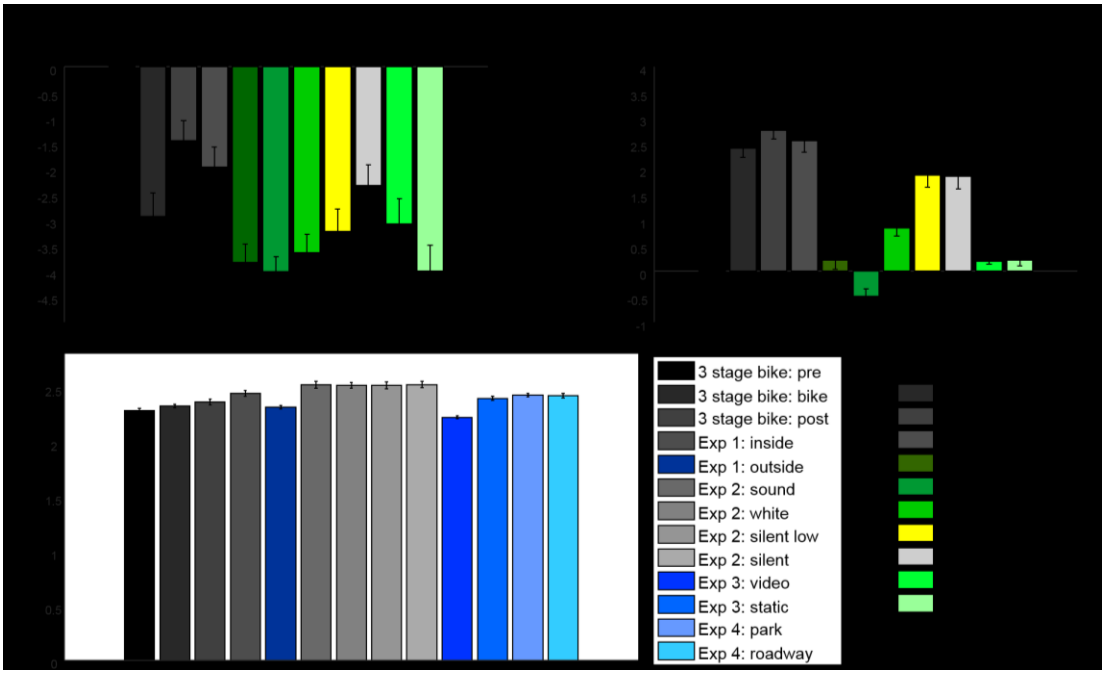

Figure 4.7 Combined experimental comparisons of the N1, P2 and alpha power. A: Bar graph of mean N1 amplitude to standard tones in 11 conditions across four auditory experiments using the same auditory oddball task. Experiment 3 is not included to avoid confusion between auditory and visual ERP components. Shades of green are used to represent experimental conditions with background sounds, and shades of grey are used to represent conditions with silent backgrounds. Yellow is used to depict the low-volume tones condition of experiment 2. Error bars depict the standard error of the mean. B: Bar graph of mean P2 amplitude to the standard tone in 11 conditions across four auditory experiments using the same auditory oddball task. Experiment 3 is not included to avoid confusion between auditory and visual ERP components. Shades of green are used to represent experimental conditions with background sounds, and shades of grey are used to represent conditions with silent backgrounds. Yellow is used to depict the low-volume tones condition of experiment 2. Error bars depict the standard error of the mean. C: Bar graphs of mean alpha power for standard tones in 13 conditions across five experiments all using an auditory or visual oddball task. Shades of blue represent experimental conditions in which the participant viewed rich visual stimuli, and shades of grey represent experimental conditions in which the participant viewed a blank screen during the experiment. Error bars depict the standard error of the mean. Experiment references: 3 stage bike (Scanlon et al., 2017a), Exp 1 (Scanlon et al., 2017b), Exp 2 (Scanlon et al., *In preparation-a*), Exp 3 (Scanlon et al., *In preparation-b*), Exp 4 (Scanlon et al., *In preparation-c*).

