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P300-Based BCI Performance Prediction through Examination of Paradigm Manipulations and Principal Components Analysis.

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ABSTRACT

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Severe neuromuscular disorders can produce locked-in syndrome (LIS), a loss of nearly all voluntary muscle control. A brain-computer interface (BCI) using the P300 event-related potential provides communication that does not depend on neuromuscular activity and can be useful for those with LIS. Currently, there is no way of determining the effectiveness of P300-based BCIs without testing a person's performance multiple times. Additionally, P300 responses in BCI tasks may not resemble the typical P300 response. I sought to clarify the relationship between the P300 response and BCI task parameters and examine the possibility of a predictive relationship between traditional oddball tasks and BCI performance. Both waveform and component analysis have revealed several task-dependent aspects of brain activity that show significant correlation with the user's performance. These components may provide a fast and reliable metric to indicate whether the BCI system will work for a given individual.

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CHAPTER 1

INTRODUCTION

Amyotrophic lateral sclerosis, commonly known as ALS or Lou Gehrig’s disease, is a progressive neurodegenerative disease in which the myelin surrounding the neurons breaks down and disappears. This leads to a gradual loss of voluntary muscle control, with sufferers requiring both caregiver and mechanical assistance to stay medically stable during the latter stages of the disease (Kubler, Winter, Ludolph, Hautzinger, & Birbaumer, 2005). If patients survive long enough, they may be diagnosed with what is known as “locked-in syndrome” or LIS, where no voluntary muscle control beyond horizontal eye movements remains (Laureys, Owen, & Schiff, 2004; Vaughan, Wolpaw, & Donchin, 1996). ALS inevitably results in the patient's death, which is why there are so few individuals living with this diagnosis. Despite diagnosing 5,600 new cases of ALS in the United States each year, the ALS Association estimates only 30,000 people have the disease at any given time (ALSA, 2008).

In addition, the full paralysis that occurs in LIS means that traditional alternative and augmentative (ACC) devices that rely on some level of muscular control cannot be used with these patients (Pellegrini et al., 2007; Torricelli, Conforto, Schmid, & D'Alessio, 2008). This can be particularly unfortunate for those with ALS, as their quality of life (QOL; a general measure of physical and psychological health) is largely predicted by the level of social support and environmental control they experience (Bromberg, 2008; Chio et al., 2004; Kubler et al., 2005). Thus, LIS may represent a severe and irreversible decline in their quality of life. Caregivers’ QOL and their ratings of the ALS patient’s QOL are indeed significantly lower than control subjects (Kubler et al., 2005). On the other hand, studies have found that people with advanced ALS do not show increased depression or decreased QOL compared to healthy or less advanced control subjects (Kubler et al., 2005). It is important to note that in many locked-in cases (including ALS) the disability is in the connections to the muscles rather than in the brain itself. Although recent research does indicate a high incidence rate of frontotemporal lobe dementia in ALS patients (Giordana et al., 2010), this is not a guaranteed symptom, and any cognitive deficits tend to be mild and nonprogressive. Thus, while locked-in patients do not possess the motor control needed for more traditional devices, brain activity is still intact and largely identical to that in healthy subjects (Vaughan et al., 1996). A brain-computer interface (BCI) could then be used as an alternative control method to provide communication and control to locked-in patients (Nijboer et al., 2008; Sellers, Vaughan, & Wolpaw, 2010; Vaughan et al., 1996). BCI technology may represent these people's greatest hope to regain communication and control, and alleviate some of the suffering both for themselves and for their caregivers.

Classes of BCIs

Invasive BCIs

Single Unit Recording. There are many different types of BCIs, each focusing on a different aspect of brain activity. The most straightforward of these techniques is single-unit recording, where electrodes are implanted into the brain, either singly or in arrays, and the activation of neurons is directly recorded. As this technique is extremely invasive, the majority of this work has been with animals, monkeys in particular. Several labs have successfully translated neuron firing in the primate motor and premotor cortices into a BCI control signal used to move a computer cursor or to perform reach and grasping tasks with a robotic arm (Donoghue, 2002; Nicolelis, 2003; O'Doherty, Lebedev, Hanson, Fitzsimmons, & Nicolelis, 2009). Preliminary work has been done with human implantations, although the results have revealed several limitations that must be overcome before this technique can be suitable for long-term use in humans, notably the need for more efficient and effective interfaces and the limited understanding of the neural areas that would yield the most useful activations (Hochberg et al., 2006; Patil, Carmena, Nicolelis, & Turner, 2004). Ultimately, the primary limitation of this technique is that the implantation of electrodes into the brain triggers several immunological responses, most notably the generation of a cellular "sheath" surrounding the electrode, which severely limits the length of time any given electrode can be used to record (Rennaker, Miller, Tang, & Wilson, 2007).

<u>Electrocorticographic (ECoG) Recording</u>. Another invasive technique uses electrocorticographic (ECoG) signals. ECoG is recorded from an electrode array that is implanted above the dura mater, recording brain activity without the interference from the skull and muscle activity that would be seen with scalp electrodes. Again, due to the invasiveness of the technique very little research has been done with ECoG-based BCIs in humans. Most of what has been done is with patients already awaiting major brain surgery such as that done for intractable epilepsy (Leuthardt, Schalk, Wolpaw, Ojemann, & Moran, 2004). Using a variety of motor imagery tests, for example visualizing moving the hands for "up" and moving the feet for "down", ECoG BCIs have shown the ability to translate sensorimotor cortex activity into one- and two-dimensional cursor control (Leuthardt et al., 2004; Schalk et al., 2008). More recent studies have explored longer term use and have found that ECoG BCIs continue to show high levels of control even without patient-specific adaptive parameters; for example, adjusting the required amplitude for a task to match day-to-day changes in the patient's brain activity (Blakely, Miller, Zanos, Rao, & Ojemann, 2009).

Noninvasive BCIs

The majority of BCI research in humans has been conducted using electroencephalography (EEG). First recorded by Hans Berger in 1929, EEG is the electrical activity of neurons firing in the brain as recorded from electrodes placed on the scalp. Specifically, EEG records the changes in the electrical field at the scalp over time, measured relative to a specific point or points on the head believed to be electrically neutral relative to the brain activity of interest. This point is referred to as the "reference electrode"; common references include the right mastoid, the nose, and a "common average reference", a virtual electrode made from the average of all recording sites (Wolpaw & Wood, 1982). The result is an accurate and nearly instantaneous measure of the changes in the overall electrical gradients at the scalp and the electric potentials at each particular electrode, again relative to the reference electrode. EEG has several advantages over other possibilities for BCI research. First, it is noninvasive, allowing it to be used in healthy and locked-in subjects with no side effects. Second, it requires little equipment, set-up time, or training, allowing it to be easily used in the home. Finally, it provides superior temporal resolution (the ability to detect changes over time), such that brain activation is transferred from the scalp, to the recording device, to the computer, and finally to an output program in a matter of milliseconds, while providing enough spatial resolution (the ability to detect changes over space) to ensure accurate readings. Figure 1 shows the basic design of any BCI.

Slow Cortical Potentials. There are many different types of EEG-based BCIs, each focusing on a different aspect of EEG activity. For example, the slow cortical potential (SCP) is an EEG feature with a well-understood physiological source that people can through operant conditioning and feedback learn to exert a high level of conscious control over, creating positive

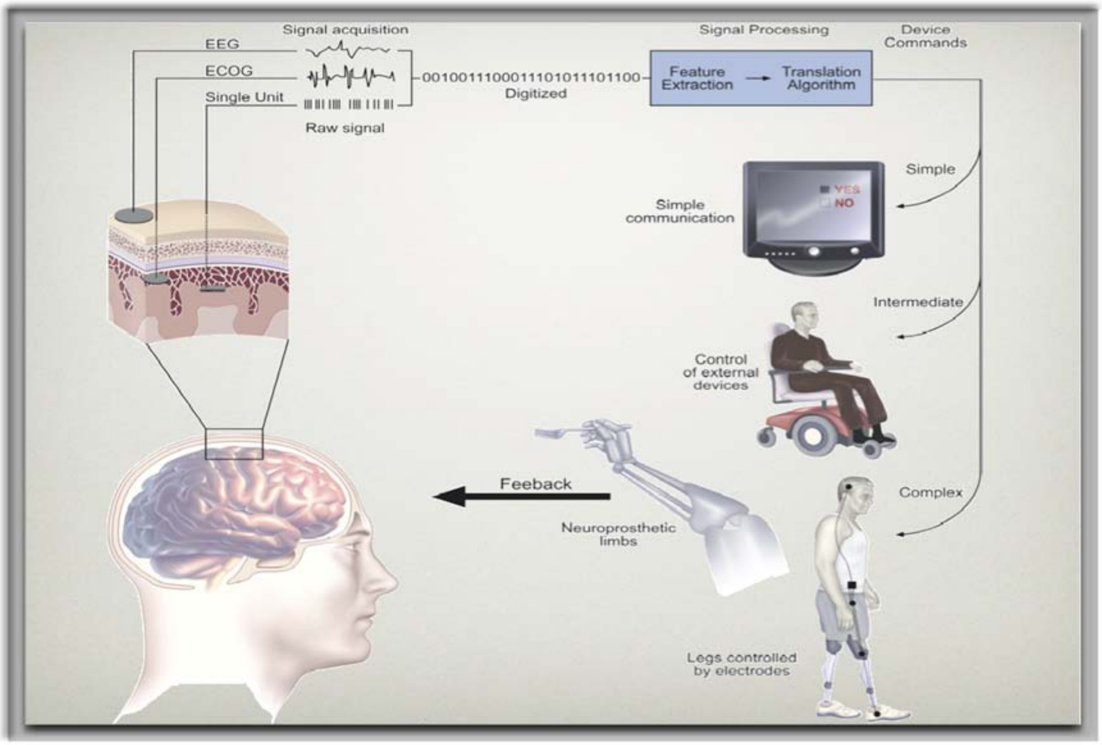

Figure 1. Standard BCI Setup. The figure shows a schematic of the essential components of a BCI system, illustrated as follows (clockwise from lower left): 1) Signal acquisition, the recording of the brain signal. This signal is then digitized for analysis. 2) Signal processing, the conversion of the raw signal into a useful device command. This involves both feature extraction, the identification of meaningful changes in the signal, and feature translation, the conversion of those signal changes into a device command. 3) Device output, the overt command or control functions that are administered by the BCI system. These outputs can range from word processing and communication to higher levels of control such as driving a wheel chair or controlling a prosthetic limb. All of these elements work in concert to give the user control over the environment. (Modified from: Leuthardt et al. (2006). The emerging world of motor neuroprosthetics: a neurosurgical perspective. *Neurosurgery,* Volume 59(1): 1-14.)

or negative shifts in the SCP amplitude over the right or left hemisphere and anterior or posterior cortex (Kubler et al., 1999). The amplitude of the SCP can then be inputted into a slope-intercept equation to generate one-dimensional movement of a computer cursor. This allows locked-in subjects to make a series of simple two-choice decisions, which can be used as-is or can form the basis for a more complex BCI such as the SCP-controlled spelling program that has been successfully used in locked-in populations (Birbaumer et al., 2000; Kubler & Birbaumer, 2008; Kubler et al., 1999).

Sensory Motor Rhythms. Similarly, Wolpaw et al. (2000) have shown that people can be trained to control the amplitude of the 8-12hz (mu) and 20-24hz (beta) EEG waves over the sensorimotor cortex through motor imagery tasks where the user visualizes but does not perform different types of motor activity (left versus right hand movement, hand versus feet movement, etc.). This was successfully used as the basis of a simple cursor-control BCI (Vaughan et al., 1996; Wolpaw et al., 2000) by entering the EEG amplitude into a slope-intercept equation to generate one-dimensional movement of a computer cursor. By adding in additional amplitudes to control additional axes – for example, using the amplitude at one electrode to control the x-axis and at another to control the y-axis – additional dimensions of control have been achieved (Wolpaw & McFarland, 2004). More recently, research with these BCIs have demonstrated accurate three-dimensional cursor control based on the EEG amplitude at a combined set of electrodes and frequency bands and have shown performance with two-dimensional cursor control tasks very similar to that seen with more invasive BCIs (McFarland, Sarnacki, & Wolpaw, 2010).

Event-related Synchronization and Desynchronization. Researchers have also examined event-related desynchronization (ERD) and synchronization (ERS) as a BCI control method.

These BCIs operate on the principle that different types of motor imagery lead to synchronization or desynchronization of different EEG components and thus increase or decrease their recorded power spectrum, respectively. By identifying the patterns of ERD and ERS that occur, it is possible to work backwards and identify the form of motor imagery the subject was using (Pfurtscheller, Brunner, Schlogl, & Lopes da Silva, 2006). This has been successfully used as a BCI control method for movement in a computer-generated virtual environment (Pfurtscheller et al., 2006) and for one-dimensional cursor control on a computer screen (Blankertz, Dornhege, Krauledat, Muller, & Curio, 2007; Blankertz et al., 2008).

P300 Event-Related Potential. Currently, the EEG signal that shows the most promise as a practical BCI system for disabled people is the P300 event-related potential (ERP). An ERP is a specific EEG potential that is time-locked to a particular stimulus or event. By averaging the EEG recorded following many instances of this event, the nontime-locked brain activity will average out and a clear time-locked ERP will be visible; this averaging is necessary due to the relatively low amplitude of ERPs compared to the sources of background noise such as muscle activity (Cohen & Polich, 1997). The P300, for example, is a positive EEG potential that occurs in response to an infrequent, task-related stimulus (Donchin, 1981; Polich, 2007). The P300 peaks at around 300 ms after the stimulus onset and tends to show a broad spatial topography across the midline and parietal electrodes using a right mastoid reference (Donchin, 1981; Polich, 2007). Figure 2 shows an averaged P300 for the rare target stimuli (X) in a standard oddball paradigm, which is a traditional method used to elicit the P300 (Picton, 1992; Ritter & Vaughan, 1969). Note the positive peak in the EEG at 375 ms, which is larger at parietal than frontal electrodes; this would be the P300.

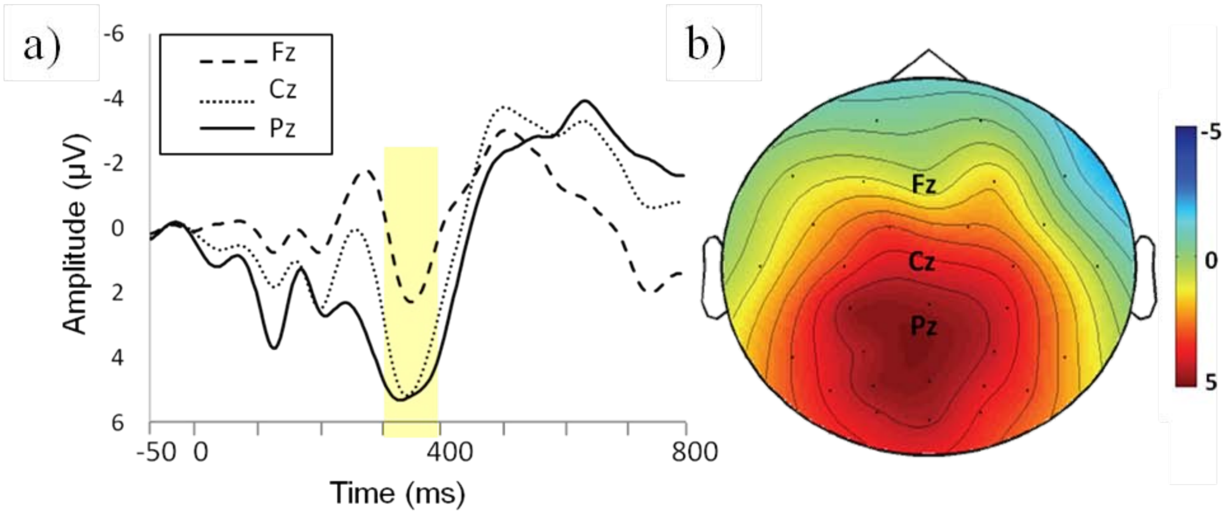

Figure 2. Selected Example of P300 Waveform. The figure shows an example of the P300 EEG response during a traditional oddball paradigm. a) Average EEG response to targets in an oddball paradigm recorded at electrodes Fz, Cz, and Pz of the 10-20 numbering scheme (Sharbrough, 1991). Both targets and nontargets evoke similar initial responses; however, the P300 (highlighted here as a positive peak at 375 ms) is specific to the targets, and acts as a marker for their occurrence. The P300 can be recorded at the highest amplitude at parietal electrodes like Pz and at lower amplitudes at the central and frontal electrodes. b) EEG scalp topography during the window highlighted in Figure 2a. Again, the P300 is heavily centered over the parietal electrodes.

