Using Portable EEG to Assess Human Visual Attention

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Abstract. Over the past ten years there has been a rapid increase in the number of portable electroencephalographic (EEG) systems available to researchers. However, to date, there has been little work validating these systems for event-related potential (ERP) research. Here we demonstrate that the MUSE portable EEG system can be used to quickly assess and quantify the ERP responses associated with visuospatial attention. Specifically, in the present experiment we had participants complete a standard "oddball" task wherein they saw a series of infrequently (targets) and frequently (control) appearing circles while EEG data was recorded from a MUSE headband. For task performance, participants were instructed to count the number of target circles that they saw. After the experiment, an analysis of the EEG data evoked by the target circles when contrasted with the EEG data evoked by the control circles revealed two ERP components – the N200 and the P300. The N200 is typically associated with stimulus/perceptual processing whereas the P300 is typically associated with a variety of cognitive processes including the allocation of visuospatial attention [1]. It is important to note that the physical manifestation of the N200 and P300 ERP components differed from reports using standard EEG systems; however, we have validated that this is due to the quantification of these ERP components at non-standard electrode locations. Importantly, our results demonstrate that a portable EEG system such as the MUSE can be used to examine the ERP responses associated with the allocation of visuospatial attention.

Keywords: EEG · ERP · Attention · Visuospatial attention · Portable technology

1 Introduction

The collection of electroencephalographic (EEG) data used to be associated with expensive (>$25,000 USD), large electrode array systems. However, in the past ten years there has been a rapid increase in the availability and number of "low-cost" EEG systems available to researchers. However, what remains problematic is the extent to which these low-cost systems record data of sufficient quality for research purposes. Indeed, in a seminal paper Picton and colleagues [2] outlined standards that a "research grade" EEG system needed to have to be able to record a level of data quality necessary to allow collection of event-related brain potential (ERP) data. In particular, the Picton

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group [2] noted that electrode type, electrode quality [3, 4], number of electrodes [5], and amplifier specifications [6] all had minimum values that were necessary to meet a sufficient research standard. Initially, the low-cost systems that were available to researchers did not meet these standards and as such there was a paucity of published research using these systems. However, in recent years the quality of low-cost EEG systems has improved sufficiently that there is now a small, but rapidly increasing number of studies that have successfully used low-cost EEG systems to conduct ERP research [7–14].

Electroencephalography provides an excellent methodology for examining human visuospatial attention. Indeed, given the excellent temporal resolution of the technique, EEG and more specifically, ERPs provide a means to directly examine neural responses and their sensitivity to the allocation of attentional resources. While there are a myriad of ERP components that have been shown to be sensitive to attentional processing, here we will focus on two specific components – the N200 and the P300.

1.1 The N200

The N200 ERP component is a negative going deflection in the ERP waveform that occurs between 180 and 300 ms post stimulus onset [15] with the scalp topography depending on the how the N200 is elicited. Specific to the present study, the N200b ([16]: simply referred to in this paper as the N200) has a topography that ranges from central to posterior and is evoked by the occurrence of infrequent stimuli during performance of the visual oddball paradigm. Indeed, the amplitude of the N200 is sensitive to target frequency – thus it is evoked by any stimulus but is increasingly more negative with increasing target rarity. Changes in the amplitude of the N200 have been yoked to visual attention [17]. Specifically, the amplitude of the N200 evoked during oddball paradigms is typically reduced when the target is stimulus is not being attended.

1.2 The P300

The P300 ERP component reflects a positive, posterior deflection in the ERP waveform that can be as early as 300 ms post-stimulus onset but that can be observed as late as 800 ms post-stimulus onset [1]. Seminal work on the P300 associated it with context-updating [18]. The context-updating hypothesis posits that the P300 is sensitive to an updating of an internal model of the world, and as a result, it is sensitive to changes in stimulus frequency. The P300 is also a marker for visuospatial attention. Specifically, previous research [19, 20] has shown that the amplitude of the P300 is reduced for non-attended stimuli. In this manner, the P300 is reflective of underlying attentional processes, even if it is not a direct measure of visuospatial attention itself. Indeed, the amplitude of the P300 has been shown to be proportional to the amount of attentional resources that are available for stimulus processing [21, 22].