4. Discussion

The present study directly examined the effectiveness of recording ERPs during mobile cycling in two different outdoor environments, using a backpack to contain and carry the EEG

system outside of the lab. We implemented new compact methods for stimulus presentation (Kuziek et al., 2017) through the use of a Raspberry Pi computer to present the auditory oddball task through headphones and to mark stimulus events within the EEG data for analysis. We also used a tablet computer to store the marked EEG data via Brain Products v-AMP 16-channel amplifier as the EEG system. We used active electrodes based on previous findings which showed favorable results for active electrodes compared to other electrode types in mobile EEG (Oliviera et al., 2016) and high impedance levels (Lazlo et al. 2014; see also Mathewson et al. 2017). Active electrodes have also been used to effectively record mobile EEG in previous studies within our lab (Scanlon et al. 2017a; Scanlon et al., 2017b). During the experiment participants were asked to avoid moving their heads from side to side or looking around the scenery to mitigate data noise due to movement. However in future studies we will aim to reduce the need for movement constraints to allow for free observation of the environment while cycling. This has been shown to be possible in previous ERP studies during video game play (Maclin et al., 2011; Mathewson et al., 2012).

4.1 Data noise

As expected, we were able to overcome noise created by mobile cycling and collect laboratory quality ERPs (figure 4.3A), however it appears that the park condition had a larger amount of baseline noise than the roadway condition (figure 4.2), with higher RMS in the baseline EEG period for both trial averaged ERP and single-trial data. This may have possibly been due to slightly higher levels of elevation change within the park. While we were careful to find two environments that were similar in elevation, real world studies often have the constraint of being unable to change what the current study can access in the real world. However, the increases in single-trial noise were less than half the magnitude of the increases in noise

observed between sitting still and cycling outside in a previous study (Scanlon et al., 2017b), in which the ERPs recorded appeared largely unaffected by this difference. Additionally, the ERP trial averaged RMS was increased in the park condition to a much smaller degree than the single trial RMS. This indicates that a great deal of the noise added was not stimulus locked and was mitigated by trial averaging. This effect can also be seen in increased beta power (15-30Hz) at Fz in the park condition, possibly also due to this increase in mechanical noise, similar to increased high-frequency oscillations in the beta range found in previous studies during stationary pedaling (Scanlon et al., 2017a) and outdoor biking (Scanlon et al., 2017b) compared to rest.

Following this observation of increased single-trial and trial-averaged noise in the park condition, one may expect to also see decreased statistical power in the park condition. However this was not the case, as when we analyzed ERP power as a function of the number of resampled trials required to achieve 80% significance, we observed that neither condition was better at both components we analyzed. While the MMN/N2b required 20 more standard and 5 more target trials to reach significance in the park condition, the P3 required 40 fewer standard and 10 fewer target trials in this condition. This pattern was opposite, with respect to noise, to what was previously observed in the comparison between laboratory and outdoor mobile environments, as the condition with more data noise observed more statistical power for the MMN/N2b and less for the P3. This implies that the statistical power may be more affected by ERP differences than RMS baseline noise.

4.2 MMN and P3 morphology

As expected there were no significant differences observed between the two conditions for the P3 and MMN/N2b components. As the participants were performing the same dual task in both conditions, it appears that the P3 component was equally reduced between the two

conditions. This is evident because the peak amplitude for the P3 for both conditions was approximately 2 μV lower than those observed in previous studies done by this lab in which there was no concurrent task (Scanlon et al., 2017a; Scanlon et al., 2017b). Given the well-established observation that performing a secondary task during an auditory oddball task will reduce cognitive resources available for the task, therefore decreasing target-standard P3 amplitude (Kramer & Strayer, 1988; Polich, 1987; Polich & Kok, 1995; Wicken et al., 1983), this observation was not unexpected.