The P300-based BCI was first developed by Farwell and Donchin (1988) to help restore communication to those with LIS. The BCI program presents the user with a 6-by-6 grid of letters, numbers, and computer commands on a computer screen. The user is either informed of one particular letter, number, or command to attend to; or, in the case of actual patient use, the user selects the desired target character to communicate. The rows and columns of the grid then flash in a random pattern. The flashes that contain the desired, attended character (i.e. the row and column that intersect at that character) form the set of rare, target stimuli, while flashes not at the target row or column form the set of frequent, nontarget stimuli. By examining which of the flashes generate a P300, the BCI system can identify both the target column and row and, through their intersection, the user's desired target character. An example of this process is shown in Figure 3b that displays the grid and an example flash used by the P300 speller; in this example, as the flashed column contains the current target letter "T", it would produce a P300. In this way the P300 speller program serves as a "virtual keyboard" that does not require motor control. The program can thus provide locked-in patients with communication by linking the speller program's output with common word-processing and e-mail programs and a level of independence by linking it with various room and environmental controls (Sellers, et al., 2010). As with traditional keyboards, however, typos must be deleted or backspaced for the end message to make sense. Because the "backspace" command in the P300 speller BCI is another target in the grid that must be selected, accurately and reliable P300 generation and identification is crucial for the user to be able to effectively communicate. It becomes very difficult to correctly spell a word or sentence with less than 70% accuracy (Kubler & Birbaumer, 2008; Sellers & Donchin, 2006; Townsend et al., 2010), and it is not possible with accuracies below

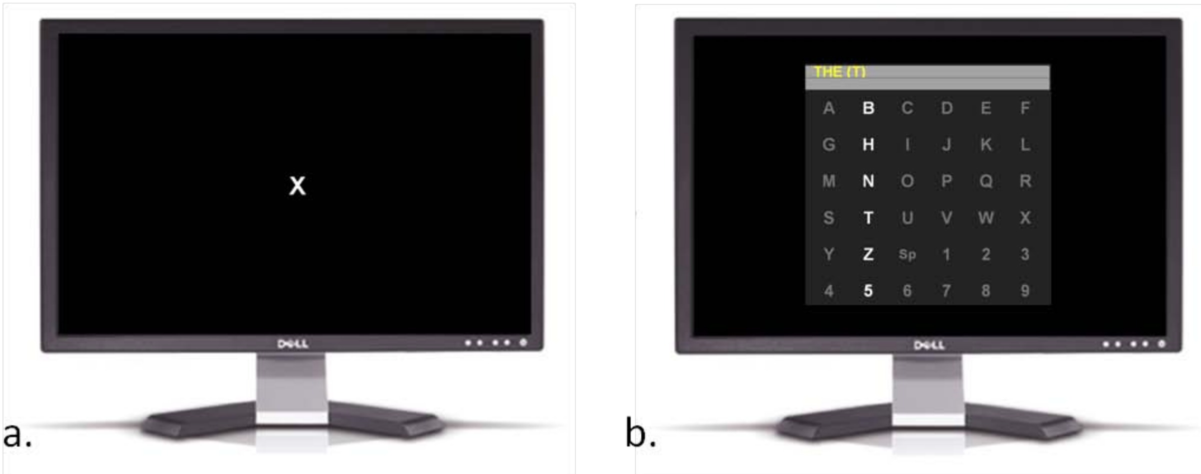

Figure 3. Images and Description of P300 Paradigms. a) In the slow (SO) and fast (FO) oddball tasks, Xs and Os are presented at fixation with a stimulus onset asynchrony (SOA) of 1 s for SO and 125 ms for FO. b) In the speller task, subjects attend to each letter of a specific word as the rows and columns flash in a random order.

50% as the user will be making more errors than correct selections (Sellers, Krusienski, McFarland, Vaughan, & Wolpaw, 2006).

The P300 BCI has been markedly improved since its initial development. Much focus has been placed on ways to improve the overall speed of the system, either through increasing the efficiency and accuracy of the user's communication, reducing the time needed for the user to learn how to use the BCI, or reducing the length and complexity of the BCI setup for the caregiver or researcher. Altering the matrix size and rate of stimulus presentation, measured by the time between the end of one flash and the start of the next (known as the inter-stimulus interval (ISI), has shown significant changes in both accuracy and efficiency as these variables change. Sellers et al. (2006) compared a 3-by-3 and 6-by-6 matrix size and a 175 ms and 350 ms ISI finding that accuracy was maximized in the 175 ms, 3-by-3 condition and efficiency was maximized in the 175 ms, 6-by-6 condition; this trade-off is something that current systems must take into account. The ability to accurately identify which flashes are generating P300s has also improved through new techniques for classifying the P300, particularly stepwise linear discriminant analysis (SWLDA) (Krusienski et al., 2006) and through the addition of data from posterior electrodes to the midline and parietal electrodes at which the P300 is traditionally maximally seen (Krusienski, Sellers, McFarland, Vaughan, & Wolpaw, 2008). In addition, several studies have examined the possibility of an auditory P300-based BCI either by substituting tones or sounds for the visual flashes or by presenting auditory and visual information concurrently. Auditory systems may be particularly beneficial for advanced LIS patients with a complete loss of eye movement. While eye movement is not necessary to orient attention (Posner, 1980) and the visual P300 speller may still function, an auditory system may be a viable and effective alternative for these people (Furdea et al., 2009; Klobassa et al., 2009).

The P300 Event-Related Potential

An understanding of the P300 BCI also requires an understanding of the P300 event-related potential (ERP). As with other ERP components, the P300 is defined by several characteristics. The most important characteristic is the context in which it is seen. The P300 as stated earlier is seen as a response to rare task-relevant stimulus. Traditionally, this is done through an "oddball" task during which the subject is presented with a random sequence of two types of stimuli, the frequent, nontarget stimulus and the rare, target stimulus, and asked to focus on the target stimuli. Averaging together the EEG recordings immediately following each target stimuli shows a strong positive peak in the EEG about 300 ms after the stimulus onset; hence the name "P300". This name is somewhat misleading as the latency does vary based on the characteristics of the oddball task it is recorded in (target frequency, task difficulty, etc.), sometimes occurring as early as 250 ms or as late as 400 ms after the target stimulus. However, it is traditionally considered to occur at 300 ms, and this provides a good metric for where to look for it in these contexts. The P300 also has a characteristic topography, showing the highest amplitude at central and parietal electrodes, slightly lower amplitude at the occipital electrodes, and little to no amplitude at the frontal electrodes.

As stated above, the traditional method for evoking the P300 is the standard oddball paradigm. While the presentation rate and modality of the stimuli in these experiments is variable (the P300 can be evoked using visual or auditory stimuli (Ritter & Vaughan, 1969; Squires & Donchin, 1976)), most oddball studies present stimuli every 1 to 2 seconds, measured either from the start of one stimulus to the start of the next (referred to as the stimulus onset asynchrony (SOA)) or from the end of one stimulus to the start of the next (referred to as the interstimulus interval (ISI)). Subjects are asked to attend to the sequence and to make note of each target stimulus that occurs, either to themselves or to the experimenter depending on the experiment. This procedure results in a clear, strong P300 peak each time the target stimulus appears, which is visible in Figure 2 as a large target-specific peak centered at 375 ms.

The P300 was first recorded in this way by Chapman and Bragdon (1964) as part of their work examining how people pay attention to stimuli. In their study subjects were required to attend to presented numerical stimuli in order to identify which was larger or smaller. These stimuli were presented in sequence, switching every 750 ms to either a blank screen or a plus symbol, which remained for a further 750 ms before switching to the next numerical stimulus. They noted a large positive increase in the average ERP over the central and parietal areas approximately 300 ms following the presentation of the numerical stimulus that did not occur for either the blank screen or the plus symbol. They concluded that this was due to the content of the presented stimuli; in essence, that the P300 indicated recognition of the stimuli they were attending to and expecting.

These findings were expanded upon the following year by Sutton et al. (1965). In this study subjects were exposed to two different types of stimulus pairs. In one pair the initial cueing stimulus was always followed by a test stimulus of the same type, either visual in the form of a brief flash of light or auditory in the form of a brief click, such that when the subject observed the cueing stimulus they could be predict with certainty what form the test stimulus would take. In the second pair a cueing stimulus was followed by a test stimulus of either form, auditory or visual at an experimenter-determined ratio, such that the subject could not predict what form the test stimulus would take. The stimuli were presented in sequence blocked by pair type, predictable or unpredictable, and the subject was asked to predict what form the test stimulus would take in the 3 to 5 seconds between the cueing and test stimulus. The results showed significant differences between the average EEG response for the predictable and unpredictable pairs. A large positive peak about 300 ms after the test stimulus – the P300 – was seen for pairs where the test stimulus was unpredictable that was not seen for pairs where the test stimulus was completely predictable. Follow-up experiments and analysis comparing the ERPs for pairs of different rarities (where the test stimulus was 33% likely or 66% likely to be auditory, for example) and for pairs where the subject correctly or incorrectly predicted the form of the test stimulus further confirm the character of the P300 as a marker for rare or "oddball" stimuli, with rare and unexpected stimuli showing a higher amplitude P300 than the common or expected stimuli. This supports and expands upon the definition provided by Chapman and Bragdon (1964).

The P300 has been explored in several different experimental paradigms since the initial studies by Chapman and Bragdon (1964) and Sutton et al. (1965). Donchin and Cohen (1967) presented subjects with two separate streams of stimuli, either a series of triangular flashes superimposed on a background of a Necker cube (an optical illusion in which the cube appears to reverse foreground and background repeatedly) or a series of square flashes superimposed on a background that repeatedly alternated between concentric circles and a star shape, depending on the subject. Subjects were told to specifically focus on either the foreground flashes or the background changes and to press a button every 10th time it flashed or changed. They found that the P300 was evoked only by the stimulus that the subject was attending to (a subject attending to the foreground would show a P300 after each foreground flash but not background change) indicating attention and task relevance as important parts of the P300. Further studies that present multiple streams of stimuli have confirmed the importance of task relevance e.g., (Pritchard, 1981). Similarly, as in Chapman and Bragdon's initial work, studies using equiprobable targets and nontargets have shown an attenuated P300 for the target stimulus (Duncan-Johnson & Donchin, 1977). The relationship between P300 amplitude and stimulus probability has also been expanded upon, with studies showing weaker but still significant increases in amplitude for rare over common stimuli independent of their classification as targets or nontargets even if the subject was informed whether the next stimulus in an oddball paradigm would be rare or common (Polich, 1990; Tueting, Sutton, & Zubin, 1970).

Polich (1990) also examined the changes in P300 amplitude during the oddball paradigm over a wider range of ISIs and stimulus probabilities. He found that particularly long ISIs (4 seconds, 10 seconds) yielded strong P300s with no significant differences in amplitude regardless of target probability (using target probabilities of .20, .50, and .80). Contrastingly, shorter ISIs (1.5 seconds, 3 seconds) resulted in both the previously observed increase in amplitude at decreased target probabilities (e.g., .10, .30, and .50) and an overall decrease in amplitude at the shorter ISI. Polich suggests that this relationship is based on the amount of available processing resources; while long ISIs allow the full amount of resources to be devoted to each target, at ISIs below 3 seconds the available resources for each target begins to decrease, resulting in the observed effect of probability. Recent research has clarified this relationship, suggesting that the variance of amplitude over probability and ISI may be due to the corresponding changes in the time between target presentations (target-to-target interval, TTI) (Croft, Gonsalvez, Gabriel, & Barry, 2003; Gonsalvez & Polich, 2002), but the underlying connection to the available processing resources remains valid.

The connection between the P300 and the amount of available cognitive resources has been further explicated through oddball studies examining workload and task difficulty. Many studies have used dual task paradigms where the subject is asked to perform two tasks concurrently, in this case an oddball task and another cognitively demanding task such as a simulated airplane landing or another oddball task (Fowler, 1994; Kramer, Wickens, & Donchin, 1985). For example, the subject is asked to focus on a cognitively demanding task (referred to as the primary task) and performance on a secondary oddball task is observed. In situations where the two tasks are competing for resources, the difficulty of the primary task will affect the amount of resources available for the secondary oddball task. Fowler (1994) examined pilots performing a simulated landing who were also asked to perform a visual or auditory oddball task, discriminating between flashes on the horizon or tones played into the cockpit. As the workload of the landing task increased through increased turbulence and other similar difficulties, the P300 latency increased. This is in essence an increase in the subject's cognitive reaction time to the oddball task due to a decrease in the amount of cognitive resources dedicated to the task. P300 amplitude, however, showed a more complex relationship, with the P300 amplitude for the auditory oddball tasks showing no correlation with the landing task difficulty and the amplitude for the visual oddball tasks increasing with the landing task difficulty. P300 latency also increased as the amount of available oxygen in the cockpit decreased, due to the induced hypoxia state decreasing the total amount of available resources and thus also decreasing the resources available to the oddball task. These changes in P300 latency show a competition for cognitive resources between the tasks and confirm the importance of available resources to the P300.

Alternately, it is possible to set up a dual-task paradigm where both the primary and secondary tasks are correlated or involve processing the same stimuli such as two tasks tracking two different aspects of the same general stimulus. In this case the primary and secondary tasks may potentially share cognitive resources, and increasing the difficulty of the primary task should increase the amount of resources used in both tasks. Kramer, Wickens, and Donchin

(1985) explored this possibility using a dual-task paradigm that varied both the difficulty of the primary task, tracking a moving cursor with a joystick, and the degree to which the secondary oddball task shared characteristics with the primary task, varying whether the subject needed to track flashes of the tracking square or a separate horizontal bar and whether the flashing square or bar was in the same or different spatial location on the y-axis as the moving cursor. In conditions where the two tasks involved processing different objects, increasing the difficult of the cursor tracking task yielded similar results to those of Fowler (1994), with increased difficulty of the primary task leading to an increase in the latency of the P300 to the secondary oddball task. However, in conditions where the tasks involved processing different properties of the same stimulus, increased difficulty resulted in an increase in the amplitude of P300 for the secondary task. Additionally, performance on the primary cursor tracking task also increased with the increased difficulty. This would be consistent with the changes seen in P300 amplitude in Fowler (1994); while the auditory oddball task was unconnected to the primary landing task and thus showed no changes in amplitude with primary task difficulty, the visual oddball task involved flashes on the horizon and might therefore show this theorized positive interaction, with increased primary task difficulty leading to increased P300 amplitude. The conclusions from these studies regarding the P300 and cognitive resources have thus been the same: the P300 is strongly affected by the amount of available resources with a decrease in amplitude and increase in latency of the P300 as the resources devoted to it decrease (Donchin, Kramer, & Wickens, 1982; Fowler, 1994; Gopher, 1986; Kramer, Trejo, & Humphrey, 1995; Kramer et al., 1985; Prinzel, Freeman, Scerbo, Mikulka, & Pope, 2003).

Habituation of the P300 is an important issue to consider for its use in BCI. While several other EEG responses used in BCI research, such as sensorimotor rhythms, are trained over time to become more consistent and more discriminative, the P300 is strongly affected by the perceived probability or unexpectedness of the target stimulus. Thus, repeating the same task over long periods of time, which leads to improvement with other EEG BCIs, may result in an attenuated P300 in the context of BCI. Decreases in amplitude have been observed in previous studies that examined P300 amplitude and latency in oddball tasks over a period of several months (Kinoshita, Inoue, Maeda, Nakamura, & Morita, 1996; Kramer, Schneider, Fisk, & Donchin, 1986), with later oddball tasks showing a decrease in observed P300 amplitude compared to the earlier tasks. Kinoshita et al. (1996) explored this further by having subjects performing two additional sessions of oddball tasks a month after the study ended (i.e., subjects were asked to return for additional sessions after they had been informed that the study had been completed). The P300 amplitude during these additional sessions returned to the levels observed in the initial sessions of the study. This suggests that the observed decrease in amplitude was due to complacency and a decrease in the attention given to the task, and a certain degree of novelty in the task should be sufficient to avoid these decreases in amplitude over time (Polich, 1989). With the motivation to spell novel and independent words using a P300 BCI, this habituation should thus not be a concern. In fact, several studies have shown the P300 BCI to provide reliable and accurate performance over periods from up to 20 consecutive sessions (Nijboer et al., 2008; Sellers & Donchin, 2006), to up to nearly 3 years (Sellers et al., 2010).

Current Issues

The primary focus of the current study is to examine two key issues that have not been adequately addressed in the BCI literature with the goal of improving our understanding and classification of the ERPs underlying the BCI spelling program. The first issue is that we cannot guarantee the P300 generated by the speller will resemble the traditional waveform shape seen in the oddball studies. The P300 BCI is arguably a more difficult task than the traditional oddball, requiring discrimination between a larger number of stimuli, shifting gaze between different areas of the screen, and tracking position, all of which could lead to an increased workload relative to the traditional oddball task. The P300 evoked during the speller may thus have a decreased amplitude and increased latency compared to the traditional oddball, as in the previously discussed research on P300 and task workload (Donchin et al., 1982; Fowler, 1994; Gopher, 1986). Similarly, there is the possibility the speller is in fact a dual-task paradigm (Sellers & Donchin, 2006), requiring focus both on the current letter and on the position in the overall word; this would also increase workload and affect the P300 (Kramer, Wickens, & Donchin, 1983). Additionally, the stimulus onset asynchrony (SOA) of 125 ms is not only significantly faster than that used by most oddball studies, raising concerns over the noted effects of fast ISIs on the P300 (Polich, 1990), but also means that the stimulus presentation rate is faster than the standard noted P300 latency of around 300 ms. This raises the potential concern of overlapping target and nontarget responses that would lead to further differences from the traditional average waveform.