1.3 Hypotheses

In the present study we wanted to determine whether or not the MUSE EEG system (www.choosemuse.com) was capable of quantifying two ERP components associated with visual processing and the allocation of visuospatial attention, the N200 and the P300. As noted above, both the N200 and the P300 have been shown to be sensitive to the allocation of attentional resources. Here, participants completed a standard visual oddball task while EEG data was recorded via a MUSE EEG system. Importantly, our experimental setup was such that task presentation and data collection were completed on a single Macbook Air laptop. Our hypothesis was simple, we predicted that the MUSE EEG system would be able to record data of sufficient quality that the N200 and the P300 ERP components would be visible in the grand average ERP waveforms. Further, we predicted that a standard mean peak detection analysis would be able to statistically verify N200 and P300 ERP component existence.

2 Methods

2.1 Participants

Sixty undergraduate students (n = 60; 34 female, mean age: 21) from the University of Victoria participated in the experiment. All participants had normal or corrected-to-normal vision, no known neurological impairments, volunteered for extra course credit in a psychology course and provided informed consent approved by the Human Research Ethics Board at the University of Victoria. The study followed ethical standards as prescribed in the 1964 Declaration of Helsinki. We note here that the data used here is subset of a larger study that specifically validated the MUSE EEG system against a more conventional large array EEG system (Brain Products ActiChamp).

2.2 Apparatus and Procedure

Participants were seated in a sound dampened room in front of a Macbook Air computer and completed a visual oddball task while EEG data were recorded via a MUSE EEG system. The oddball task was coded in the MATLAB programming environment (Version 8.6, Mathworks, Natick, U.S.A.) using the Psychophysics Toolbox extension [23].

During the oddball task participants saw a series of blue (MATLAB RGB value = [0 0 255]) and green (MATLAB RGB value = [0 255 0]) coloured circles that appeared for 800 to 1200 ms in the center of a dark gray screen (MATLAB RGB value = [108 108 108]). Prior to the onset of the first circle and in between the presentation of subsequent circles a black fixation cross was presented for 300 to 500 ms (MATLAB RGB value = [0 0 0]). Participants were not told that the frequency of the blue and green circles differed: the blue circles appeared less frequently (oddball: 25%) than the green circles (control: 75%) with the sequence order of presented circles being completely random. Participants were instructed to mentally count the number of blue circles (oddballs) within each block of trials. Participants completed 3 blocks of 40 trials during performance of the oddball task. For a full time line of the task see Fig. 1.