4.3 N1 and P2 morphology

Previous studies indicated that ambient noise during an oddball task decreased the P2 and increase N1 amplitude for both standards and targets during the auditory oddball task due to a process of filtering out irrelevant sounds in order to perform the task (Scanlon et al., 2017b; Scanlon et al., In preparation-a). We initially expected that we would find a similar difference in this study, with a reduced P2 and increased N1 while participants were cycling next to noisy roadway compared to the quiet park. However this was not the case, as no significant differences were found for the P2 component. This may indicate that the excess noise of the roadway did not sufficiently create the necessity to filter out ambient noise, or, that this noise filtering process was present during both conditions. If one compares the current study to Scanlon et al. (2017a) or Scanlon et al. (2017b), the P2 amplitude in both current conditions appears to be at least 2 μV smaller than the indoor conditions of the previous studies. This leads us to deduce that the lower amount of ambient noise in the park condition was sufficient for the P2 to be reduced to an equal degree as the roadway condition, and therefore this effect was observed equally in both conditions. In contrast to this however, there was a significant difference in the N1 between the two conditions with a larger N1 amplitude while participants performed the task near the

roadway. This is consistent with the increase in ambient noise shown in previous studies. This deviation indicates that while the N1 and P2 had previously been assumed to be modulated simultaneously to represent the same process, this may not be the case. Here, it appears that the level of ambient background noise had the ability to augment the N1, but any amount of ambient noise is sufficient to reduce the P2.

The N1-P2 complex is believed to be reflective of pre-attentive sound processing within the auditory cortex (Näätänen & Picton, 1987). The components of this complex, including the P1, N1 and P2 have been demonstrated to relate to several temporally overlapping processes which originate near or within the primary auditory cortex (Näätänen & Picton, 1987; Wolpaw and Penry, 1975; Wood & Wolpaw, 1982). P2 in particular has been shown to relate to cognitive functions such as working memory, memory performance and semantic processing during contextually based tasks (Federmeier & Kutas, 2002; Dunn et al., 1998; Lefebvre et al., 2005). The P2 is also thought to reflect a component of top-down cognition and perceptual processing, and may represent a process of inhibiting one's perception of unimportant or repetitive stimuli in order to perform a task (Freunberger et al., 2007; Luck & Hillyard, 1994). Additionally, the P2 has been hypothesized to reflect a process of suppressing the perception of irrelevant stimuli to allow stimulus discrimination within a primary task (Getzmann et al., 2016; Kim et al., 2008; Potts, 2004; Potts et al., 1996). The auditory P2 appears to relate to the subjective difficulty of stimulus discrimination, as both the auditory P2 and N1-P2 complex have been reliably found to have increased amplitude following discrimination training (Atienza et al., 2002; Hayes et al., 2003; Reinke et al., 2003; Trainor et al., 2003; Tremblay et al., 1997, 2002, 2001). More specifically to our task, one study showed a decrease in auditory P2 amplitude during a speech discrimination task while participants had to ignore irrelevant background speech in a 'cocktail

party' scenario, compared to a condition with no background distractions (Getzmann et al., 2016). This could explain why the P2 appears to have been reduced in both conditions, as the auditory P2 appears to be reduced any time stimulus discrimination in the task is more difficult, and therefore any amount of ambient noise could have this effect.