Second, at the moment there is no good a priori way of determining how well a person can use the system. The current method requires first going through several sessions of training and analysis to identify the individual user's BCI proficiency, at the end of which the user may prove to be unable to reach the necessary threshold for accurate use. It is unclear why some subjects succeed at this task where others fail, whether the difference lies in their ability to understand the task and to focus on the targets or in some physical difference in their P300 generation. It is possible that these differences in performance may also be seen in the traditional oddball tasks, and that observing the differences through these shorter, simpler tasks would be a faster way of assessing a person's potential with the P300 BCI; however, given the aforementioned differences between the P300 speller and the oddball tasks, it is also possible that there are no direct connections between performances at these two types of experiments. In either case, a better understanding of the connections between people's performance and P300 generation and their success with the P300 speller is needed, both directly to help in predicting success and indirectly to guide further research into examining the possible underlying psychological or neurological differences that lead to success or failure.

The goal of the current study is to address the following issues. First, we plan to compare the ERPs generated in a variety of oddball paradigms including a standard oddball with an SOA of 1s, a fast oddball with an SOA of 125 ms (matching the P300 speller), and the P300 speller, to determine which characteristics change as the ISI and stimulus type changes. Second, we plan to compare these characteristics to the subject's subsequent performance on a speller task to determine if there are predictive relationships between the P300 in the standard oddball paradigm and P300 speller performance. These analyses will elucidate the similarities and differences between the P300 speller and the traditional oddball paradigm and may provide a fast and reliable metric to determine if the P300 speller will work for a given individual.

CHAPTER 2

HYPOTHESIS

First, we expect the grand average ERPs will differ between the tasks based on the known aspects of the P300. Given the effect of shorter ISIs, ERPs generated by the slow oddball will be higher amplitude and longer latency than those generated by the fast oddball condition. Due to the increased complexity of the speller task, we expect that speller ERPs will be lower amplitude than for either the fast or slow oddball paradigm, with latency to the P300 similar to that of the fast oddball. Second, we expect that the amplitude of the fast ISI oddball will predict success with the P300 speller; that is, we expect a significant positive correlation between the amplitude of the P300 in the fast oddball task and performance in the speller task. Latency within each of the three tasks is not expected to vary significantly between subjects and a correlation between latency and speller success is not expected. Finally, we expect principal components analysis to reveal further significant differences between the average ERPs of the high accuracy and low accuracy subjects. Specifically, we expect that EEG components related to the speller task (primarily the P300) will explain a larger amount of the EEG variance in the high accuracy subjects than in the low accuracy subjects, and that task-irrelevant EEG activity such as activity associated with the 8 Hz presentation rate will explain a significant amount of variance (due to the large proportion of nontargets in all three tasks) but be unrelated to user performance. These results can confirm the hypothesis that a user's performance is determined by the ability to properly focus on the task and perform the cognitive processing necessary for accurate and reliable generation of the P300.

CHAPTER 3

METHODS

Participants

Volunteers were recruited from the East Tennessee State University Psychology Department subject pool. All volunteers completed a consent form and questionnaire prior to participation and were excluded if they suffered from a neurological disease that could affect their results (e.g., ALS, multiple sclerosis, or epileptic seizures). Forty-eight volunteers signed up to participate in the study; of these, 31 successfully completed all required sessions and were included in the analysis.

Materials

Volunteers were measured and fitted for an EEG recording cap (Electro-Cap International). The electrode caps are placed so that the 32 embedded tin electrodes match the appropriate positions on the volunteer's scalp according to the modified 10-20 positioning montage (Sharbrough, 1991). A conductive gel is used to provide a low impedance connection between the scalp and the electrode. Impedances were maintained at or below 10 kΩ, and EEG signals are amplified and recorded using two g.tec (Guger Technologies) 16-channel USB bioelectric amplifiers.

Data Processing

The EEG signal is digitized at a rate of 256 Hz and band-pass filtered between 0.5 and 30 Hz. The amplified signals are processed by the BCI2000 software (Schalk, McFarland, Hinterberger, Birbaumer, & Wolpaw, 2004), with the program output divided between the experimenter's laptop screen and a second monitor in front of the subject. All data collection and analysis was performed using a right mastoid reference in keeping with previous work using the P300 BCI Speller (Sellers & Donchin, 2006).

After data collection, the EEG data were further processed during offline analysis to remove background noise and high amplitude artifacts using the EEGLAB (Delorme & Makeig, 2004) and NeuroScan (Compumedics) programs. Each EEG epoch (the period of time following each presented stimuli) was baseline corrected based on the 50 ms immediately preceding the stimulus to reduce the effect of long-term shifts in the baseline EEG amplitude and focus on the immediate changes due to the stimulus. A 30 Hz lowpass filter with 24dB octave attenuation was run to remove high frequency noise such as the common 60 Hz background generated by power cables. Finally, epochs with amplitudes exceeding +/- 100 microvolts were identified and excluded from the analysis, as this would indicate a recording artifact unrelated to the user's brain activity. These transformations help to ensure that the analyses performed were primarily driven by the user's own brain activity.

Protocol

The study consisted of 2 one-hour sessions carried out on separate days. The first session consisted of two variations of the traditional oddball paradigm shown in Figure 3. Subjects sits in a chair facing the computer screen and are told that a series of Xs and Os will flash on the screen. Subjects are then asked to note to themselves every time the rare 'X' target stimuli occurs while ignoring the frequently presented 'O' nontarget stimuli (Figure 3a). Task strategies such as mentally counting the Xs or internally voicing 'X' each time one occurs are offered but subjects are told to use whatever strategy allows them to accurately note every target occurrence. Subjects are also told to remain calm, still, and relaxed during recording to reduce the amount of noise in the recording due to muscle tension or blink artifacts. The first four runs follow the *slow* oddball paradigm, which uses a 1sec SOA and a flash duration of 125 ms. Each run consisted of 26 target and 125 nontarget stimuli and thus a total run time of approximately 2 minutes 15 seconds. The next three runs follow the *fast* oddball paradigm that simulates the presentation rate of the P300 speller paradigm (125 ms) and runs for 102 target and 498 nontarget stimuli, for a total run time of approximately 1 minute 20 seconds. The probability of the 'X' stimulus was 17% and the probability of the 'O' stimulus was 83%, which is matched to the target probability of the P300 speller task.

The second session uses the P300 spelling paradigm. As in the oddball task, the subject is asked to focus on the computer screen and to note each time a specific character flashes. The same strategies and instructions as the previous session are repeated to insure similar user behavior between the two sessions. In the speller task the characters are arranged in a 6-by-6 grid with the rows and columns of the grid flashing in a random sequence. Each row and column of the grid is flashed 13 times, such that there are 156 flashes for each character, 26 targets and 130 nontargets. Each run consists of multiple letters set to spell out a specific word. For example, one run may consist of spelling the word "THE" by focusing on the letters 'T', 'H', and 'E' in order, with short pauses between each letter to allow the user to switch focus to the next letter. The user is informed of the word to spell at the start of each run, and the system shows at the top of the screen both the current word and the current target letter in parentheses (see Figure 3b). The first five runs are conducted without the user receiving feedback on which letter was selected by the BCI system, as the system has not yet adjusted to the user's P300 location and latency; the selections are thus unconnected to their performance and feedback would be potentially hazardous to their training. The subject is asked to spell, in turn, "THE", "QUICK", "BROWN", "FOX", and "JUMPS". After this, a stepwise linear discriminant analysis

(SWLDA) (Draper & Smith, 1981) is performed to determine which electrode locations show the maximal P300 to the target flashes.

SWLDA is an analysis method that classifies the differences between two or more group within a data set as a linear combination of their features – in this case, how the target and the nontarget stimuli differ based on the waveforms they evoked at each electrode. In stepwise linear discriminant analysis the classifier is built sequentially. The total set of features is examined to determine which will most improve the current model's ability to discriminate between the classes; this feature is added to the linear model, then the remaining features are examined to determine the next feature that best discriminated between the two classes. After the model is tested to make sure that both features still account for a significant amount of discriminability, and the process repeats in this forward and backward manner until none of the remaining features significantly improve the model (using the predefined criteria for entry and exit from the model of entry at $p < 0.10$ and removal at $p > 0.15$; previous studies have determined these values to be adequate (Sellers et al., 2006)). For the current study SWLDA provides a user-specific linear classifier that shows the electrode locations and the time points at that location where the user shows the most reliable differences in EEG activity for targets versus nontargets. This classifier can then be used in future trials to discriminate between target and nontarget responses to determine which character it appears the user was attending to, and to provide immediate online feedback based on this prediction. The final four runs are thus run using this classifier, with users receiving feedback on which letter the system determines they were focusing on after each letter in a run, as if they were freely spelling using the BCI. The words to spell for these four runs are, in order, "OVER", "THE", "LAZY", and "DOG".

Analysis

Several different analyses were performed to satisfy the goals of the study. First, the EEG data were divided into epochs centered around each stimulus from 50 ms before stimulus onset to 800 ms after and averaged to provide average target and nontarget ERP both for each subject individually and across all subjects in each respective task. The amplitude and latency of major ERP peaks showing target to nontarget differences in the average waveforms were compared across task and performance to identify any significant differences. Here, we refer to performance as online accuracy or offline-determined accuracy at an optimal number of stimulus flashes. The optimal number of flashes is determined by the written symbol rate (WSR) (Furdea, et al., 2009), which is calculated as follows:

$$\mathrm{WSR} = \frac{2\left[\dfrac{\log_2 N + P\log_2 P + (1-P)\log_2\left(\dfrac{1-P}{N-1}\right)}{\log_2 N}\right] - 1}{T}$$

where *N* is the number of targets, *P* is the probably that the target is accurately classified (determined by the SWLDA results for the subject), and *T* is the trial duration in minutes. The number of flashes that gives the highest WSR is determined to be the optimal number, as shown in Figure 4, and the user's accuracy at this number of flashes is used as an additional performance measure. These analyses will provide a better understanding of how the latency and amplitude of the P300 changes between tasks and which, if any, of these aspects serves as a predictor of success.

We also performed a principal components analysis (PCA). Similar to SWLDA, which is also a way of organizing and explaining the variance in a dataset, PCA identifies the features and variables that explain the amount of variance in the data, instead of the ones that discriminate between the specific classes of interest (Pearson, 1901). In the case of the current study's

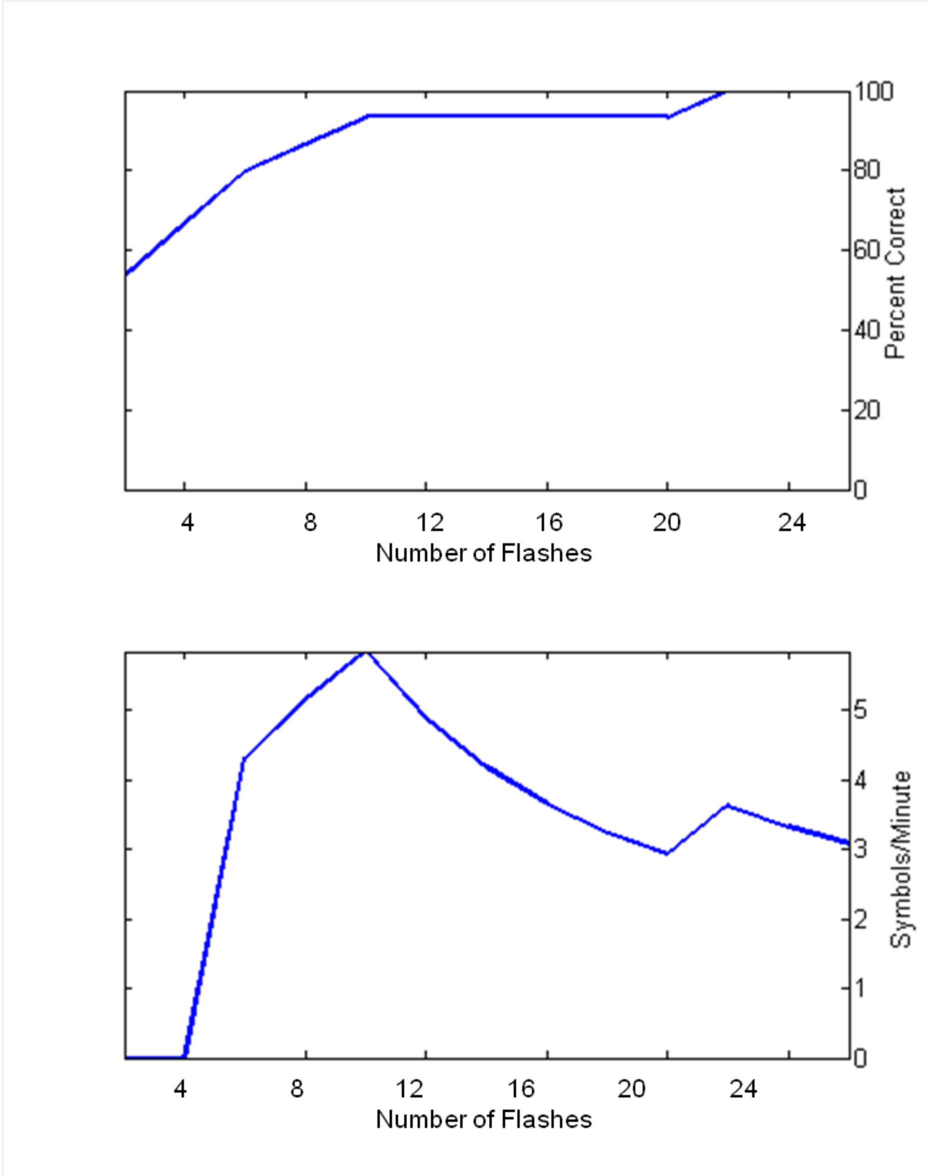

Figure 4. Changes in Accuracy and Communication Rate over Number of Flashes. The figure shows the changes in potential accuracy and written symbol rate (WSR) as increasing number of flashes (sequences) are presented before a character selection. Accuracy continues to increase with additional sequences, while WSR increases until accuracy asymptotes or improvements in accuracy do not make up for the increased time required for additional flashes. The number of flashes that yields the peak WSR is referred to as the optimal sequences and the accuracy with this number of flashes is the optimal accuracy.

epoched EEG waveforms, PCA can be used to reduce the composite EEG waveform recorded at the scalp into a set of orthogonal spatial and temporal component coefficients (referred to as the “factor loadings”) and their corresponding weights (referred to as the “factor scores”) (Kayser & Tenke, 2003). The factor loadings are classified by the amount of variance within the epoched EEG dataset that they explain and the temporal point of maximal loading; although, as with EEG, the factor loadings do not directly represent brain activity, they do demonstrate spatial and temporal characteristics that are shared with the components that make up the recorded ERP waveform. PCA will thus serve both to identify the factor loadings (and the corresponding ERP components) that explain a significant amount of variance within and between the EEG responses to target and nontarget stimuli and to examine relations between these factors in the three tasks as well as their relationship to speller performance (Chapman & McCrary, 1995; Kayser & Tenke, 2003, 2006; Tenke, Kayser, Stewart, & Bruder, 2010). By examining the relationship between high and low accuracy subjects, it is possible to improve our understanding of the quantitative difference between their waveforms and form a more accurate conclusion about the differences in EEG activity that correlate with and predict success with the P300 speller.

The PCA employed an unrestricted covariance-based analysis, with factors identified to maximize the amount of variance explained by each factor loading. The orthogonal loadings were aligned with a Varimax rotation prior to analysis (Kayser & Tenke, 2003). The PCA focused on identifying the most relevant factors, classified as those that explained a high level of variance within the data set, loaded primarily within a single temporal window, showed temporal loadings similar to a visible peak in the average EEG response for targets in the task at hand and showed spatial loadings consistent within known ERP topographies for similar tasks. For each of the relevant factors, one or more statistical models were created to describe the main source for that factor through combination and averaging of the factor scores at the important electrodes in the factor's spatial loading. The overall factor score of the model was then calculated for each subject and correlated to accuracy on the speller task to identify any significant effects.

Statistics

All statistical analysis was performed using the standard toolsets of MATLAB 2009b (MathWorks) and PASW Statistics 17 (IBM). The waveform analysis consisted of two types of analyses. First, the average level of EEG activity within the target and nontarget epochs was calculated by averaging together the absolute value of the amplitude at each time point within the epochs at each electrode for each subject. A paired t-test identified any differences across target and nontarget condition, and the correlation of these values with the user's performance on the P300 speller, both at the maximum number of stimulus presentations (i.e., 130 nontarget and 26 target flashes) and their optimum number of stimulus presentations that used the WSR (see text above and Figure 4). Second, a peak analysis was performed by identifying the highest peaks (or lowest troughs) in a 100 ms window centered on the visible peaks in the average target and nontarget response and examining the correlation between the amplitude and latency of these peaks with both measures of performance. In the PCA factor analysis, an ANCOVA was performed to examine the relationship between the factor scores for the generated models and speller performance at the maximum number of flashes across all users, controlling for the laterality of the factor model, the target and nontarget conditions, and the interactions between them. These analyses were repeated for each of the three tasks to identify any differences or similarities in the relationships based on task.

