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Towards a Brain Computer Interface Based on the N2pc Event-Related Potential

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***Abstract*— Research over the last decade has shown that brain-computer interfaces (BCI) based on electroencephalography (EEG) can provide an alternative input paradigm for both clinical and healthy populations. Currently, the majority of BCI paradigms rely on a limited number of brain potentials; thus there remain many EEG signals to be explored for BCI applications. One such signal is the N2pc event-related potential (ERP). The N2pc is an ERP elicited 150ms to 350ms post-stimulus onset in response to target detection in visual search tasks. During this time window, target detection causes a negative deflection in the ERPs measured contralaterally to the target, allowing the lateralization of the target to be determined. Here we explore the feasibility of an N2pc-based BCI paradigm by analyzing the classification performance of participants based on data collected during an N2pc elicitation task. We quantify performance as a function of two variables; channel selection and the number of trials averaged together to obtain the ERP. Preliminary results indicate that with as few as three trials, the N2pc can be classified at nearly 90% accuracy in some individuals. These results could directly lead to the development of a new BCI paradigm, which we plan to realize in future work through the construction of a speller interface.**

I. INTRODUCTION

Brain-computer interfacing (BCI) seeks to create a direct neural link between humans and computers, generally via the measurement of brain potentials using electroencephalography (EEG), analyzed with signal classification techniques. When successful, this neural link serves as an alternative input device that can be used to communicate or effect behavioral outcomes. Although other neural imaging techniques may be used to control a BCI [16], most rely on EEG due to its low cost, ease of use, and relative portability. Since EEG signals are based on the underlying neural activities, they can be measured completely independently of motor function. This allows EEG-based BCIs to restore function in those with spinal damage, or even to help amyotrophic lateral sclerosis (ALS) patients, who may be experiencing locked-in syndrome, establish a communication link with the outside world [11]. In addition to their clinical uses, EEG-based BCIs have the potential to enable new methods of interaction with computers for healthy individuals [14].

Although there have been more than 1100 cumulative BCI publications as of 2010 [7], the set of EEG signals utilized in these studies has remained limited. There has been a tendency to focus on three types of EEG signals: the P300 [6], motor-imagery [2], and steady-state visually evoked potentials (SSVEP) [1]. While these signals are efficacious due to their high signal-to-noise (SNR) ratio, 50 years of event-related potential (ERP) research have elucidated a much wider range of prospective BCI control signals. One such signal is the N2pc, an ERP related to visual search ERP, that we investigate here [12].

The N2pc is a signal related to the lateral orienting of attention in visual search tasks. First described by Luck [12], its functional significance is still debated [13], but it has been classically linked to the suppression of task-irrelevant distractors [12]. The signal is primarily observed in electrode sites over the occipital lobes contralateral to the target. Although its latency varies based on the task, it is generally observed around 200ms after target presentation [12]. Localization studies using magnetoencephalography have revealed that the N2pc is actually made up of two subcomponents. The early component is primarily generated in the parietal lobe, but is not seen in EEG signals. The latter component generates the N2pc ERP and is localized to the lateral posterior region of the cortex, which has been linked to the filtering of distracting items [8]. The discovery of the N2pc has enabled research on the mechanisms of visual search and target selection [5], but has not been explored in the context of BCI applications. Since the N2pc effectively identifies the visual hemifield containing the desired target, classification of the N2pc could be used as a form of binary search [4].

One advantage of the N2pc over other EEG potentials used for BCIs is that it is an inherently based on covert attention. Whereas SSVEPs and P300 can utilize covert mechanisms, their performance is greatly degraded in these situations. Using overt attentional signals, a recent study by Volosyak [15] reported an average accuracy of 96.79% to identify five classes. By comparison, in a study of covert classification of SSVEP signals by Kelly [9], participants only achieved a mean accuracy of 71% with two classes. In cases that require the covert orienting of attention, such as in patients with "locked-in" syndrome, one approach to improving this limited performance is through the use of alterative EEG paradigms. This is one of the primary motivations of the development of an N2pc BCI.

This work explored the development of a BCI based on the N2pc ERP. First, we elicited the N2pc using an existing paradigm developed by Eimer [5]. Then we conducted an analysis of classification performance as a function of (1) the

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channels used and (2) number of ERP trials (which we term *repetitions*) to ascertain the feasibility of an N2pc BCI. ERP signals are inherently noisy measurements, it is not likely that the N2pc will be reliably classified in single trials. In order to circumvent this limitation, it is common for multiple repetitions be averaged together to increase SNR. Before a real-time BCI can be developed, it is important to understand how many repetitions are necessary to achieve acceptable performance with the N2pc. Following the classification analysis we then discuss the potential implications of our initial results and give recommendations on how to further develop a BCI speller interface based on this paradigm.