While the N1 and P2 are clearly related in a cluster of processes that take place within the N1-P2 complex, they appear here to serve similar but distinct functions. Previous research has proposed that the N1 itself appears to reflect several different auditory processes, with up to six distinct components (Näätänen & Picton, 1987). The most alterable of these being influenced by several contextual factors including a 'sensory acceptance-rejection' factor, which appears to attenuate all responses to uninteresting, irrelevant or unpleasant sensory inputs while enhancing responses to pleasant, interesting or important stimuli. The N1 tends to appear with shorter latency and larger amplitude when the attended and unattended sounds can be easily distinguished by physical cues such as pitch or location (Näätänen, 1982, 1992). For example, the N1 has been shown to increase when an auditory stimulus occurs in the location where an individual is attending, (Teder-Sälejärvi, et al. 1998) to allow an individual to enhance the auditory perception of this stimuli. This effect is increased in individuals who are blind (Roder et al., 1999). Overall, N1 amplitude is said to increase as a function of increased attentional allocation to a particular auditory input channel, which correlates to increased behavioural accuracy for targets in that channel (Hink, Voorhis, Hillyard, & Smith, 1977). Functionally, the amplitude and latency of the N1 is believed to represent the quantity of sensory information moving through an early auditory channel selection mechanism selection (Hillyard. Hink, Schwent, & Picton, 1973), greater processing of attended channel information (Näätänen, 1982; Okita, 1981), as well as how well-matched the eliciting stimulus and cue characteristics are

within the attended auditory input channel (Näätänen, 1992). In this study, it appears that while participants had to filter out noise in both conditions, the roadway condition required a larger amount of attention and processing of the task tones in order to perform the task, and therefore the N1 was increased and response rate was marginally increased in this condition.

4.4 Behavioural differences

As in previous studies, the difference between conditions did not appear to carry forward into behavioural differences in the oddball task, as there was no significant differences in reaction time. This again indicates that the N1 may reflect a compensatory process, allowing the mind to put greater focus on a target when distractions are present. However, a marginal increase in response rate in the roadway condition may indicate an increase in attention to the task tones in that condition, which can also be related to the increased N1 component amplitude in that condition.

4.5 Experimental set-up

In this study participants were asked to cycle as slow as they could comfortably go in order to minimize movement noise in both conditions. Therefore we believe that none of the effects on ERP's or data noise were due to the effect of exercise on the brain. The purpose of cycling in this study, similar to our previous work with stationary cycling (Scanlon et al., 2017a) and outdoor cycling (Scanlon et al., 2017b), was to allow a type of movement during tasks which minimizes data noise created by wire movements. For example, during walking and running, an individual's head will often move up and down with each step, allowing wire movements and artifacts to be created, while cycling allows one to move in a relatively smooth straight-forward motion. However cycling is commonly used activity which requires steering control, balance,

situational awareness to be done properly, which makes this a unique and rich activity to be explored within cognitive neuroscience.

This experimental setup also has some drawbacks in terms of the amount of equipment required to be carried around with the participant in the backpack. A large tablet computer was used for EEG data acquisition, while a small Raspberry Pi was used for stimulus presentation. We have recently started testing the use of miniature computer systems, such as the Latte Panda, and plan to use this in future studies. Further, the amplifier used was bulky and required long electrode wires to reach from the head to the backpack. Recent advances with EEG systems which are wireless and made specifically for mobile EEG (Debener et al., 2015; Zink et al., 2016; Krigolson et al., 2017; Hashemi et al., 2016) would greatly improve the portability of our system.

4.6 Combined Experimental comparisons

Figure 7 depicts the main measures (i.e. the N1, P2 and alpha power) from all four studies in this thesis as well as another previous study using the same task. Figure 7A demonstrates that experimental conditions in which the participant performed the task in non-ideal conditions (i.e., with background noise or low volume) had a higher N1 amplitude than conditions in which the task was performed in ideal conditions (i.e. silent background with normal volume). This demonstrates the effect of attention on N1 amplitude, as non-ideal conditions require the participant to 'tune in' to the stimulus more than they might have to in ideal conditions. Figure 7B shows that experimental conditions in which the participant performed the task in the presence of background sounds had generally lower P2 amplitude than conditions in which the task was performed in silence. This helps to demonstrate the way the P2 represents 'tuning out' distracting sounds in auditory tasks. The dichotomy between the functions of the N1