CHAPTER 4

RESULTS

Slow Oddball

Average Waveforms

Figure 5 shows the average waveform response for targets and nontargets across all 31 subjects at each electrode in the slow ISI oddball task. All waveforms shown are referenced to the right mastoid, which is consistent to what was used as input to SWLDA for online performance feedback. Several notable target and nontarget differences are apparent, as can be seen more clearly on the enlarged inset (Figure 5b). A positive peak centered at 375 ms for the target stimuli can be seen at the central-parietal and parietal-occipital electrode locations, with the largest target to nontarget difference being seen on the central and parietal electrodes. This topography is representative of the P300 component in a standard oddball (Polich, 2007). A negative peak at 300 ms is seen at on the frontal electrodes, decreasing towards the midline, with the most frontal electrodes (F7, F8, FP1, and FP2) showing a much broader peak, which fits the pattern of the N200 ERP component that is also often seen in oddball tasks (Patel & Azzam, 2005). A broad late negativity peaking at 450 to 650 ms can be seen on the posterior electrodes, decreasing in amplitude from occipital to central; in contrast, the frontal electrodes show a broad positivity in the same time window, most likely due to an electrical dipole (Wood, 1982). Additional positive peaks are seen at 250 ms on nearly all electrodes but with little target to nontarget difference on electrodes outside the posterior and at 175 ms with a topographical distribution similar to the previously mentioned 375 ms positive peak. Most notably in the nontarget waveforms is a negative peak around 175 ms at the midline and channels directly lateral to the midline, which is consistent with a visual N200 non-target response. A late

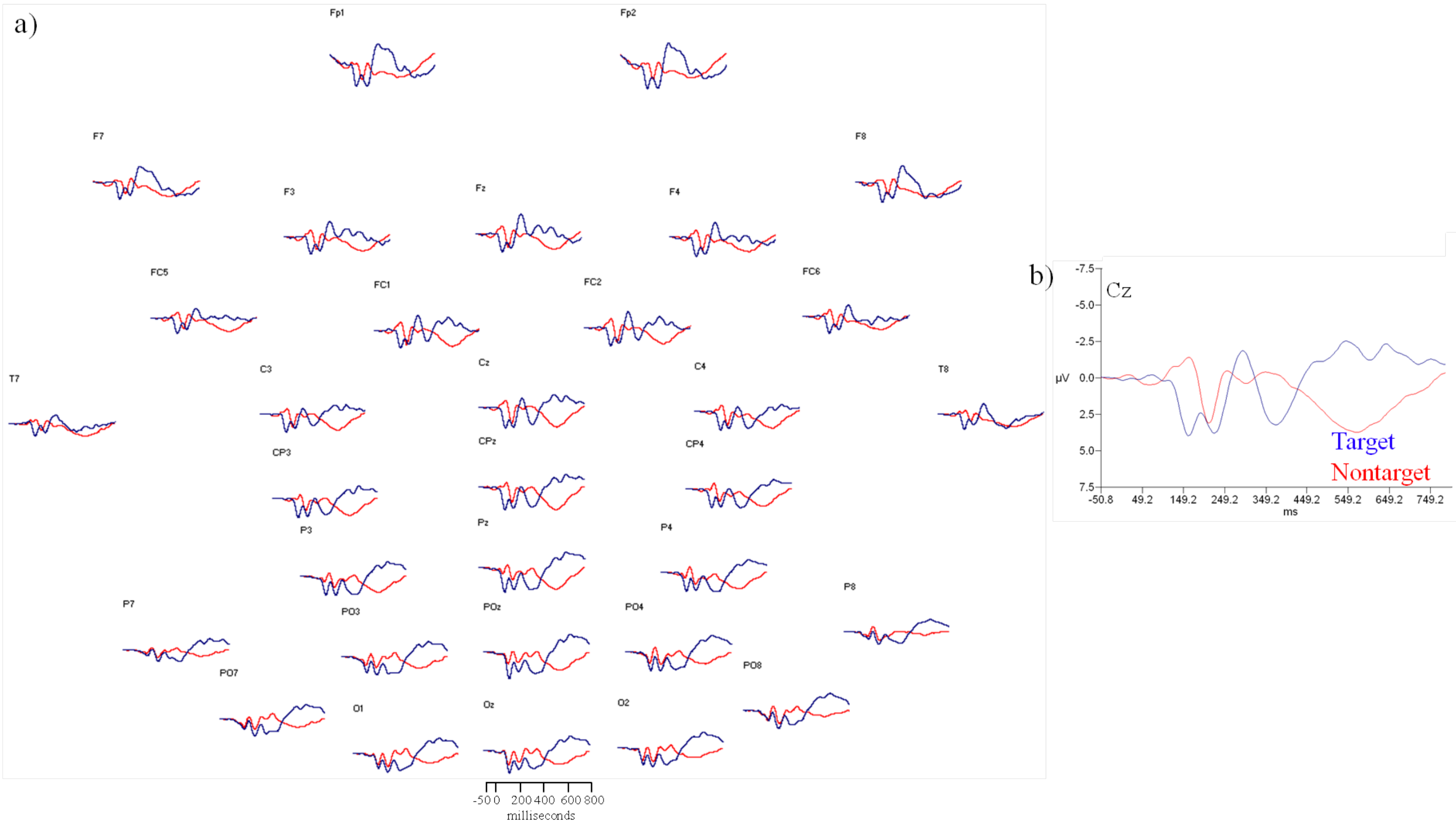

Figure 5. Average Target and Nontarget Waveforms for the Slow Oddball Task. a) Thirty-two channel averaged target and nontarget waveforms for all 31subjects, in the slow oddball task. b) Enlarged view of the average waveforms at electrode Cz. Scale and coloring is congruent for a) and b). Several differences for targets compared to nontargets can be seen in this enlarged panel, primarily a larger positivity at 375 ms for targets.

nontarget positivity is also evident at approximately 570 ms.

Principal Components Factors

Figure 6 shows the PCA factor loadings for the slow oddball task that were determined to be relevant to the current study. Factors were classified as relevant if they explained a significant amount of the variance between targets and nontargets in the task and if their spatial and temporal factor loadings resembled known ERP components, primarily the P300 but also the P200, which is associated with visual attention and processing; the N200, which is associated with error monitoring the perception of stimulus novelty; and the N400, which is associated with the semantic processing of stimuli and may be relevant to the speller task. (Folstein & Van Petten, 2008; Hyde, 1997; Kutas & Hillyard, 1980; Luck & Hillyard, 1994; Patel & Azzam, 2005; Polich, 2007). Figure 6a shows the factor loading over time for the four relevant factors in the slow oddball task, with the time of peak loading labeled. Figure 6b shows the spatial factor loading for each of the four factors at the time of peak of loading, and each is labeled by the time of peak loading and the polarity of the corresponding peak in the average target waveform, with the amount of variance explained by the factor listed additionally. As can be seen, the N204 factor shows a strong negative loading at electrodes PO7 and PO8 and accounts for 6.79% of the variance. Figure 7 further investigates each factor by comparing the target and nontarget factor score topographies. The figure shows the factor scores for the target (left column) and nontarget conditions (middle column) in the slow oddball task and the factor loading across time and the average response from a representative electrode for the factor (right). As shown, the factor loadings and the waveform are highly similar, with a clear similarity between the 204 ms peak in the factor score and the 200 ms negative peak in the target waveform. The other factors

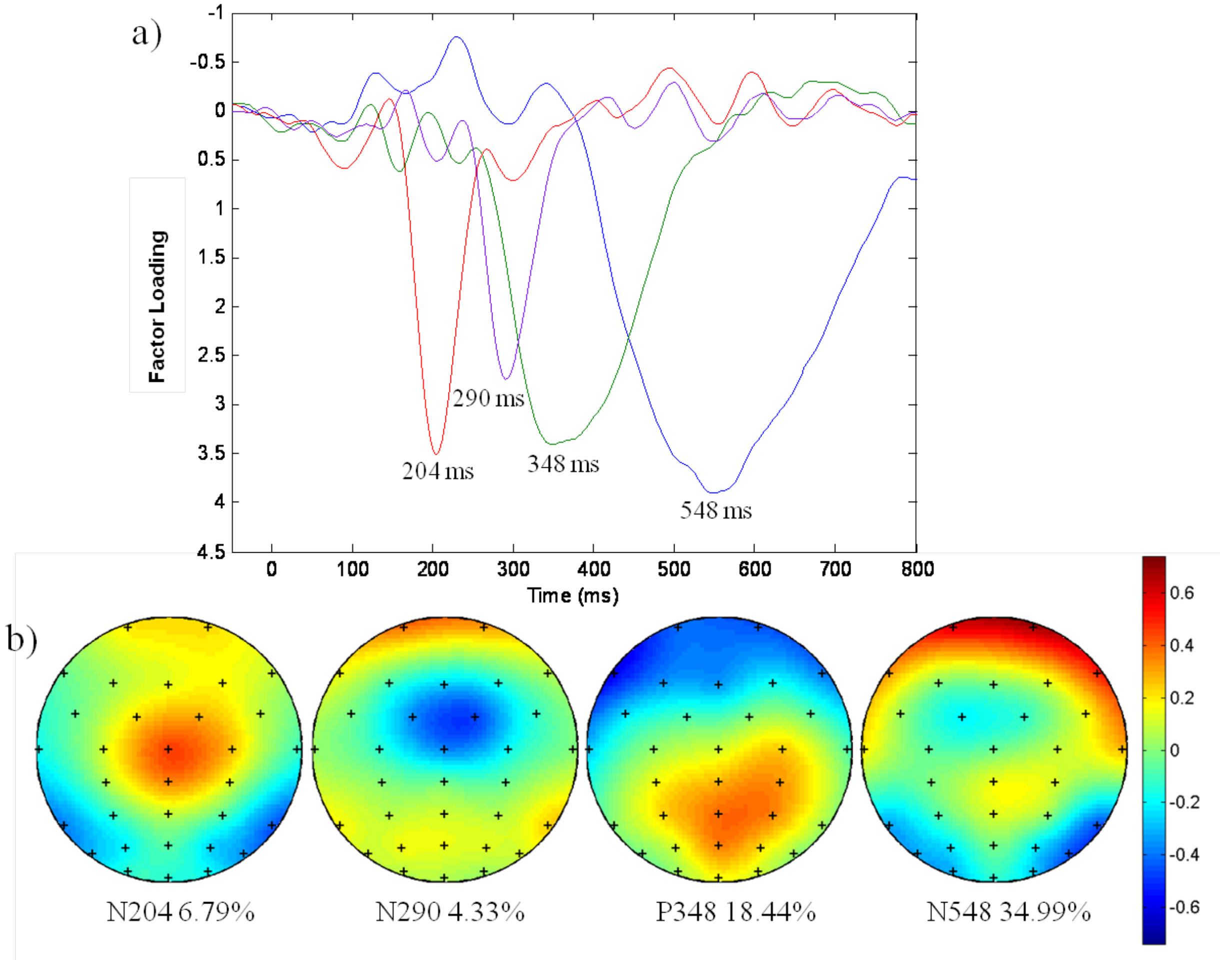

Figure 6. Spatial and Temporal Factor Loadings for the Slow Oddball Task. a) Varimax-rotated factor loadings across time for the four factors of interest in the slow oddball task. Factors are labeled by the time of their peak loading. b) Spatial factor loadings at the time of peak loading for each electrode and the four factors of interest in the slow oddball task. Factors are labeled by the time of their peak loading, the percent variance explained by the factor, and the polarity of the corresponding peak in the average EEG waveform for targets.

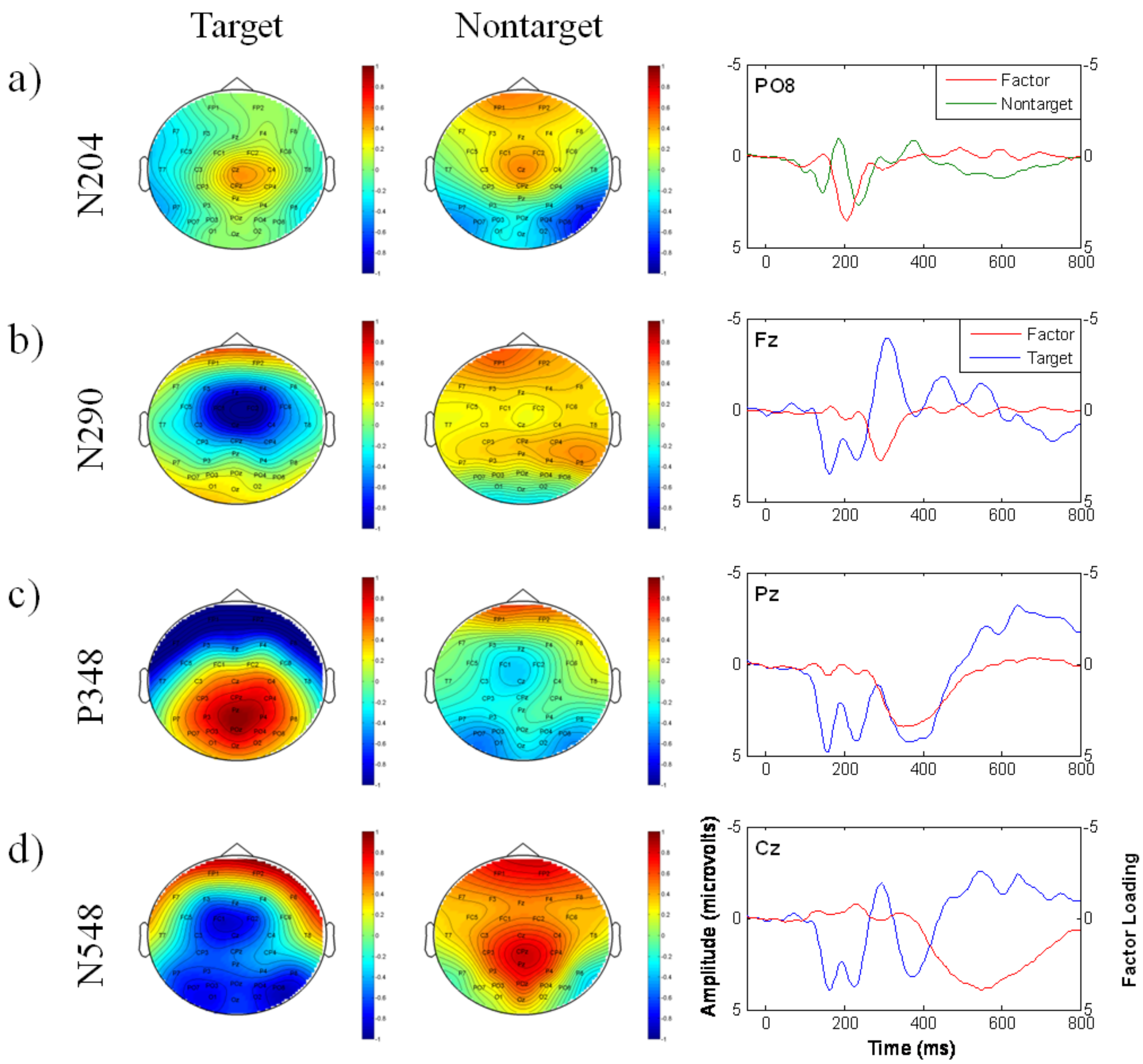

Figure 7. Factor Waveforms and Target Waveform Comparison for the Slow Oddball Task. Factor scores at each electrode for target (left) and nontarget stimuli (middle) at the time of peak loading for each of the factors of interest in the slow oddball task. Factors are labeled by the time of their peak loading and by the polarity of the corresponding peak in the average target waveform. The average representative electrode target waveform and factor loading over time is shown for each of the four factors of interest across all 31 subjects (right). Waveform amplitude is shown on the left axis, while factor score is shown on the right. Electrodes were chosen as representative of the factor's corresponding EEG peak.

identified as relevant for this task were the N290 factor, which shows a negative loading at Fz and Cz and accounts for 4.33% of the variance; the P348 factor, which shows a positive loading at Pz and POz and accounts for 18.44% of the variance; and the N548 factor, which shows a negative loading at Cz, PO7, and PO8, and accounts for 34.99% of the variance.

By examining the ERP peaks that specific factors load onto in conjunction with the spatial and temporal factor loadings, we can begin to describe the specific ERP components that drive the factors. The N204 factor loads primarily on a negative 200 ms peak that is strongest in the lateral parietal-occipital electrodes (Figure 7a), which could represent the N200 component associated with error monitoring (Patel & Azzam, 2005), while the N290 factor scores correspond to the negative 300 ms peak in the target waveforms in the frontal and central channels (Figure 7b), and is likely the N200 component just prior to the P300 component (Patel & Azzam, 2005). The P348 factor scores are highest for the target waveforms at parietal electrode locations, and are temporally focused on the positive 375 ms peak (Figure 7c). It thus appears to be the P300 component of the waveform, as suggested earlier for this peak (Polich, 2007). In contrast to the previous factor loadings, the N548 factor has strong negative scores on central and parietal-occipital electrodes in the target waveforms. Also unlike the others, it does not load onto a single peak but onto the overall broad late negative peak from 450 to 700 ms seen in the target waveforms (Figure 7d). Although the N548 factor does not load on a specific component of interest, it explains a significant portion of the variance and is clearly related to the target to nontarget waveform difference in the 450 to 700 ms time period and is therefore relevant to the task. Given these results, two factors in particular were noted as potential predictors of success: the P348 factor, which loads primarily on the P300, and the N548 factor, which explains nearly 35% of the target to nontarget variance. These factors are considered in subsequent analyses.