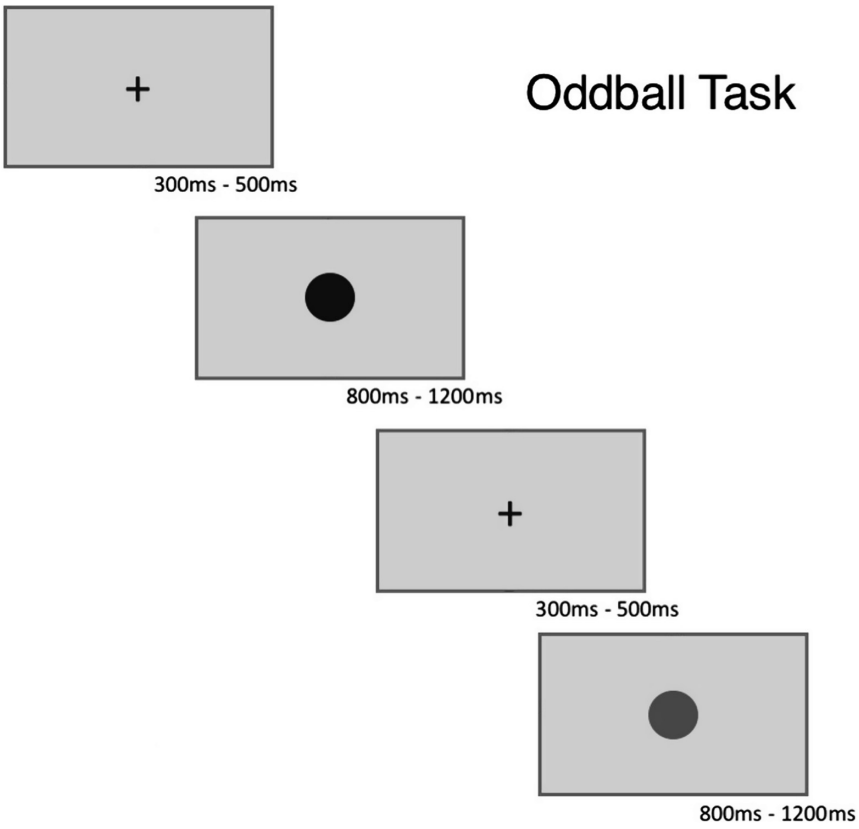

Fig. 1. Experimental timeline of the oddball task

2.3 Data Acquisition

EEG data in the MUSE group were recorded from a MUSE EEG headband with research preset AD (500 Hz sampling rate, no onboard data processing: InteraXon, Ontario, Canada) (see http://developer.choosemuse.com/hardware-firmware/hardware-specifications for full technical specifications). The MUSE EEG system has electrodes located analogous to Fpz, AF7, AF8, TP9, and TP10 with electrode Fpz utilized as the reference electrode. Using the muse-io SDK we streamed data from the MUSE EEG system directly to MATLAB via the open sound control (OSC) protocol (see http://www.neuroeconlab.com/muse.html for all configuration, setup, and acquisition methods and software). In essence, following the presentation of each experimental stimulus of interest we directly sampled 1000 ms of streaming data into MATLAB – subject to a small, varying inherent timing lag due to the Bluetooth connection (see http://developer.choosemuse.com/protocols/data-streaming-protocol). We tested the latency and variability of the latency of the Bluetooth EEG data stream by sending a series of 5000 TTL pulses into the MUSE auxiliary port from MATLAB and measuring the time

it took for these pulses to "return" and be visible in the sampled EEG data. This test demonstrated a mean lag of 40 ms (±20 ms). It is important to note that this time includes the transmission time of the TTL pulse to the MUSE, the time back from MUSE system via Bluetooth, the conversion to an OSC format via muse-io (the MUSE SDK software), and time needed to read the OSC message stream into MATLAB. We also note here, however, this variability was in part due to a few samples ($n < 10$) with extreme latencies.

2.4 Data Processing

The MUSE EEG were converted from the MUSE data into a format suitable for analysis in Brain Vision Analyzer (this software is available at http://www.neuroeconlab.com/muse-analysis.html).

The EEG data were first referenced online to electrode Fpz and as such we did not re-reference the data offline. Data were then filtered with a dual pass Butterworth filter with a passband of 0.1 Hz to 15 Hz in addition to a 60 Hz notch filter. The data were then segmented from the onset of the stimulus of interest to 600 ms after. Next, a baseline correction was applied to each segment using a window from 0 ms to 50 ms – a window that was chosen as we did not record EEG data prior to stimulus onset with the MUSE system. An artifact rejection algorithm was then implemented; as a result of this procedure segments that had gradients of greater than 10 μV/ms and/or an absolute difference of more than 100 μV were discarded. Finally, we pooled the data for electrodes TP9 and TP10 into a common pooled TP channel.

The segmented data were then separated by experimental condition (oddball, control) and event-related potential averages were created for each condition (oddball, control). Finally, a difference waveform was created by subtracting the control waveforms from the oddball waveforms. For each conditional and difference waveform, a grand average waveform was created by averaging corresponding ERPs across all participants. ERP components of interest were quantified by first identifying the time point of maximal deflection from zero μV on the grand average difference waveform in the time range of the component where this deflection was maximal (N200: 240 ms; P300: 335 ms). All peaks were then quantified on an individual basis by taking the mean voltage ± 25 ms of the respective time points for each participant.