and P2 can especially be seen in the silent-low condition of experiment 2, as this condition had an enhanced N1 with a non-affected P2, demonstrating that the low-volume task required enhanced attention, with no requirement to tune out irrelevant information. The two conditions of experiment 4 also demonstrate this dichotomy, as both of these conditions have a larger N1 amplitude than any of the conditions performed in an ideal auditory situation, and the roadway condition has a significantly higher N1 than the park condition. However the P2 amplitude for both of these outdoor conditions is near zero and much lower than any condition in which the task was performed in silence, demonstrating that while there was no P2 difference within this experiment, the P2 was likely reduced in both conditions due to background sounds in the outdoor environment.

Figure 7C demonstrates that conditions in which the participants performed the task while viewing a visually rich stimulus had generally lower alpha power than those in which the task was performed while viewing a blank computer screen. This demonstrates the way alpha relates to visual attention and ecologically valid environments, as alpha has been shown to increase with decreasing attentional focus, with especially high power when an individual's eyes are closed (Berger, 1929; Adrian & Matthews, 1934; Mathewson et al., 2011). Here it appears that when participants are drawn to pay attention to the visual aspects of their environment, alpha is reduced. In comparison, when tasks are performed in visually impoverished environments, alpha appears to be high because there is nothing to draw their visual attention.

4.7 Future directions

This research program had the ultimate goal of measuring ERPs which naturally occur in the real world, in order to gain a deeper understanding of how the brain functions in during everyday life. We have recently begun testing EEG set-up which uses video capture and coding

to identify moments in the EEG data when interesting events happen in an individual's environment. We have also started to test the use of virtual reality (VR) to create environments and allow stimulus presentation, which also opens up the possibility of testing the brain in any unlimited number of simulated environments.

4.8 Conclusion

In this study we showed that we were able to carry out a fully mobile cycling ERP study in which the environment itself is the independent variable. We also demonstrated that the environment in which one performs a task is enough to alter brain activity, and that the N1 and P2, while functionally related, clearly represent two separate processed in the early auditory system. It appears that the N1 increases when a situation requires increased attentiveness to a stimulus, while the P2 is altered any time the auditory task is more difficult to discriminate. As shown in previous studies, this effect appears to be independent of movement, alpha power and behavioural measures.

Discussion

Within this thesis we performed several studies, both outside and inside the lab, that allow us to better understand what cognitive processes take place in rich, ecological environments that are absent within the laboratory environment. We were also able to gain a better understanding of the specific function of the N1 and P2 components as well as alpha waves as they relate to dealing with environmental distraction. Finally, in two of these studies we showed that we were able to perform cognitive neuroscience experiments outside of the lab during mobile, outdoor tasks.

Auditory N1 and P2

The N1-P2 complex has been shown to reflect preattentive sound processing within the auditory cortex (Näätänen & Picton, 1987). The components of this complex include the P1, N1 and P2, and appear to be related to several processes that overlap temporally and originate within or near the primary auditory cortex (Näätänen & Picton, 1987; Wolpaw and Penry, 1975; Wood & Wolpaw, 1982). Through the four experiments in this thesis, we demonstrated that experimental conditions in which the participant performed the task in non-ideal conditions (i.e., with background noise or low volume) had a higher N1 amplitude than conditions in which the task was performed in ideal conditions (i.e., silent background with normal volume; Figure 4.7A). Previous research suggests that one of the main functions reflected in the N1 is a 'sensory acceptance-rejection' factor, which appears to attenuate all responses to irrelevant, uninteresting, or unpleasant sensory inputs while enhancing responses to important, interesting or pleasant stimuli (Näätänen & Picton, 1987). The auditory N1 has been shown to appear with shorter latency and larger amplitude when attended and unattended sounds are easily distinguishable by physical cues such as location and pitch (Näätänen, 1982, 1992). For example, previous studies