Fast Oddball

Average Waveforms

Figure 8 shows the average waveform response for targets and nontargets in the fast ISI oddball task. A notable 8 Hz pattern, similar to a sine wave, can be seen in both the target and nontarget waveforms (more for nontargets than targets, as seen in Figure 8b) – this aligns with the stimulus presentation rate and likely represents activity associated with the immediate visual processing of the stimuli. Positive peaks at 165, 250, and 400 ms can be seen on all electrodes anterior of Pz, although the 250 ms and 400 ms peaks do not show a significant target to nontarget difference on the frontal electrodes. The 250 ms peak may be the P300 component due to its latency and high target to nontarget difference at the central and parietal electrodes while the 165 ms peak may be the earlier P200 (Luck & Hillyard, 1994). A strong 400 ms negative peak can be seen on the parietal and at slightly lower amplitude on the central electrodes, and may be an earlier version of late negativity seen in the slow oddball task. A strong 300 ms negative peak is also seen on the frontal and central electrodes. The occipital electrodes show a noticeably different waveform, with a broad 300 ms positive peak and a broad 450 ms negative peak, potentially indicating a slightly different latency for the P300 and late negativity on these electrodes. A comparison of Figures 5 and 8 shows that the slow oddball and fast oddball paradigms produce different waveform morphologies, with the fast oddball showing an overall decrease in amplitude, more for nontargets than targets, sharper peaks, a noticeable 8 Hz component, and a relative decrease in early activity at the occipital electrodes.

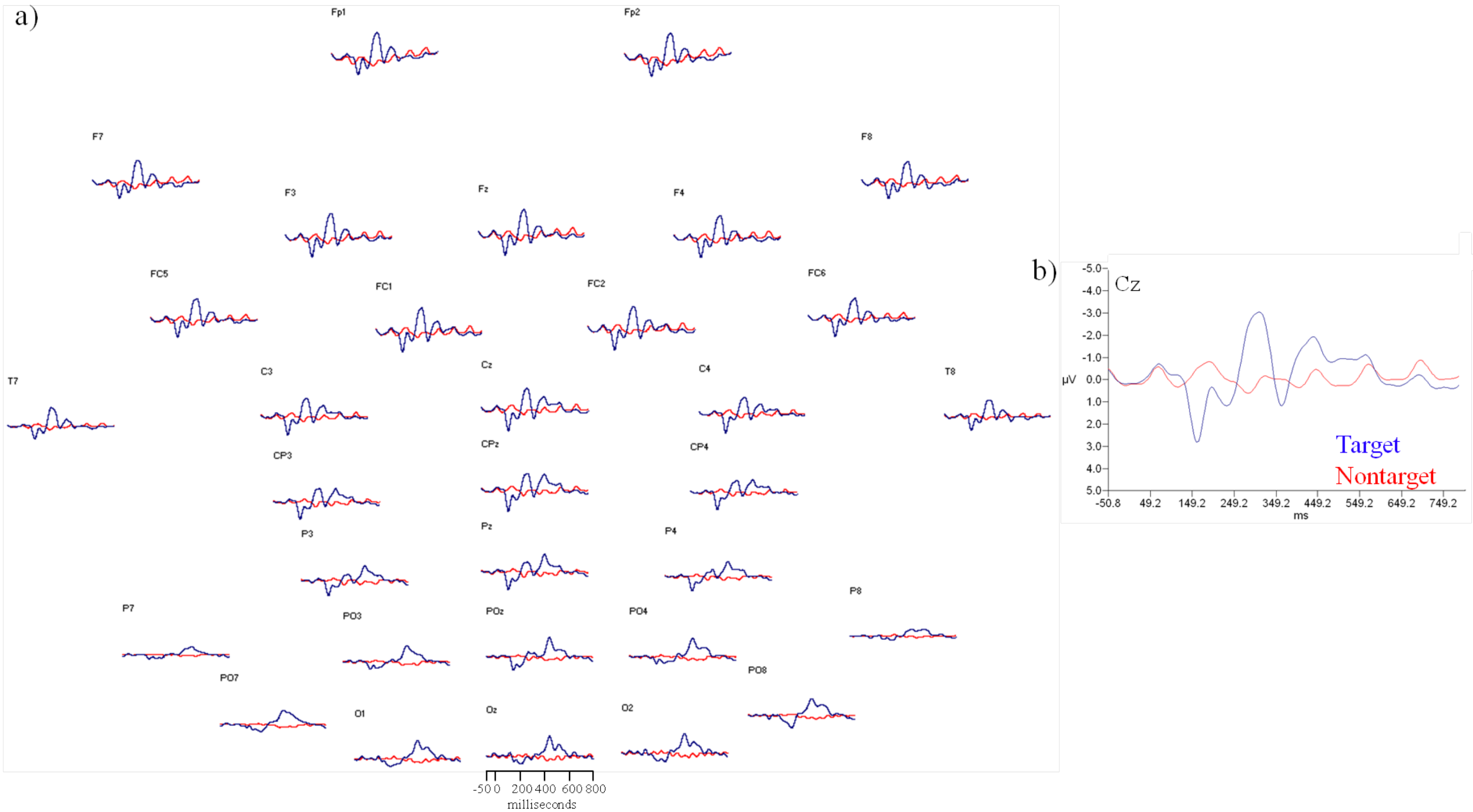

Figure 8. Average Target and Nontarget Waveforms for the Fast Oddball Task. a) Thirty-two channel averaged target and nontarget waveforms for all 31 subjects in the fast oddball task. b) Enlarged view of the average waveforms at electrode Cz. Scale and coloring is congruent for a) and b). Significant target peaks can be seen at 150 and 300 ms. Several differences can be seen between the average waveforms for the fast and slow oddball tasks, notably the overall decrease in amplitude and the presence of an 8 Hz wave in the nontarget waveforms.

Principal Components Factors

The relevant factors for the fast oddball are shown in Figures 9 and 10. Figure 9 shows the spatial and temporal loadings for the relevant factors, while Figure 10 shows the target and nontarget differences in factor score (left) and the comparison of the factor loading with the average target waveform (right). Three relevant factors were identified, the N247, N298, and N446 factors, which together explain 29.51% of the variance for this task. The N247 factor shows a negative loading over P7 and P8 and explains 5.04% of the variance in this task. The N247 is labeled as such as it does load onto a negative peak in the target waveform, as can be seen in Figure 10b; however, this peak does appear to be overshadowed on most electrodes by the positive peaks immediately to either side of it at 175 ms and 300 ms. As such, it is possible that the negative peak acts to dampen the underlying positive peak, and the potential exists for this factor to be loading onto a positive component at 250 ms. Given this latency and parietal topography, the N247 factor may in fact represent the P300 for this task, and it should thus be considered potentially significant. The N298 factor, which explains 17.32% of the variance, shows two noticeable loadings. First, it shows high negative factor scores on all channels anterior of the parietal cortex, which matches its loading onto the 300 ms negative peak seen in the target waveform for these channels (Figure 10c). This strong negative topography indicates that this factor may represent the N200 (Folstein & Van Petten, 2008). Second, it also shows a slight loading onto the positive peak at 165 ms, suggesting the N298 factor may also represent at least a portion of the P200 component (Luck & Hillyard, 1994). The N446 factor shows a strong negative loading on the parietal and occipital electrodes and is associated with the broad negative peak seen for the target waveforms (Figure 10d), confirming its similarities to the late negativity seen in the slow oddball task (Figure 7d). The N446 factor explains 7.15% of the variance in this

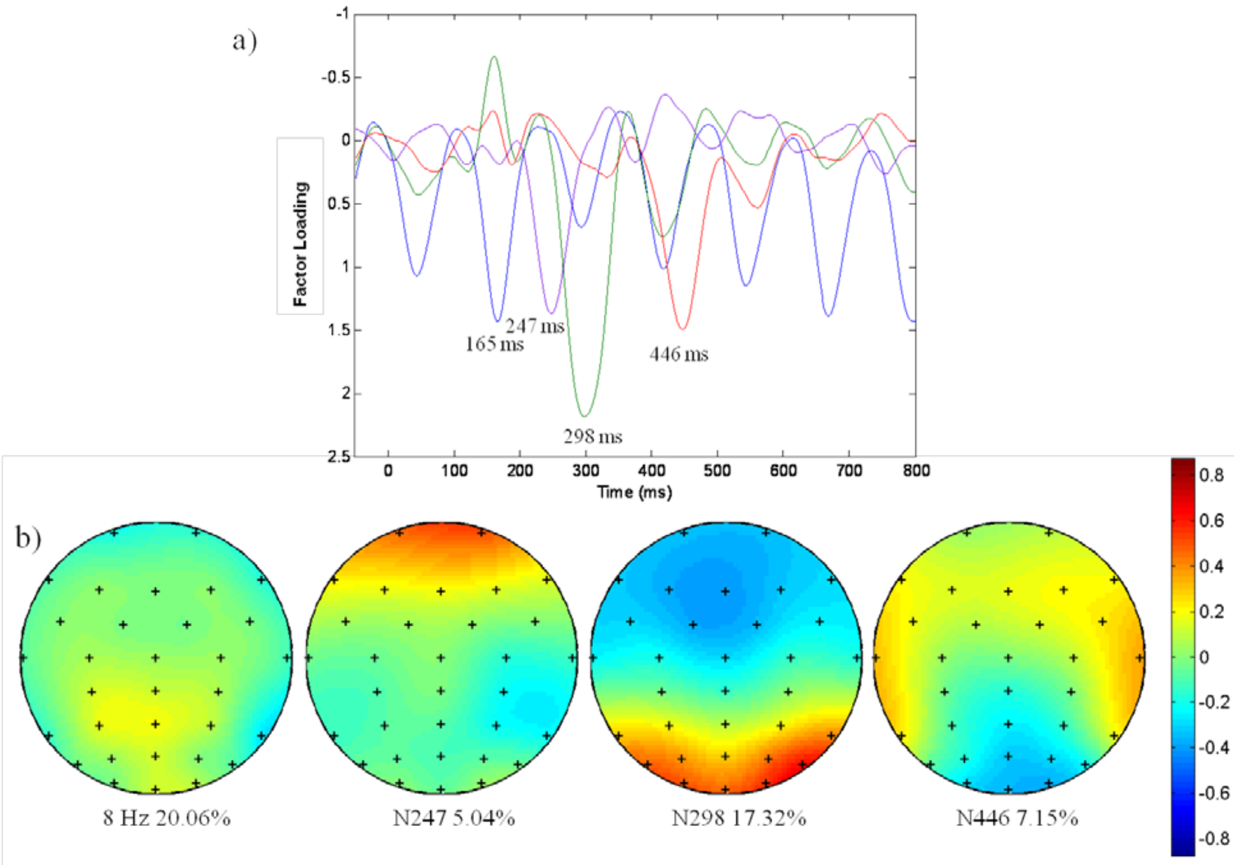

Figure 9. Spatial and Temporal Factor Loadings for the Fast Oddball Task. a) Varimax-rotated factor loadings across time for the three factors of interest in the fast oddball task. Factors are labeled by the time of their peak loading. b) Spatial factor loadings at the time of peak loading for each electrode and the four factors of interest in the fast oddball task. Factors are labeled by the time of their peak loading, the percent variance explained by the factor, and the polarity of the corresponding peak in the average EEG waveform for targets. The 8 Hz factor at left was identified but removed from later analysis as it models task-irrelevant activity.

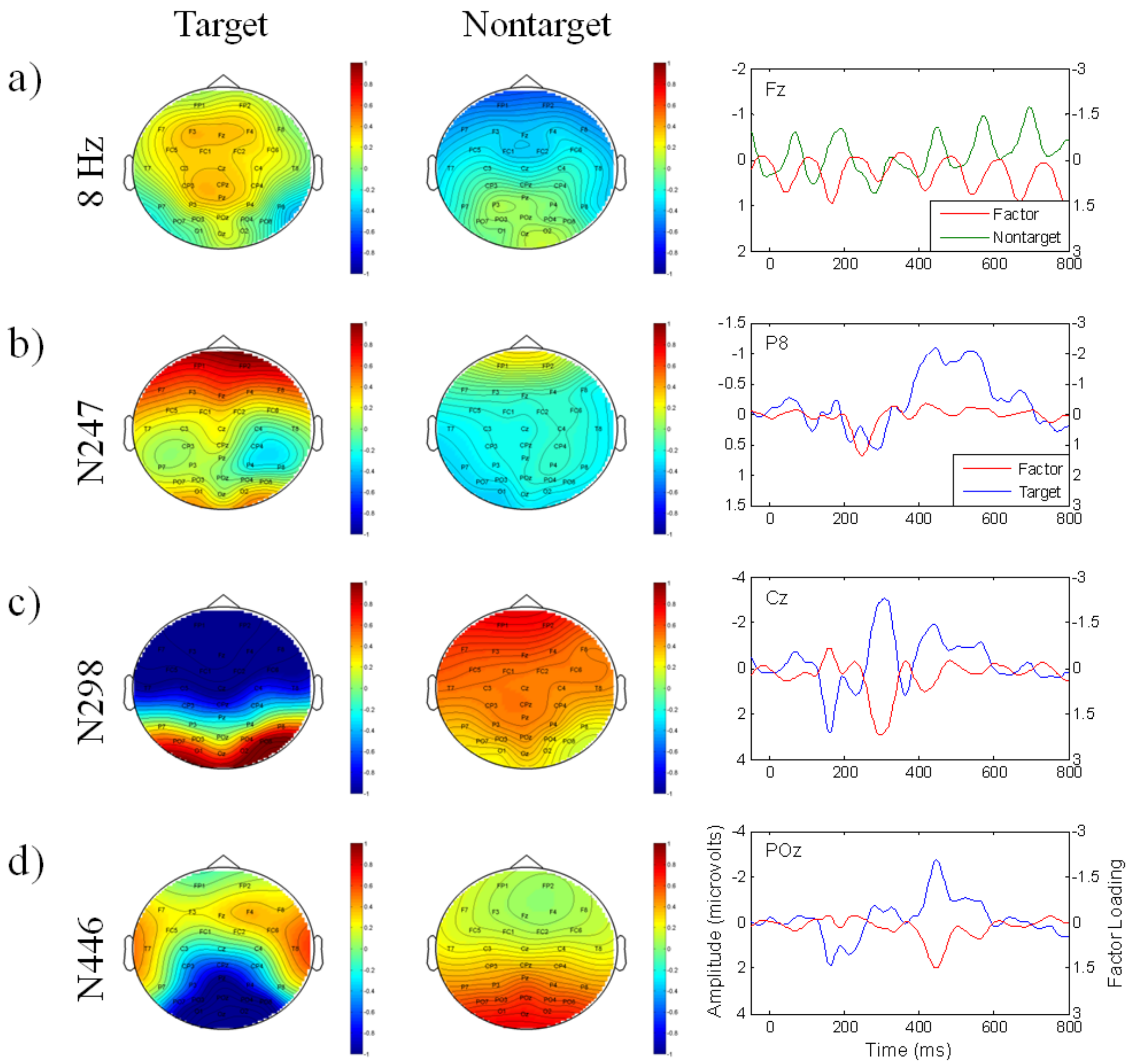

Figure 10. Factor Scores and Target Waveform Comparison for the Fast Oddball Task. Factor scores at each electrode for target (left) and nontarget stimuli (middle) at the time of peak loading for each of the factors of interest in the fast oddball task. Factors are labeled by the time of their peak loading and by the polarity of the corresponding peak in the average target waveform. The average representative electrode target waveform and factor loading over time is shown for each of the three factors of interest across all 31 subjects (right). Waveform amplitude is shown on the left axis, while factor score is shown on the right. Electrodes were chosen as representative of the factor's corresponding EEG peak.

task. Finally, an additional factor initially identified as the N165 was also considered; however, as is clear from Figures 9 and 10a this factor was in fact modeling the strong 8 Hz wave seen for the nontargets in this task. Despite explaining 20.06% of the variance in the task, which is logical given that 5/6 of the stimuli in the task are nontargets, the factor was removed from further analysis, as we are primarily interested in target effects on performance. On the other hand, a failure to see this factor for a given subject may be suggestive of inattention or inability to sufficiently understand the task; thus, it may be worthwhile to investigate in the future. Each of the three remaining relevant factors shows potential as a predictor of success; the N247 factor is the one most likely of the three to represent the P300, while the N298 and N446 show strong loadings and explains large amounts of the target to nontarget variance (17.32% and 7.15%, respectively).