2.5 Data Analysis

For all analyses the same statistical procedures were used. For each component (N200, P300) analyses were conducted on the mean peak amplitudes extracted from the difference waves. To confirm the differences between conditions of each component, we compared the mean peak difference data to zero using three statistical methods: 95% confidence intervals, t-tests ($\alpha = 0.05$), and 95% highest density Bayesian credible intervals.

3 Results

Our analyses of the grand average difference waveforms revealed components with a timing consistent with the N200 and P300 (see Fig. 2). Furthermore, all statistical tests determined that there was indeed a difference in the N200 and P300 component peaks as a function of experimental condition for all analyses (see Fig. 3).

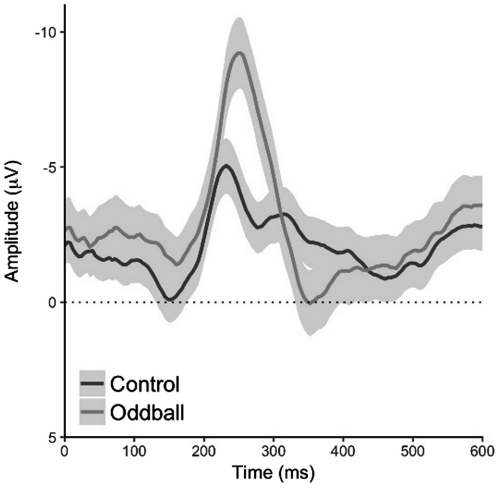

Fig. 2. Grand average conditional waveforms locked to the onset of the target and non-target stimuli at the averaged TP electrode. To allow meaningful interpretation of differences, the waveforms are shown with 95% confidence intervals.

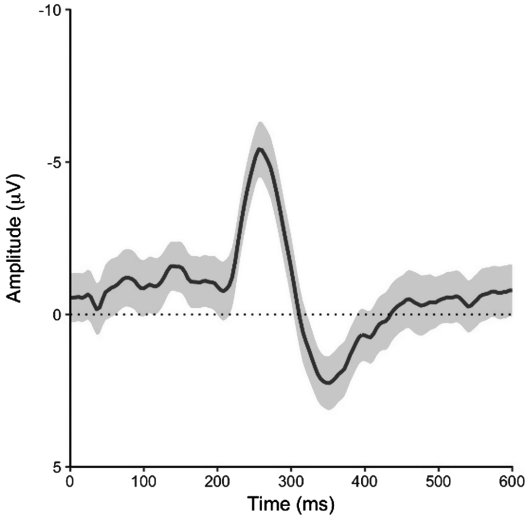

Fig. 3. The grand average difference waveform locked to the onset of the target and non-target stimuli at the averaged TP electrode. To allow meaningful interpretation of differences, the waveform is shown with its 95% confidence interval.

3.1 The N200

Our analysis of the MUSE data revealed a component was similar to the standard N200 ERP component (M_d = −4.85 μV [−5.95 μV −3.76 μV], $t(59) = -8.89$, $p < .0001$, Bayesian HDI: μ = −4.80 μV [−5.91 μV −3.69 μV]).

3.2 The P300

Again, our analysis of the MUSE data revealed an ERP component similar to previous accounts of the P300, albeit quantified at a non-standard electrode site (M_d = 1.37 μV [0.39 μV 2.35 μV], $t(59) = 2.80$, $p = .0069$, Bayesian HDI: μ = 1.36 μV [0.36 μV 2.36 μV]).

3.3 Resampling Analysis

To provide readers with a measure of the reproducibility of our result, we also implemented a resampling analysis wherein we pulled 10,000 samples from the existing data with increasing sample sizes from 2 to 60. For each sample size (e.g., n = 10), a single samples t-test against zero was conducted for each of the 10,000 samples. Plotted in Fig. 4 are the percentage of tests that were significant for each sample size.