have demonstrated that the N1 increases when an auditory stimulus originates from a location where an individual was already attending (Teder-Sälejärvi, et al. 1998), and this effect is enhanced in individuals who are blind (Roder et al., 1999). N1 amplitude in particular is believed to increase as a function of increased attentional allocation and processing of a particular auditory 'channel' (Hink, Voorhis, Hillyard, & Smith, 1977). Functionally, the amplitude and latency of the N1 is believed to reflect the quantity of sensory information moving through an early mechanism of auditory channel selection mechanism (Hillyard. Hink, Schwent, & Picton, 1973), increased processing of attended channel information (Näätänen, 1982; Okita, 1981), as well as an indicator of how well-matched the eliciting stimulus and cue characteristics are within the attended auditory input channel (Näätänen, 1992). In the four studies in this thesis, experimental conditions in which the task was performed in a non-ideal auditory situation had a higher N1. This could be because these situations required an increase in attention or 'tuning in' in order to perform this sensory acceptance-rejection mechanism and better process the task stimuli with auditory distractions present.

We also showed that experimental conditions in which the participant performed a task in the presence of background sounds or scenery had generally lower auditory P2 amplitude than conditions in which the task was performed without distractions (Figure 4.7B). The auditory and visual P2 components have been shown to relate to cognitive functions such as memory performance, working memory, and semantic processing during contextually based tasks (Federmeier & Kutas, 2002; Dunn et al., 1998; Lefebvre et al., 2005). The P2 is also believed to reflect a component of perceptual processing and top-down cognition, and may represent a process of inhibiting the perception of repetitive or unimportant stimuli in order to perform a task (Freunberger et al., 2007; Luck & Hillyard, 1994). Additionally, some studies have

hypothesized the P2 to reflect a process of suppressing irrelevant stimuli to allow better stimulus discrimination within a primary task (Getzmann et al., 2016; Kim et al., 2008; Potts, 2004; Potts et al., 1996). Specifically, the auditory P2 appears to relate to the subjective difficulty of a stimulus discrimination task, as both the P2 and N1-P2 complex have been reliably found to increase in amplitude following discrimination training (Atienza et al., 2002; Hayes et al., 2003; Reinke et al., 2003; Trainor et al., 2003; Tremblay et al., 1997, 2002, 2001). More specifically to this thesis, one study by Getzman et al. (2016) showed a decrease in P2 amplitude in a speech discrimination task while participants had to ignore irrelevant concurrent speech in a 'cocktail party' scenario, compared to a condition with no background distractions. This helps to demonstrate why the P2 appeared to have reduced amplitude in any experimental conditions with background noise (Figure 4.7B), as this may represent a function of 'tuning out' distracting noises in auditory tasks.

The dichotomy between the functions of the auditory N1 and P2 can especially be seen in the silent-low condition of experiment 2, as this condition had an enhanced N1 with a non-affected P2, demonstrating that the low-volume task required enhanced attention, with no requirement to tune out irrelevant information. The two conditions of experiment 4 also demonstrate this dichotomy, as both of these conditions have a larger N1 amplitude than any of the conditions performed in an ideal auditory situation, and the roadway condition has a significantly higher N1 than the park condition. However the P2 amplitude for both of these outdoor conditions is near zero and much lower than any condition in which the task was performed in silence, demonstrating that while there was no P2 difference within this experiment, the P2 was likely reduced in both conditions due to background sounds in the outdoor environment.