II. Methods

A. Participants and Setup

Four right-handed college-aged participants (three males, one female) provided data for the purpose of this pilot study. All participants were members of the Bretl BCI laboratory. A James Long 128-channel EEG amplifier (model TCP-128BA), set at 10,000 gain, was used to collect continuous EEG sampled at 128Hz, filtered from 0.3 to 30Hz, from 10-5 channels FPZ, C3/4, P7/8, P5/6, P3/4, Pz, PO3/4, PO7/8, O1/2, and Oz. For artifact detection, six electrooculogram (EOG) electrodes were used: two on the outer canthus of each eye (to detect horizontal eye movements), and two above and below each eye (to detect blinks). The electrodes were all referenced online to the right mastoid, but re-referenced before analysis to the average of both mastoids. The ground electrode was situated on the right earlobe.

B. Experimental Design

The purpose of the first experiment was to determine how many trials of EEG data are necessary for reliable detection of the N2pc. We used the design of Eimer [5] to gather data for classification. By choosing to work with a proven experimental design, we maximized the likelihood of N2pc elicitation in our initial experiments.

A ring of numbers (integers from 2-9) was placed in a circle around a central fixation cross. The radius of the ring subtended a 2.7° angle. Two digits were randomly selected to serve as the target and distractor. Each of these two digits was randomly colored red, green, or blue, while all other digits and the fixation-cross remained white. Red digits corresponded to targets, whereas blue and green were both distractors. The subjects were instructed to hit "K" on the keyboard if the red digit was odd, "J" if the red digit was even, and no key if there was no red digit. Key presses were discarded, as they do not pertain to the N2pc; they were used just to increase subject engagement in the task.

Each trial consisted of three phases: stimulus display, fixation, and blink. The stimulus display lasted 150ms before being replaced by a white fixation cross for 1000ms which was then followed by a red fixation cross for an additional 1850ms. Subjects were instructed to blink during the red cross in order to avoid artifacts in the data window. Each experimental session contained four blocks of 150 trials, but only 66% of these trials contained targets. Of those target trials, only 75% contained lateralized targets. This means that approximately 50% of all the trials had targets presented laterally that could be used for analysis. The lateralization and presence of a target was determined randomly.

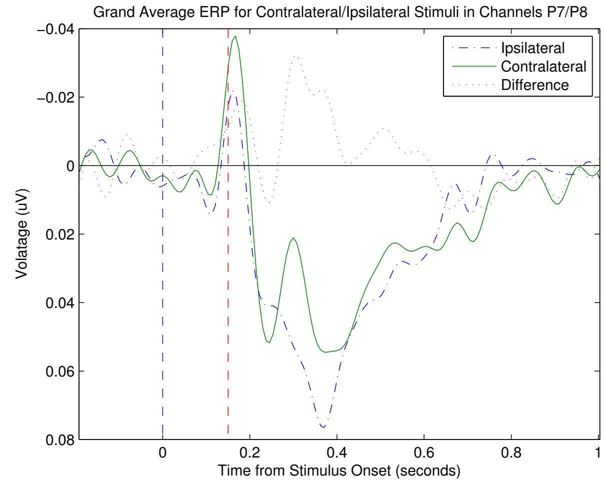

Fig. 1. Grand average ERP from four participants across 968 trials based on data from channels P7 and P8. The N2pc can be seen as a positivity in the channel that is contralateral to the desired stimulus. The peak of the difference wave has a latency of approximately 300ms after stimulus onset (blue dashed line). Stimulus offset is denoted as the red dashed line. For the purpose of presentation, the data in these figures are lowpass filtered to 15Hz.

C. Pre-Processing

For the purpose of data analysis and artifact rejection (body movements, blinks, blocking, power-line noise, and horizontal eye movements), individual trials were first extracted from the raw data. These trial periods include a time period of 200ms prior to and 1000ms following stimulus onset. Every channel of the 1200 collected trials was heuristically analyzed by the experimenters, trials judged to contain artifacts were rejected from further analysis. Following artifact rejection 968 trials were retained. This represents roughly 80.67% of the trials presented.