Speller

Average Waveforms

Figure 11 shows the average target and nontarget waveforms for the speller task. A clear 200 ms positive peak and 500 ms negative peak, which may correlate to a P300-like response and the late negativity seen in the previous tasks, can be seen on nearly all electrodes. The latency differences may be related to the rapid stimulus presentation rate. These peaks are highest in amplitude on the central and parietal electrodes. An additional 350 ms negative peak can be seen on the frontal electrodes, although this may represent a slightly earlier onset of the late negativity in these channels. As with the fast oddball, an 8 Hz pattern is present in the nontarget waveform for this task. This pattern represents most of the activity at the occipital electrodes for both targets and nontargets, with some low amplitude peaks for the targets at the times seen on other electrodes. Some of the central electrodes (Cz, CPz, and Pz, for example)

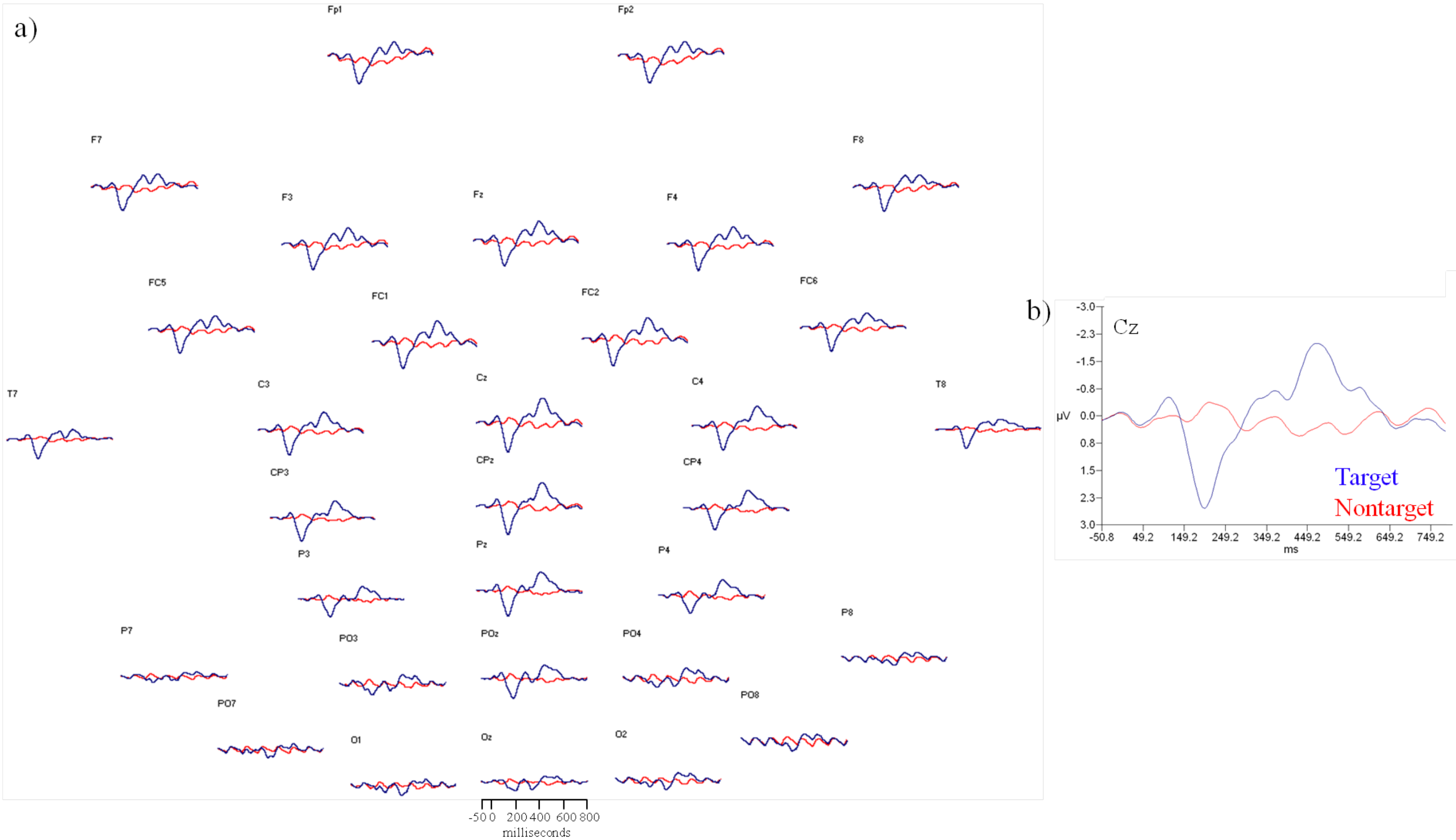

Figure 11. Average Target and Nontarget Waveforms for the Speller Task. a) Thirty-two averaged target and nontarget waveforms for all 31 subjects in the speller task. b) Enlarged view of the average waveforms at electrode Cz. Scale and coloring is congruent for a) and b). The target waveform shows a strong positive peak at 200 ms and a broad negative peak centered at 475 ms. The non-target waveform shows the same 8 Hz wave as in the fast oddball task.

show an additional small negative peak at 100 ms, although this may be part of the 8hz pattern and thus not significantly different between targets and nontargets.

Principal Components Factors

Figures 12 and 13 show the topography and time course of the relevant factors for the speller task. Figure 12 shows the spatial and temporal loadings for the relevant factors, while Figure 13 shows the target (left) and nontarget (middle) factor score and the comparison of the factor loading with the average target waveform (right). Three relevant factors were identified for this task – the P200 (hereafter written as $P200_f$ (for P200 factor) to avoid confusion with the known P200 ERP component), P352, and N466 factors – which together explain 58.89% of the target to nontarget variance in the speller task. The $P200_f$ factor loads shows high negative factor scores on the lateral parietal and occipital electrodes and positive factor scores on all other electrodes and explains 16.50% of the variance in this task. Examining Figure 13a, it is clear that this factor loads on the strong 200 ms positive peak seen in the target waveform. The P352 factor, in comparison, shows nearly the opposite factor topography, with positive factor scores on the lateral parietal and occipital electrodes and negative factor scores on most of the other electrodes and explains 18.40% of the variance. The factor loads onto a small but significant positive peak for the target waveform on the parietal and occipital electrodes (Figure 13b). Both of these factors may represent the P300 for this task: the P352 factor is well within the known latency range of the P300, and although the $P200_f$ is quite a bit earlier, given the stated concerns over the short ISI of the speller task a 200 ms P300 may not be out of the question. Finally, the N466 factor shows a clear similarity to the late negativity factors seen in the previous two tasks (Figures 7d and 10d), with a strong negative loading focused on the central electrodes and an association with the broad negative peak from 400 to 600 ms in the target waveform

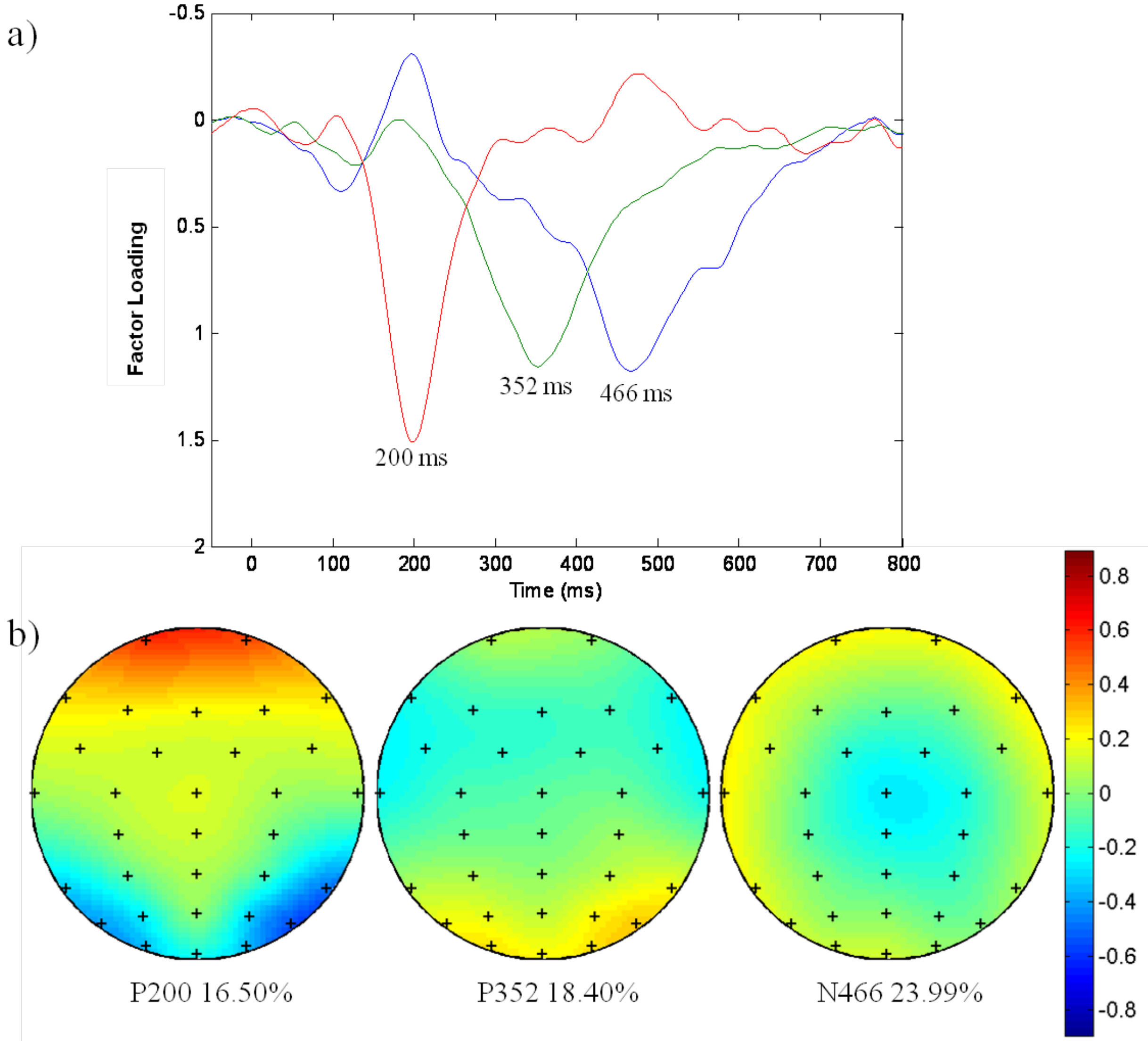

Figure 12. Spatial and Temporal Factor Loadings for the Speller Task. a) Varimax-rotated factor loadings across time for the four factors of interest in the speller task. Factors are labeled by the time of their peak loading. b) Spatial factor loadings at the time of peak loading for each electrode and the three factors of interest in the speller task. Factors are labeled by the time of their peak loading, the percent variance explained by the factor, and the polarity of the corresponding peak in the average EEG waveform for targets.

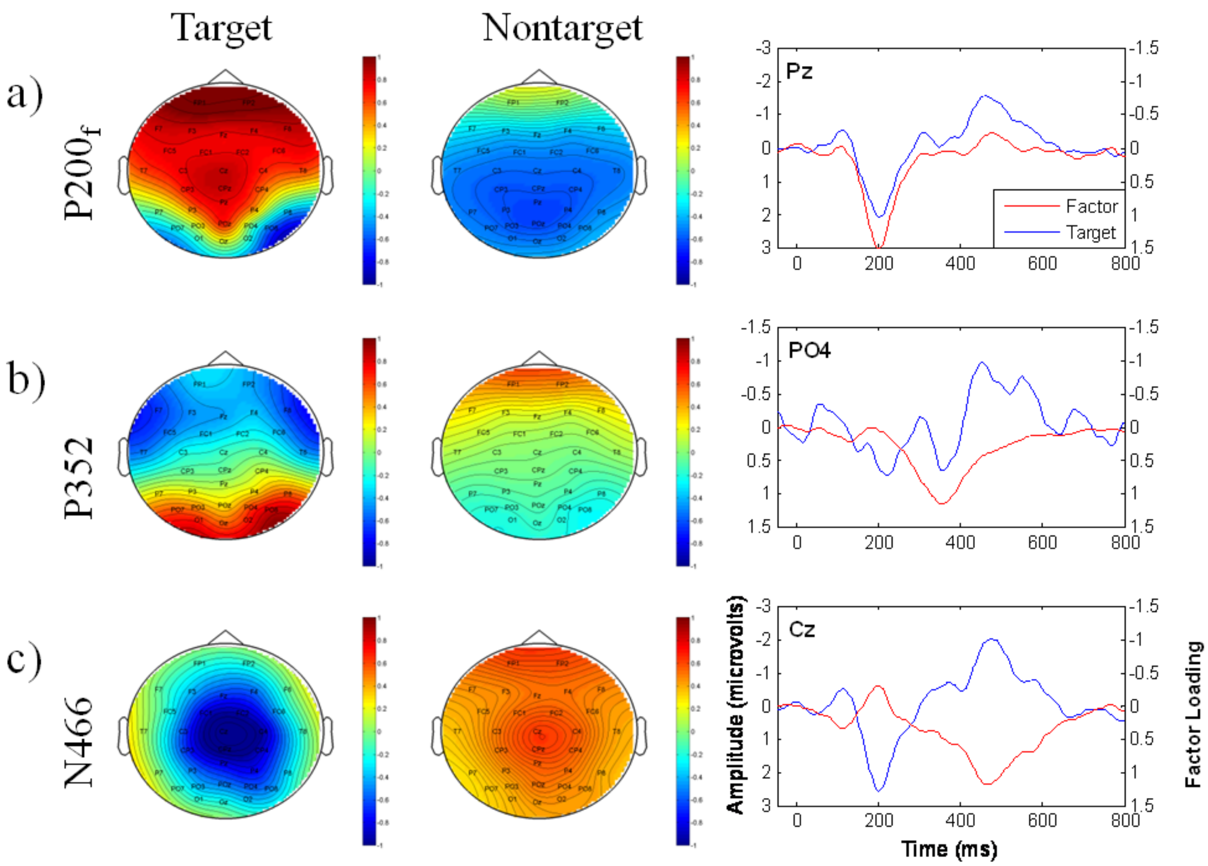

Figure 13. Factor Scores and Target Waveform Comparison for the Speller Task. Factor scores at each electrode for target (left) and nontarget stimuli (right) at the time of peak loading for each of the factors of interest in the speller task. Factors are labeled by the time of their peak loading and by the polarity of the corresponding peak in the average target waveform. The average representative electrode target waveform and factor loading over time is shown for each of the three factors of interest across all 31 subjects (right). Waveform amplitude is measured on the left axis, while factor score is measured on the right. Electrodes were chosen as representative of the factor's corresponding EEG peak.

(Figure 13c). The N466 factor explains 23.99% of the variance in this task. As with the fast oddball, each of these three factors is of interest for further analysis, both due to the amount of variance explained and their loading onto ERP components of interest.

Performance

Accuracy

Performance on the spelling task varied considerably between subjects both online (after 26 target flashes) and offline at the optimum number of flashes. Table 1 shows for each subject accuracy and number of flashes online and at the optimized number of flashes and the number of character selections per minute that could be made given the experimental parameters used in the current study. Ten of the 31 subjects achieved accuracies greater than 90% at the optimum number of flashes (making 0 or 1 errors in selection). Twelve subjects achieved accuracies of less than 70% at the optimum number of flashes (at least 4 errors), and the remaining 9 performed between the two. Online results were more accurate overall due to the higher number of flashes: 18 subjects achieved accuracies greater than 90% and 8 achieved accuracies of less than 70%. Average accuracy was 82% online and 76% offline.

Factor Analysis

A composite factor score was calculated for each of the relevant factor models by averaging the factor scores of the important electrodes and in certain cases subtracting the factor scores of electrodes that the factor loaded negatively onto. These composite scores were then examined through a repeated measures analysis for possible main and interaction effects of target condition, laterality (whether the factor was bilateral or focused on one side of the head), and performance on the speller task, both at the maximum and optimum number of sequences. All effects were examined for significance at the $p < .05$ level following a Bonferroni correction.

Table 1.

Online and Offline Performance in the Speller Task. The table shows for each of the 31 user the selection accuracy during the experiment (left), the number of target flashes that would maximize written symbol rate (WSR) (middle right), the selection accuracy determined offline at this optimum number of flashes (middle left), and the WSR, measured as successful selections per minute, that would be obtained at these values. Online accuracy was recorded at 26 target flashes for all subjects.

User	Online Accuracy	Offline Accuracy	Offline Flashes	Offline WSR
1	100	64	7	10.96
2	50	57	13	5.98
3	93	93	18	9.77
4	93	100	17	11.75
5	100	79	8	13.79
6	79	79	22	6.36
7	100	86	13	11.12
8	100	86	15	9.95
9	100	86	5	21.00
10	93	71	17	6.70
11	36	36	26	1.72
12	71	64	22	4.64
13	100	100	8	20.57
14	50	50	15	2.89
15	100	93	14	11.94
16	100	93	15	11.31

User	Online Accuracy	Offline Accuracy	Offline Flashes	Offline WSR
17	100	100	6	24.68
18	100	86	26	6.30
19	71	71	13	8.28
20	100	86	17	9.00
21	100	93	10	15.35
22	43	43	26	2.24
23	21	21	26	0.76
24	93	93	20	8.96
25	93	93	14	11.94
26	86	71	15	7.41
27	79	79	12	10.34
28	100	100	13	14.52
29	86	86	26	6.30
30	43	43	26	2.24
31	86	64	10	8.61

In all tasks, the performance measure used was the subject's accuracy at the maximum number of target flashes.