Visual P2

While both the auditory and visual P2 appear to be modulated by discrimination between important and non-important perceptual information, previous literature suggests that the visual P2 appears to be modulated in the opposite direction from the auditory P2. That is, the visual P2 has been shown to have increased amplitude when inhibiting the processing of repetitive, unimportant or irrelevant stimuli (Freunberger et al., 2007; Korsch, Frühholz, and Herrmann, 2016; Phillips and Takeda 2009). For example, Korsch, Frühholz, and Herrmann (2016) demonstrated a significantly larger P2 amplitude during incongruent trials of a Flanker Conflict Task, in which participants were required to evaluate a task-relevant stimulus while ignoring several task-irrelevant stimuli. In our visual task, a larger P2 was shown when individuals were required to perform the task with a relatively repetitive and unimportant background (Noise screen), and a lower P2 amplitude was found while individuals viewed a relatively interesting ecological background (biking video; Chapter 3). In this way, it appears that the visual P2 works in a similar way to alpha power, in that it decreases in the presence of interesting and relevant visual stimuli, while increasing to inhibit the processing of unimportant stimuli.

Alpha Oscillations

Finally, we demonstrated that conditions in which the participants performed the task while viewing a visually rich stimulus had generally lower alpha power than those in which the task was performed while viewing a blank computer screen (Figure 4.7C). Alpha has long been known to reflect an individual's state of awareness (Mathewson et al., 2011), as it has been shown to increase with decreasing attentional focus, with the highest power when an individual's eyes were closed (Berger, 1929; Adrian & Matthews, 1934). Spontaneous increases in alpha oscillations have been linked with poorer performance on several cognitive tasks (e.g.,

Linkenkaer-Hansen et al., 2004; Mo et al., 2004; Babiloni et al., 2006; Del Percio et al., 2007; Hanslmayr et al., 2007; Mazaheri et al., 2009) as well as higher threshold detection rates across a number of stimulus types (Ergenoglu et al., 2004; Palva et al., 2005; Romei et al., 2008a,b; van Dijk et al., 2008; Mathewson et al., 2009). Additionally, increased alpha has been associated with the successful inhibition of visual distractor items in order to aid representations in working memory (Hamidi et al., 2009; Sauseng et al., 2009). The results in this thesis demonstrate how alpha relates to visual attention and awareness within ecologically valid environments, as when participants are drawn to pay attention to the visual aspects of their environment (i.e. any time they are outside or viewing a video), alpha is reduced. In comparison, when tasks are performed in visually impoverished environments (i.e. with only a blank screen to view), alpha is high because there is nothing to draw attentional awareness.

Conclusions and closing remarks

At the present moment, most cognitive neuroscience research tends to take place in highly isolated situations. In order to avoid any type of data noise, experiments are often required to deprive participants of expose to any extraneous light, sound and movement. This creates a disconnect between the laboratory environment and the real world, as we cannot accurately generalize results from these isolated situations to the rich visual and auditory environments we experience in our everyday lives. Mobile EEG is working to bring EEG out of these isolated situations and into the real world, however before we can remove the experiments from the lab, we need to first understand what parts of cognitive processing are changed when uncontrolled stimuli are present during a task. The goal of the current research was both to perform cognitive tasks in an outdoor mobile environment, and to understand what aspects of cognition change when one performs the same task with and without varying levels of isolation from the real

world. We found that situations in which one views any type of visual scenery, alpha power and visual P2 are decreased. This indicates that outdoor ecological environments draw our attention much more than sterile laboratory environments. We also found an increased auditory N1 component in all non-ideal auditory task situations, indicating that situations with background noise or in which the task is more difficult to hear, one must focus their attention a little more in order to compensate. We found a decreased auditory P2 component in situations in which auditory background noise was present, indicating that ecological environments require us to be constantly inhibiting the processing of unimportant and extraneous stimuli in order to perform tasks in the same way we do with no distractions. Finally, the dichotomy in results between the N1 and P2 components demonstrates the way in which attention can be separated into distinct processes of 'tuning in' relevant task stimuli while 'tuning out' distractions in the environment. Altogether, these results demonstrate the many components of attention and how they contribute to the brain functioning in everyday life, and the way we were able to investigate these mechanisms demonstrates the benefit to performing cognitive neuroscience experiments away from the confines of the laboratory.

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