III. Results

A. ERP Analysis

For ERP analysis, trials from pairs of hemispherically lateralized opposing channels were unified into ipsilateral and contralateral data sets. For example, channels P7 and P8 are a two channels with opposite lateralization on the scalp, and would comprise one such pair. These data sets were then base-lined to the average voltage in the 200ms preceding stimulus onset. All trials across all participants were then collapsed into a grand average effect of ipsilateral versus contralateral target presentation. The grand average ERPs for the channel pair of P7/P8 are plotted in Figure 1. Using a Student T-test, the period of 250-350ms following stimulus onset was found to be significantly different ($p < .01$) between ipsilateral and contralateral electrode sites.

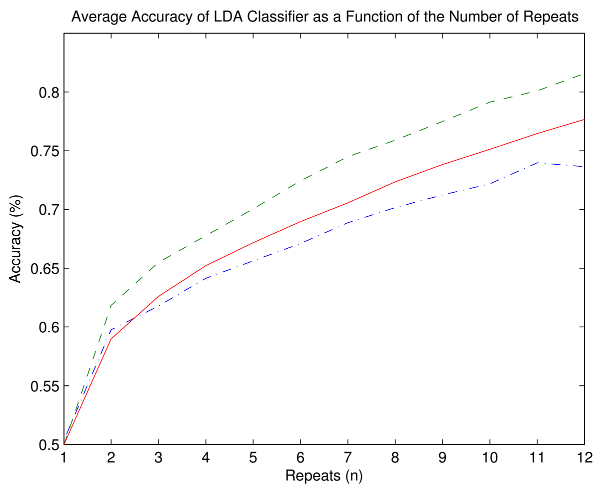

Fig. 2. LDA classifier performance as a function of the number of trials (n) averaged together. Results are plotted for two channels (dash-dotted line, P7 and P8), eight channels (dashed line, P7, P8, PO7, PO8, PO3, PO4, O1, and O2), and all recorded channels (solid line).

B. Classification Analysis

The goal of classification was to determine the lateralization of the N2pc. Based on the significant differences seen in the grand average ERPs, the mean voltages in the 250-300ms timeframe following stimulus onset was chosen as a classification feature. Visual inspection revealed this feature to be consistent across channels P7/8, PO7/8, PO3/4, and O1/2.

1) Classification Across Participants: 40 (20 target left and 20 target right) random training sets were taken from the data (without replacement) obtained for all subjects and used to train a classifier utilizing Linear Discriminant Analysis (LDA). These training sets were comprised of n randomly selected trials, which were then averaged together. Another 40 (20 target left and 20 target right) sets of n averaged samples were then randomly taken (without replacement) from the complete data set and used as a test set. This process was then repeated 500 times. Figure 2 shows the average classification results for n = 1:12.

2) Classification Within Participants: Further analysis of the individual participants proceeded in a similar manner to that used for the combined data set; this is plotted in Figure 3. 30 training trials and 30 test trials were selected at random and classification was obtained using LDA. There were a greatly reduced number of trials for each individual as compared with the combined data set; as such, the classification performance was compared within participants for n = 1:3 trials per average. Since performance was seen to vary between participants, it was logical to assume that the spatial distribution of the N2pc would vary as well. Each possible combination of channels was searched to find the set of channels that yielded the highest classification performance. The process was then repeated 500 times to obtain average performance.

TABLE I
LDA HIGHEST CLASSIFICATION ACCURACY AND ASSOCIATED CHANNELS BY PARTICIPANT

	2 Repetitions	Channels	3 Repetitions	Channels
S01	79.3%	P8 PO7 OZ	83.5%	P8 PO7 OZ
S02	84.3%	C4 PO4 OZ	89.7%	C4 PO4 OZ
S03	71.8%	P8 PO7	75.3%	P8 O1
S04	60.5%	C4 P7 OZ	64.4%	P5 P7 OZ