In the slow oddball task the P348 factor was tested using a central-parietal model (Cz, Pz, and POz, no laterality), showing a significant main effect of target condition (see Table 2). The N548 factor was tested using a frontal-central model (FC1, Fz, and Cz on the left, FC2, Fz, and Cz on the right), showing a significant effect of target condition. A secondary parietal-occipital model (PO7, PO3, and O1 on the left, PO8, PO4, and O2 on the right) showed no significant effects. The N290 factor was tested using a frontal-central model (FC1, Fz, and Cz on the left, FC2, Fz, and Cz on the right), showing a significant effect of target condition. The P204 factor was tested using a central model (C3 and Cz on the left, C4 and Cz on the right), showing a significant main effect of laterality and an interaction effect of target and laterality. A secondary temporal model (T7 on the left, T8 on the right) showed no significant effects. Notably, none of the models tested showed a significant between subject effect of performance. This supports the hypothesized differences between the P300 speller task and the traditional oddball task.

In the fast oddball task the model for the N247 factor focused on the central to parietal electrodes (C3, CP3, P3, P7 on the left, C4, CP4, P4, P8 on the right) and showed a significant main effect of performance and a significant interaction effect of target and performance (see Table 3). The N446 factor was tested using a parietal-occipital model (Pz, POz, and Oz, no laterality) and a temporal-frontal model (T7, FC5, F3, F7 on the left, T8, FC6, F4, F8 on the right). The parietal-occipital model showed significant effects of target condition, while the temporal-frontal model showed no significant effects. Lastly, the N298 model was tested using a parietal-occipital model (PO3, PO7 and O1 on the left, PO4, PO8, and O2 on the right), but found no significant effects. From this, it may be concluded that the characterization of the

Table 2.

Repeated Measure Analysis for the Slow Oddball Task. Repeated measure analysis of variance results are listed for the factors and models with significant main effect or interaction effects. All F scores are at (1, 29) degrees of freedom. p values shown are following Bonferroni correction. Power is the calculated likelihood of avoiding Type II errors at a = .05 when distinguishing between conditions and subjects based on the effect. Significant effects of target condition can be seen for all factors tested, but no significant effects are seen for user performance.

Factor	Model	Effect	F	p	Power
P204	Central	Laterality	5.339	0.028	0.608
		Laterality X Target	4.921	0.035	0.573
N290	Frontal-Central	Target	4.592	< .001	0.544
P348	Midline	Target	13.811	< .001	0.949
N548	Frontal-Central	Target	4.613	< .001	0.546

Table 3.

Repeated Measure Analysis for the Fast Oddball Task. Repeated measure analysis of variance results are listed for the factors and models with significant main effect or interaction effects. All F scores are at (1, 29) degrees of freedom. p values shown are following Bonferroni correction. Power is the calculated likelihood of avoiding Type II errors at a = .05 when distinguishing between conditions and subjects based on the effect. Significant main and interaction effects of performance can be seen for the N247 factor.

Factor	Model	Effect	F	p	Power
N247	Central-Parietal	Performance	13.078	0.001	0.983
		Target X Performance	7.906	0.009	0.776
N446	Parietal-Occipital	Target	13.945	<.001	0.95

N247 factor as loading onto the P300 for this task was accurate, as the N247 model was the only model to show a significant main effect of performance for the fast oddball task.

In the speller task the model for the N466 factor focused on the frontal and central electrodes (Fz, FC1, Cz, CPz, and C3 on the left, Fz, FC2, Cz, CPz, and C4 on the right) and showed significant interaction effects of target condition and performance and of target condition, laterality and performance for performance at maximum sequences (see Table 4). The model for the $P200_f$ factor focused on the large central loading (Cz and Pz, no laterality), showing a significant main effect of performance and a significant interaction effect between target and performance for performance both at maximum and optimum sequences. A secondary model in the parietal and parietal-occipital electrodes (P7, PO7 on the left, P8, PO8 on the right) showed no significant effects. Lastly, the model for the P352 factor focused on the parietal-occipital and occipital electrodes (PO3, PO7, O1 on the left, PO4, PO8, O2 on the right), but showed no significant effects. The significant main effect of performance for the $P200_f$ factor model supports the idea of it loading onto a short latency P300 in this task. Additionally, the late negativity N466 factor model also showed significant interaction effects with performance, suggesting it may also be relevant to user performance.

Factor and Waveform Comparison

To further examine potential differences based on speller performance, subjects were divided into high and low performance groups based on their online performance. Eighteen high performance subjects and 8 low performance subjects were included in the analysis. The average factor scores for the three factors that showed significant main or interaction effects of performance (the N247 factor in the fast oddball task and the $P200_f$ and N446 factors in the speller task) and the average target response at an electrode relevant to the factor were calculated

Table 4.

Repeated Measure Analysis for the Speller Task. Repeated measure analysis of variance results are listed for the factors and models with significant main effect or interaction effects. All F scores are at (1, 29) degrees of freedom. p values shown are following Bonferroni correction. Power is the calculated likelihood of avoiding Type II errors at a = .05 when distinguishing between conditions and/or subjects based on the effect. Significant effects of performance can be seen for both the $P200_f$ and N466 factor, although the N466 factor does not show a significant main effect.

Factor	Model	Effect	F	p	Power
$P200_f$	Central-Parietal	Performance	4.941	0.034	0.575
		Target X Performance	6.335	0.018	0.682
N466	Frontal-Central	Laterality X Performance	6.687	0.015	0.705
		Target X Laterality X Performance	7.523	0.01	0.755

for the high and low performance groups and compared to identify any systemic differences between the two.

The results for this analysis are shown in Figures 14. Figure 14a shows the average factor score topographies for targets for the N247 factor in the fast oddball task. As can be seen, the average topography for the high performance users resembles both the factor loading topography in Figure 9 and the target factor score topography in Figure 10a. In contrast, the low performance users show an overall negative factor score and a slightly altered topography; the negative peaks see at the central-parietal electrodes shifts forward to the central electrodes for the lower performance users, and the gradient to the frontal and occipital peaks is greatly reduced. The right column of Figure 14a shows the average target waveforms for the high and low performance users in the fast oddball task at electrode PO8. As can be seen, the high performance users show much higher amplitude for the positive peak at 300 ms.

Figures 14b and 14c show the comparisons for the $P200_f$ and N466 factors, respectively, in the speller task. These figures show similar results to those seen for the fast oddball N247 factor. The average factor score topographies for the high performance users strongly resembles the factor loading (Figure 12) and overall target factor scores (Figure 13a) for these factors - a frontal positivity to parietal-occipital negativity for the $P200_f$ factor, a large central negativity for the N466 factor - while the low performance users shows slightly altered topography shape and a relative decrease in both factor scores and factor score ranges. The high performance users also show increased amplitude in the target waveforms, with higher amplitude for the positive peak at 200 ms and lower amplitude for the negative peak at 475 ms, compared to the low performance uses. Overall, these comparisons support the results seen in the repeated measures analysis, showing a significant effect of user performance on factor scores for these three factors and confirming the hypothesized increases in target amplitude for high performance users.

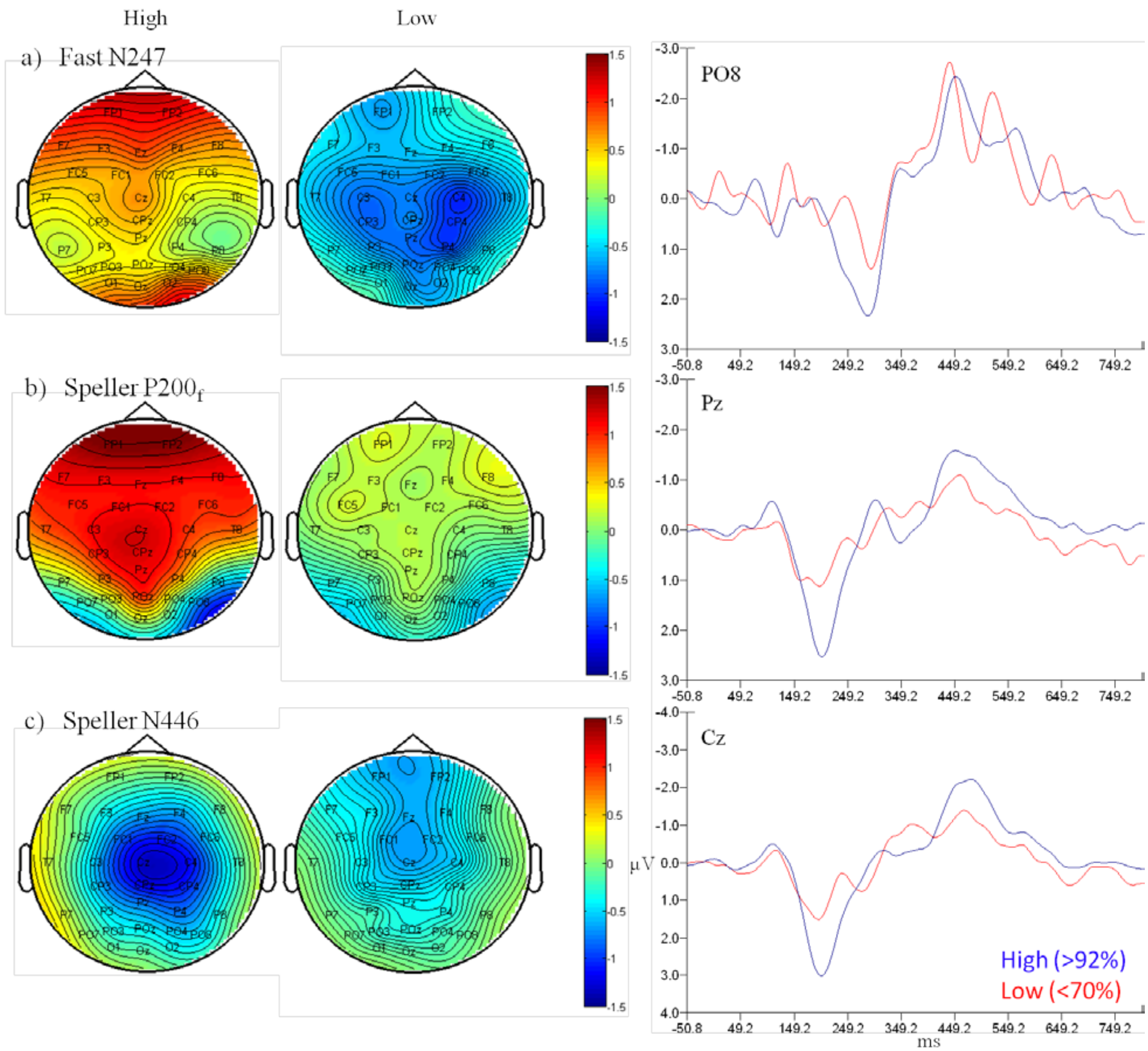

Figure 14. Comparison of High and Low Performance Groups by Factor and Waveform. The figure shows the comparison of results between high and low performance subjects for the three factors with significant performance effects. The left and middle columns show the differences in the factor score topography for the high and low performers, the right column shows target amplitude across time at an electrode representative of the factor. a) Comparison of results for the N247 factor in the fast oddball task. The topography for high performance subjects resembles both the overall average target topography and the spatial factor scores for the fast

N247 factor, while the low performance subjects show slightly more central negative peaks and an overall negative polarity. The high performance subjects also show a much higher amplitude positive peak at 300 ms in the target waveform. b) Comparison of results for the $P200_f$ factor in the speller task. The topography for high performance subjects again strongly resembles both the overall average target topography and the spatial factor loading for the $P200_f$ factor, while the low performance subjects show a comparative decrease in factor score. The high performance subjects show higher amplitude peaks in the target waveform at 200 ms and at 475 ms. c) Comparison of results for the N446 factor in the speller task. As before, the topography for the high performance subjects strongly resembles the overall average target topography. The topography for the low performance subjects shows both a more frontal peak and a marked decrease in factor score compared to the high performance subjects. As with the $P200_f$ factor, the high performance subjects show higher amplitude peaks in the target waveform at 200 ms and at 475 ms.

CHAPTER 5

DISCUSSION

Two interesting effects can be seen through the initial comparisons shown in Figures 5-13. First, there is a demonstrable difference between the responses to each task. The average waveforms are noticeably different between the three tasks, with different shape, amplitude, and latency for both the targets and nontargets. The component analysis also showed several differences, with the three tasks generating factors with markedly different temporal and spatial factor loadings. Second, it points to several potential predictors of performance. Several of the factors produced by the component analysis were seen to correlate both with significant target peaks in the average waveforms and with known ERP components, primarily the P300. The likelihood of these components showing performance related-differences in factor scores was thus very high.

The repeated measures analysis in turn indicated significant effects of target condition for nearly all the models examined; those without a significant target condition effect were generally secondary models for a factor where the primary model did show the target effect. Several also showed a laterality effect, indicating that the factor strength did vary by hemisphere. These effects were generally seen in the models concerning the occipital or temporal electrodes, where a laterality effect would be expected; the former due to dominance effects in visual processing, and the latter due to the common lateralization of language tasks to the left temporal lobe, which would understandably play a role in the P300 speller.

Of particular interest are the three models that showed a significant main or interaction effect of performance: the central-parietal model for the fast N247 factor, the central-parietal model for the speller $P200_f$ factor, and the frontal-central model for the speller N466 factor. The performance effect for the first two is expected given the importance of the P300 to the oddball and speller tasks. Interestingly, the model for the P348 factor in the slow oddball task did not show this same relationship with performance. This would further support the idea of qualitative differences in waveform morphology between the two data sets, likely driven by the difference in ISI between the slow oddball and the fast oddball and P300 speller and the mentioned effects this can have on the P300. The third significant model does appear to load somewhat in the P300 range but is primarily a late negativity factor. Given the significant effects of performance for this late negativity factor in the speller task but not for the late negativity factor models in the fast or slow oddball tasks, this provides more evidence of significant differences in the underlying EEG components between the speller and oddball tasks. Finally, direct comparison of the average factor scores between the high and low performance users confirms these factors' relationships with performance, showing clear differences between the factor score topographies for the two groups. Overall, the analysis confirms our hypotheses: there are significant differences in activity between the target and nontarget conditions of the slow oddball, fast oddball, and speller tasks; the PCA-identified factors appear to be associated with significant and relevant brain activity; and a subset of these factors could be used for prediction of performance in future studies.

CHAPTER 6

CONCLUSIONS

Two primary conclusions can be drawn from these results. First, it is clear that there are task-related differences in the P300. The target and nontarget waveforms are visibly different between all three tasks, with the speller task showing lower amplitude responses than the two oddball tasks (likewise for the fast oddball compared to the slow oddball task), and the speller and fast oddball tasks both show decreased peak latency for several peaks relative to the slow oddball. Similarly, the factor loadings for the fast oddball, slow oddball, and speller tasks also differ, indicating significant differences in how the waveform variance is explained for the three tasks. Overall, there appear to be more similarities between the fast oddball and the speller than the slow oddball and the speller, which is understandable given the stated importance of ISI for the P300. The factors suggest that this shorter ISI does alter the waveform morphology: the factor models for the P300 in the fast oddball and speller tasks showed a correlation with performance, while the factor model for the slow oddball did not.

Second, there do appear to be several markers for successful or unsuccessful performance that may be used in the future to predict speller performance. Significant correlations with performance were seen for three of the factor models examined: the fast oddball N247 factor and the speller $P200_f$ and N466 factors. The presence and factor score of these or temporally and spatially similar factors could be used in future research to determine likelihood of success using the P300 BCI. Ultimately, these factor characteristics represent an interesting area of future research, both to confirm predictive capabilities and to determine underlying neurological causes. While most of the differences between users would logically be a result of the strength of their P300, the significant effects of performance seen for the speller N466 factor do bear further examination. Given the nature of the P300 speller, it is possible that late negativity may be a process similar to or associated with the N400 seen by Kutas and Hillyard (1980), which was generated in response to unexpected semantic stimuli.

One additional effect that was noted is the overall increase in number of significant correlations for performance measured at the maximum number of flashes compared to performance measured at the optimum number of flashes. While this is understandable – as the study used the full data set for analysis, there would logical be stronger correlations to the performance measure that was also based on the full data set – it does suggest performance at and number of optimum flashes may be a useful condition to keep in mind for future studies. A better understanding of the response differences that lead some subjects to maintain high levels of accuracy at low numbers of flashes and others to drop off quickly may help further our understanding of the P300 and improve the efficacy of P300-based BCI.

Furthermore, the large 8 Hz factor seen in the fast oddball task suggests another path of potential research. While the observed 8 Hz sine wave is task irrelevant activity, and will occur in any situation where the user is observing visual stimuli with the same 125 ms ISI, it still does require the user to be attending to the stimuli for the 8 Hz to show up. As such, it may serve as a general marker of attention and thus as an exclusion criteria for the P300 BCI – if users cannot focus their attention sufficiently to generate an 8 Hz pattern for the fast oddball, it would logically be impossible for them to focus enough to successfully use the P300 speller. It is unknown how effective this criterion would be, as presumably this level of inattention would be directly observed and addressed by the experimenter during system without needing to perform the PCA, but it remains a potential predictor that should be examined by further research.