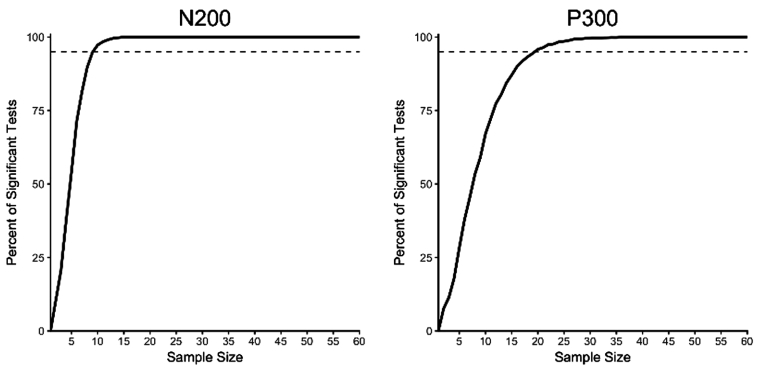

Fig. 4. The resampling analysis. The curve reflects a fit of the percentage of significant single sample t-tests for each sample size from 2 to 60.

4 Discussion

Our results clearly demonstrate that we were able to see and statistically quantify two ERP components associated with the processing and allocation of visuospatial attention, the N200 and the P300. Specifically, both the N200 and P300 ERP components

were clearly visible in the grand average conditional and difference waveforms. Further, a peak detection analysis statistically verified the existence of these two ERP components. We also implemented a resampling analysis that demonstrated that the N200 ERP component was reliably visible with a sample size of 10 participants. In terms of the P300, the resampling analysis demonstrated that a larger sample size of 20 participants is needed to reliably quantify this ERP component. The larger sample size needed to quantify the P300 is possibly related to the fact that we had to use non-standard ERP electrode locations with the MUSE EEG system (i.e., TP9 and TP10 as opposed to more standard posterior midline electrodes used to examine this component).

Importantly, our results show that we can measure some of the electroencephalographic correlates of visuospatial attention with in a simple and efficient manner. Attention has been studied quite extensively with electroencephalography. Indeed, in a prominent review paper in 2000, Luck and colleagues [24] reviewed 30 years' worth of research on the major findings of electroencephalographic studies of attention. Typically, ERP studies of attention focus on the P100 and the N100 components. However, with our technique and from pilot data in our lab to date we have not been able to detect these components. Most likely, this is due to the relatively small effect size seen in differences with these components and given the noise inherent in markerless approach we used with the MUSE system the "temporal jitter" in our data washes these components out. Conversely, the N200 and the P300 are quite large in terms of voltage effect size and thus we are able to observe them with our approach. As outlined above, the N200 and P300 have been shown to be sensitive to the allocation of visuospatial attention [15–21]. Thus, the MUSE EEG system and the approach used here can be quantify some of the processes that underlie, or at least sensitive to, the allocation of visuospatial attention.

Our data provide further support for the use of low-cost, portable EEG systems such as the MUSE for field research [9]. More specifically, our results increase the research capability of researchers to collect EEG data in clinical settings and out in the "real world" by demonstrating a simple to use, portable, low-cost methodology for collecting ERP data. Given these factors (ease of use, cost, etc.), researchers using this technology will now have the ability to collect large numbers of participants with relative ease. Supporting this, the data collected in the present study was done on average in less than 6 min per participant – a time that includes EEG system setup, task performance, and post experiment cleanup. Further, we remind the reader that our setup was done with a single MacBook Air laptop computer and a single MUSE EEG system – there were no wired connections thus further increasing the portability of the system. Indeed, the portability of data collection with MUSE is being demonstrated by a variety of projects in our laboratory – we have collected data from doctors working in hospitals, in a monastery in Nepal, and even from rock climbers during ascent of a climbing wall. We note here that to some extent our approach replicates previous work [25, 26] but our technique greatly improves the portability and ease of use of mobile ERP data collection.

5 Conclusions

In the present study, we have demonstrated that it is possible to quantify two of the electroencephalographic correlated of visuospatial attention – the N200 and the P300 – in a quick and efficient manner using the MUSE EEG system. Further, we demonstrate that this can be done with a single laptop computer. Combined with the low invasiveness of the system (it is a headband) and the Bluetooth connection our methodology opens the doors to the study of visuospatial attention in a variety of novel contexts.

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