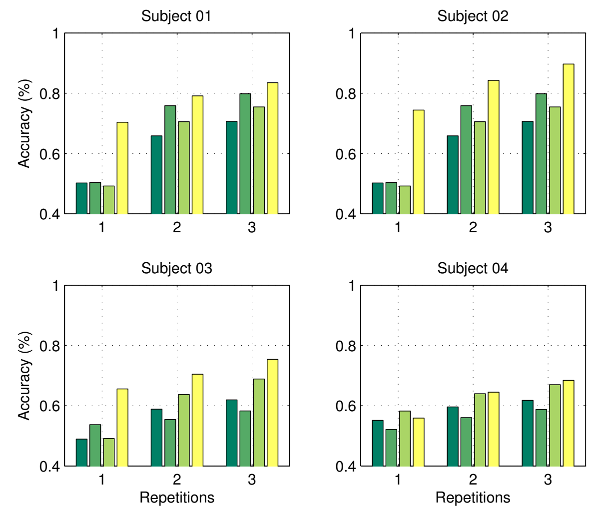

Fig. 3. Classification accuracy using LDA for each participant as a function of the number of trials (n) averaged together. Results are plotted for all channels (darkest color), two channels (P7 and P8, second darkest), eight channels (P7, P8, PO7, PO8, PO3, PO4, O1, and O2), and the best channels as revealed through search (lightest color).

IV. DISCUSSION

Our results, although preliminary, provide evidence that the N2pc can be classified at an accuracy that compares well with other BCIs based on covert attention [9]. Although expected, the results also demonstrate that the correct classification of a target character is a function of the number of repeats and the channels selected for classification. The performance in our experiment is subject dependent, with two participants achieving better than 75% accuracy with an average of only three trials across the eight channels with visible differences in the N2pc. One of the other two participants, achieved an accuracy only marginally better than chance, while the last participant achieved less than 70% accuracy using three trials. These differences could be attributable to differences in the ease of detection of the N2pc response, but may also be the result of other factors. By searching the available channels for the best possible set of electrodes, we were able to further improve classification performance to nearly 90% in one participant, and three of four participants achieved greater than 75% accuracy. The classification results for the combined data set with higher numbers of repetitions continue to improve; future work should acquire more data for each individual participant.

Considering other potential limitations and suggestions for improving the current study. Our task was limited to the detection of colored digits and participants reported that it was boring. This may have negatively impacted some of the recordings, motivational factors such as engagement and reward have previously been shown to have an impact on the amplitude of the N2pc [10]. A wider range of electrodes and reference locations should be considered, based on the data we obtained from this study. More channels from the parietal region of the scalp could improve performance by allowing the clearest possible signals to be extracted from the scalp. Changes in harware may also improve recordings, tin electrodes were used in the present work, in the future the use of non-polarizing Ag/AgCl electrodes will be explored as well as different amplifier filter settings.

Additional research is needed to determine classification performance in an experimental setting that better simulates target applications. For text communication, this would mean using the desired alphabet with the appropriate number of characters. It has been previously demonstrated that the amplitude of the N2pc is positively correlated with display size [13]. Since there are more letters in the English alphabet than numbers used here, this might directly (and positively) impact the amplitude of our measured potentials. The N2pc is also sensitive to stimulus duration [3], with shorter stimulus durations leading to high amplitudes. The faster an application could be run, the more information that can be transferred per unit time. A study that quantifies the differences in N2pc amplitude across participants as a function of display time would be beneficial to application design.

In terms of applications of these results, it seems plausible that the N2pc could be used to drive the selection process in a binary search. By displaying half of an alphabet on the left side and half on the right side, the N2pc could be used to determine which side the target is on. Following classification, we could decrease our search space to the side designated by the N2pc and thus, in a manner similar to a regular binary search, arrive at the appropriate letter. One difficult issue that has not been addressed by this work relates to error detection. If the spelling system were to misclassify a character and eliminate it from the visual cue, how would the user communicate that misclassification? In the simple binary classification scheme we propose, it would be very difficult to determine when the classifier had made a mistake, because the misclassified letter would disappear from the display. Misspellings could be left uncorrected, which could be aggravating to the user, but likely would not make the system unusable. Another option would be to create a hybrid BCI system that seeks to detect errors through classification of another type of ERP, the feedback related negativity. This might also argue for a different type of search scheme.

There are many variables still to be considered, yet this covert attentional paradigm achieved nearly a 90% classification rate in one of the participants with as few as three trial repetitions. If trials were to proceed at 1.5s each, it could be assumed that 12 or more classification decisions could be made every minute. If five selections were required per character, spelling rates of greater than two characters per minute could be achieved. This spelling rate is comparable to the fist iterations of the p300 speller by Farwell and Donchin [6]. Improvements to the system could make it a competitive alternative to existing EEG BCI paradigms and enable new types of BCI applications. Future work will focus on refining the classification schemes presented here and building towards a real-time system.

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