Ultimately, the current research has identified several characteristics of the P300 in the traditional oddball and P300 speller tasks that could be used to predict a subject's ability to successfully use a P300-based BCI. While further research is still needed to confirm the strength of this relationship and to determine the accuracy of experimenter predictions of success based on these criteria, should the patterns seen here continue, it may represent a significant improvement in our ability to predict performance. Compared to the current methods, involving gathering several test sessions of data, this would significantly reduce the amount of time needed to determine a person's ability to use the P300 BCI. This would have positive effects both in experimental settings, allowing experimenters to quickly narrow down their participants to those who could achieve the level of control necessary for the study, and in potential clinical settings, to determine if the BCI is viable option for a locked-in patient to regain communication and control. In addition, through experimental study of the prediction criteria and how they differ between high and low performance users, we may gain a better understanding of the underlying differences between the two groups – for example, whether the differences in the late negativity factor between the two groups is also seen in tasks designed to specifically evoke the N400 – and potentially may develop targeted training methods to improve the ability of low performance users and expand the population who can successfully use the BCI. Finally, we have identified several ways in which the P300 elicited by the speller program is similar to and different from the response to more traditional oddball tasks. Understanding of these differences – of the shifts in latency and alterations in the underlying components – may lead to improvements in the efficiency of the P300 speller itself and further expand the number of people the system is capable of helping. Ultimately, the results reported here represent the first step in a line of a research dedicated to the improvement and expansion of the P300-based BCI.

REFERENCES

ALSA. (2008, September). Who gets ALS. Retrieved from http://www.alsa.org/als/who.cfm?CFID=1556427&CFTOKEN=69426212c3284d5b-3692B3DB-188B-2E62-80F4588A79DBA0BF, December 5, 2009.

Berger, H. (1929). Uber das Electrenkephalogramm des Menchen. *Archiv fur Psychiatrie und Nervenkrankheiten, 87*, 527-570.

Birbaumer, N., Kubler, A., Ghanayim, N., Hinterberger, T., Perelmouter, J., Kaiser, J., et al. (2000). The thought translation device (TTD) for completely paralyzed patients. *IEEE Trans Rehabil Eng, 8*, 190-193.

Blakely, T., Miller, K. J., Zanos, S. P., Rao, R. P., & Ojemann, J. G. (2009). Robust, long-term control of an electrocorticographic brain-computer interface with fixed parameters. *Neurosurg Focus, 27*(1), E13.

Blankertz, B., Dornhege, G., Krauledat, M., Muller, K. R., & Curio, G. (2007). The non-invasive Berlin Brain-Computer Interface: Fast acquisition of effective performance in untrained subjects. *Neuroimage, 37*, 539-550.

Blankertz, B., Losch, F., Krauledat, M., Dornhege, G., Curio, G., & Muller, K. R. (2008). The Berlin Brain--Computer Interface: Accurate performance from first-session in BCI-naive subjects. *IEEE Trans Biomed Eng, 55*, 2452-2462.

Bromberg, M. B. (2008). Quality of life in amyotrophic lateral sclerosis. *Phys Med Rehabil Clin N Am, 19*(3), 591-605, x-xi.

Chapman, R. M., & Bragdon, H. R. (1964). Evoked responses to numerical and non-numerical visual stimuli while problem solving. *Nature, 203*, 1155-1157.

Chapman, R. M., & McCrary, J. W. (1995). EP component identification and measurement by principal components analysis. *Brain Cogn, 27*, 288-310.

Chio, A., Gauthier, A., Montuschi, A., Calvo, A., Di Vito, N., Ghiglione, P., et al. (2004). A cross sectional study on determinants of quality of life in ALS. *J Neurol Neurosurg Psychiatry, 75*, 1597-1601.

Cohen, J. D., & Polich, J. (1997). On the number of trials needed for P300. *International Journal of Psychophysiology, 25*(3), 6.

Croft, R. J., Gonsalvez, C. J., Gabriel, C., & Barry, R. J. (2003). Target-to-target interval versus probability effects on P300 in one- and two-tone tasks. *Psychophysiology, 40*, 322-328.

Delorme, A., & Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *J Neurosci Methods, 134*(1), 9-21.

Donchin, E. (1981). Presidential address, 1980. Surprise!...Surprise? *Psychophysiology, 18*, 493-513.

Donchin, E., & Cohen, L. (1967). Averaged evoked potentials and intramodality selective attention. *Electroencephalogr Clin Neurophysiol, 22*, 537-546.

Donchin, E., Kramer, A. F., & Wickens, C. (1982). Probing the cognitive infrastructure with event-related brain potentials. In Frazier, M.C., & Crowbee, R.B. (Eds.), *Proceedings of the workshop on flight testing to identify pilot workload and pilot dynamics* (pp. 371-387). Washington, DC: AFFTC-JR-82-5, Edwards Air Force Base.

Donoghue, J. P. (2002). Connecting cortex to machines: Recent advances in brain interfaces. *Nat Neurosci, 5 Suppl*, 1085-1088.

Draper, N. R., & Smith, H. (1981). *Applied regression analysis* (2d ed.). New York: Wiley.

Duncan-Johnson, C. C., & Donchin, E. (1977). On quantifying surprise: the variation of event-related potentials with subjective probability. *Psychophysiology, 14*, 456-467.

Farwell, L. A., & Donchin, E. (1988). Talking off the top of your head: Toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalogr Clin Neurophysiol, 70*, 510-523.

Folstein, J. R., & Van Petten, C. (2008). Influence of cognitive control and mismatch on the N2 component of the ERP: a review. *Psychophysiology, 45*, 152-170.

Fowler, B. (1994). P300 as a measure of workload during a simulated aircraft landing task. *Hum Factors, 36*, 670-683.

Furdea, A., Halder, S., Krusienski, D. J., Bross, D., Nijboer, F., Birbaumer, N., et al. (2009). An auditory oddball (P300) spelling system for brain-computer interfaces. *Psychophysiology, 46*, 617-625.

Giordana, M., Ferrero, P., Grifoni, S., Pellerino, A., Naldi, A., & Montuschi, A. (2010). Dementia and cognitive impairment in amyotrophic lateral sclerosis: A review. *Neurological Sciences*, 1-8.

Gonsalvez, C. L., & Polich, J. (2002). P300 amplitude is determined by target-to-target interval. *Psychophysiology, 39*, 388-396.

Gopher, D., Donchin, E. (1986). Workload: An examination of the concept. In K. R. K. Boff, Lloyd; Thomas, James P. (Ed.), *Handbook of perception and human performance, vol. 2: Cognitive processes and performance* (pp. 1-49). Oxford, England: John Wiley & Sons.

Hochberg, L. R., Serruya, M. D., Friehs, G. M., Mukand, J. A., Saleh, M., Caplan, A. H., et al. (2006). Neuronal ensemble control of prosthetic devices by a human with tetraplegia. *Nature, 442*, 164-171.

Hyde, M. (1997). The N1 response and its applications. *Audiol Neurootol, 2*, 281-307.

Kayser, J., & Tenke, C. E. (2003). Optimizing PCA methodology for ERP component identification and measurement: Theoretical rationale and empirical evaluation. *Clin Neurophysiol, 114*, 2307-2325.

Kayser, J., & Tenke, C. E. (2006). Principal components analysis of Laplacian waveforms as a generic method for identifying ERP generator patterns: I. Evaluation with auditory oddball tasks. *Clin Neurophysiol, 117*, 348-368.

Kinoshita, S., Inoue, M., Maeda, H., Nakamura, J., & Morita, K. (1996). Long-term patterns of change in ERPs across repeated measurements. *Physiol Behav, 60*, 1087-1092.

Klobassa, D. S., Vaughan, T. M., Brunner, P., Schwartz, N. E., Wolpaw, J. R., Neuper, C., et al. (2009). Toward a high-throughput auditory P300-based brain-computer interface. *Clin Neurophysiol, 120*, 1252-1261.

Kramer, A. F., Schneider, W., Fisk, A., & Donchin, E. (1986). The effects of practice and task structure on components of the event-related brain potential. *Psychophysiology, 23*(1), 33-47.

Kramer, A. F., Trejo, L. J., & Humphrey, D. (1995). Assessment of mental workload with task-irrelevant auditory probes. *Biol Psychol, 40*(1-2), 83-100.

Kramer, A. F., Wickens, C. D., & Donchin, E. (1983). An analysis of the processing requirements of a complex perceptual-motor task. *Hum Factors, 25*, 597-621.

Kramer, A. F., Wickens, C. D., & Donchin, E. (1985). Processing of stimulus properties: Evidence for dual-task integrality. *J Exp Psychol Hum Percept Perform, 11*, 393-408.

Krusienski, D. J., Sellers, E. W., Cabestaing, F., Bayoudh, S., McFarland, D. J., Vaughan, T. M., et al. (2006). A comparison of classification techniques for the P300 Speller. *J Neural Eng, 3*, 299-305.

Krusienski, D. J., Sellers, E. W., McFarland, D. J., Vaughan, T. M., & Wolpaw, J. R. (2008). Toward enhanced P300 speller performance. *J Neurosci Methods, 167*(1), 15-21.

Kubler, A., & Birbaumer, N. (2008). Brain-computer interfaces and communication in paralysis: extinction of goal directed thinking in completely paralysed patients? *Clin Neurophysiol, 119*, 2658-2666.

Kubler, A., Kotchoubey, B., Hinterberger, T., Ghanayim, N., Perelmouter, J., Schauer, M., et al. (1999). The thought translation device: a neurophysiological approach to communication in total motor paralysis. *Exp Brain Res, 124*, 223-232.

Kubler, A., Winter, S., Ludolph, A. C., Hautzinger, M., & Birbaumer, N. (2005). Severity of depressive symptoms and quality of life in patients with amyotrophic lateral sclerosis. *Neurorehabil Neural Repair, 19*, 182-193.

Kutas, M., & Hillyard, S. A. (1980). Reading senseless sentences: Brain potentials reflect semantic incongruity. *Science, 207*, 203-205.

Laureys, S., Owen, A. M., & Schiff, N. D. (2004). Brain function in coma, vegetative state, and related disorders. *Lancet Neurol, 3*, 537-546.

Leuthardt, E. C., Schalk, G., Wolpaw, J. R., Ojemann, J. G., & Moran, D. W. (2004). A brain-computer interface using electrocorticographic signals in humans. *J Neural Eng, 1*(2), 63-71.

Luck, S. J., & Hillyard, S. A. (1994). Electrophysiological correlates of feature analysis during visual search. *Psychophysiology, 31*, 291-308.

McFarland, D. J., Sarnacki, W. A., & Wolpaw, J. R. (2010). Electroencephalographic (EEG) control of three-dimensional movement. *Journal of Neural Engineering, 7*. doi: 10.1088/1741-2560/7/5/056013.

Nicolelis, M. A. (2003). Brain-machine interfaces to restore motor function and probe neural circuits. *Nat Rev Neurosci, 4*, 417-422.

Nijboer, F., Sellers, E. W., Mellinger, J., Jordan, M. A., Matuz, T., Furdea, A., et al. (2008). A P300-based brain-computer interface for people with amyotrophic lateral sclerosis. *Clin Neurophysiol, 119*, 1909-1916.

O'Doherty, J. E., Lebedev, M. A., Hanson, T. L., Fitzsimmons, N. A., & Nicolelis, M. A. (2009). A brain-machine interface instructed by direct intracortical microstimulation. *Front Integr Neurosci, 3,* 20.

Patel, S. H., & Azzam, P. N. (2005). Characterization of N200 and P300: Selected studies of the event-related potential. *Int J Med Sci, 2,* 147-154.

Patil, P. G., Carmena, J. M., Nicolelis, M. A., & Turner, D. A. (2004). Ensemble recordings of human subcortical neurons as a source of motor control signals for a brain-machine interface. *Neurosurgery, 55*(1), 27-35; discussion 35-28.

Pearson, K. (1901). On lines and planes of closest fit to systems of points in space. *Philosophical Magazie, 2*, 559-572.

Pellegrini, N., Pelletier, A., Orlikowski, D., Lolierou, C., Ruquet, M., Raphael, J. C., et al. (2007). Hand versus mouth for call-bell activation by DMD and Becker patients. *Neuromuscul Disord, 17,* 532-536.

Pfurtscheller, G., Brunner, C., Schlogl, A., & Lopes da Silva, F. H. (2006). Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks. *Neuroimage, 31*, 153-159.

Pfurtscheller, G., Leeb, R., Keinrath, C., Friedman, D., Neuper, C., Guger, C., et al. (2006). Walking from thought. *Brain Res, 1071*, 145-152.

Picton, T. W. (1992). The P300 wave of the human event-related potential. *J Clin Neurophysiol, 9*, 456-479.

Polich, J. (1989). Habituation of P300 from auditory stimuli. *Psychobiology, 17*(1), 19-28.

Polich, J. (1990). Probability and inter-stimulus interval effects on the P300 from auditory stimuli. *Int J Psychophysiol, 10*, 163-170.

Polich, J. (2007). Updating P300: an integrative theory of P3a and P3b. *Clin Neurophysiol, 118*, 2128-2148.

Posner, M. I. (1980). Orienting of attention. *Q J Exp Psychol, 32*(1), 3-25.

Prinzel, L. J., 3rd, Freeman, F. G., Scerbo, M. W., Mikulka, P. J., & Pope, A. T. (2003). Effects of a psychophysiological system for adaptive automation on performance, workload, and the event-related potential P300 component. *Hum Factors, 45*, 601-613.

Pritchard, W. S. (1981). Psychophysiology of P300. *Psychol Bull, 89*, 506-540.

Rennaker, R. L., Miller, J., Tang, H., & Wilson, D. A. (2007). Minocycline increases quality and longevity of chronic neural recordings. *J Neural Eng, 4*(2), L1-5.

Ritter, W., & Vaughan, H. G., Jr. (1969). Averaged evoked responses in vigilance and discrimination: A reassessment. *Science, 164*, 326-328.

Schalk, G., McFarland, D. J., Hinterberger, T., Birbaumer, N., & Wolpaw, J. R. (2004). BCI2000: a general-purpose brain-computer interface (BCI) system. *IEEE Trans Biomed Eng, 51*, 1034-1043.

Schalk, G., Miller, K. J., Anderson, N. R., Wilson, J. A., Smyth, M. D., Ojemann, J. G., et al. (2008). Two-dimensional movement control using electrocorticographic signals in humans. *J Neural Eng, 5*(1), 75-84.

Sellers, E. W., & Donchin, E. (2006). A P300-based brain-computer interface: Initial tests by ALS patients. *Clin Neurophysiol, 117*, 538-548.

Sellers, E. W., Krusienski, D. J., McFarland, D. J., Vaughan, T. M., & Wolpaw, J. R. (2006). A P300 event-related potential brain-computer interface (BCI): The effects of matrix size and inter stimulus interval on performance. *Biol Psychol, 73*, 242-252.

Sellers, E. W., Vaughan, T. M., & Wolpaw, J. R. (2010). A brain-computer interface for long-term independent home use. *Amyotroph Lateral Scler, 11*, 449-455.

Sharbrough, F. W. (1991). Advances in epilepsy surgery offer patients new hope. *Minn Med, 74*(10), 9-12.

Squires, K. C., & Donchin, E. (1976). Beyond averaging: the use of discriminant functions to recognize event related potentials elicited by single auditory stimuli. *Electroencephalogr Clin Neurophysiol, 41*, 449-459.

Sutton, S., Braren, M., Zubin, J., & John, E. R. (1965). Evoked-potential correlates of stimulus uncertainty. *Science, 150*, 1187-1188.

Tenke, C. E., Kayser, J., Stewart, J. W., & Bruder, G. E. (2010). Novelty P3 reductions in depression: characterization using principal components analysis (PCA) of current source density (CSD) waveforms. *Psychophysiology, 47*, 133-146.

Torricelli, D., Conforto, S., Schmid, M., & D'Alessio, T. (2008). A neural-based remote eye gaze tracker under natural head motion. *Comput Methods Programs Biomed, 92*(1), 66-78.

Townsend, G., LaPallo, B. K., Boulay, C. B., Krusienski, D. J., Frye, G. E., Hauser, C. K., et al. (2010). A novel P300-based brain-computer interface stimulus presentation paradigm: moving beyond rows and columns. *Clin Neurophysiol, 121*, 1109-1120.

Tueting, P., Sutton, S., & Zubin, J. (1970). Quantitative evoked potential correlates of the probability of events. *Psychophysiology, 7*, 385-394.

Vaughan, T. M., Wolpaw, J. R., & Donchin, E. (1996). EEG-based communication: Prospects and problems. *IEEE Trans Rehabil Eng, 4*, 425-430.

Wolpaw, J. R., & McFarland, D. J. (2004). Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans. *Proc Natl Acad Sci U S A, 101*, 17849-17854.

Wolpaw, J. R., McFarland, D. J., & Vaughan, T. M. (2000). Brain-computer interface research at the Wadsworth Center. *IEEE Trans Rehabil Eng, 8*, 222-226.

Wolpaw, J. R., & Wood, C. C. (1982). Scalp distribution of human auditory evoked potentials. I. Evaluation of reference electrode sites. *Electroencephalogr Clin Neurophysiol, 54*(1), 15-24.

Wood, C. C. (1982). Application of dipole localization methods to source identification of human evoked potentials. *Annals of the New York Academy of Sciences, 388*, 139-155.

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Schwartz, N.E., Krusienski, D.J., Frye, G.E., Hauser, C.K., Vaughan, T.M., Johnson, G.D., & Sellers, E.W. (2009, October). *The P300 Brain-Computer Interface: Prediction of Success Through Waveform Analysis.* Poster session presented at the annual meeting of the Society for Neuroscience, Chicago, IL.

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