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Improving Brain-Computer Interface Performance: Giving the P300 Speller Some Color.

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Improving Brain-Computer Interface Performance: Giving the P300 Speller Some Color

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by

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ABSTRACT

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Individuals who suffer from severe motor disabilities face the possibility of the loss of speech. A Brain-Computer Interface (BCI) can provide a means for communication through non-muscular control. Current BCI systems use characters that flash from gray to white (GW), making adjacent character difficult to distinguish from the target. The current study implements two types of color stimulus (grey to color [GC] and color intensification [CI]) and I hypotheses that color stimuli will; (1) reduce distraction of nontargets (2) enhance target response (3) reduce eye strain. Online results (n=21) show that GC has increased information transfer rate over CI. Mean amplitude revealed that GC had earlier positive latency than GW and greater negative amplitude than CI, suggesting a faster perceptual process for GC. Offline performance of individual optimal channels revealed significant improvement over online standardized channels. Results suggest the importance of a color stimulus for enhanced response and ease of use.

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CHAPTER 1

INTRODUCTION

Human beings place a great importance on communication, and rightly so. Without communication we would be unable to share our ideas, our feelings, or our past. If necessity is the mother of invention, consider all the inventions to improve communication, from the alphabet to the internet. A quote from John A. Piece sums this concept “Communication is not only the essence of being human, but also a vital property of life” (n.d., p.1). If our mind is sharp yet our body has failed, we would still have the necessity to communicate but lack the ability. A system is being developed to fulfill this need.

A Brain Computer Interface (BCI) is a specific type of human-machine interaction. It is a direct link between the human brain and a computer. These types of systems can provide an important communication outlet for those who are “locked-in” by amyotrophic lateral sclerosis (ALS), brain stem stroke, or head trauma. Locked in syndrome (LIS) refers to a condition where all voluntary muscles, except those that control eye movement, are completely paralyzed. ALS is a progressive motoneuron disease that causes irreversible loss of motor function. About 6,000 people are diagnosed with ALS each year in the U.S. (Mitsumoto, Przedborski, & Gordon, 2006). As the disease progresses it becomes difficult, if not impossible for the individual to speak. Eventually almost all muscle control will be lost, this is referred to as “locked-in”. A person with ALS can choose to accept artificial ventilation. However, more than 90% do not choose this option, resulting in only 10% living more than 10 years after diagnosis (Mitsumoto, 1994). Many people choose not to accept ventilation systems because they expect to have lower quality of life as a direct result of losing the ability to communicate (Albert et al., 2005).

Currently, people with ALS are the most likely to benefit from a BCI because of their severe motor disability. Less disabled people are able to use alternative and augmentative communication (AAC). AAC is any form of nonspeech communication, an example would be eye blinks or physical gestures with more advanced forms including communication boards, touch screen devices, computers with voice output, and head or eye tracking. However, head and eye tracking require ideal circumstances to operate effectively (Beukelman, Fager, Ball, & Dietz, 2007). Although AAC is faster than current BCI systems, AAC relies on motor control. The loss of motor control makes BCI one of the few means of independent communication for a person that is locked-in.

Types of BCI

BCI systems can be noninvasive (i.e., electroencephalographic [EEG]-based), recording electrical activity from the scalp, or invasive, recording activity from the cortical surface or from neurons within the brain (Hochberg, 2006; Kennedy, Bekay, Moore, Adams, & Goldwaithe, 2000). Invasive methods provide larger amplitude and improved signal to noise ratio (Leuthardt, Schalk, Wolpaw, Ojemann, & Moran, 2004). These advantages have lead to improved BCI performance (Birbaumer, 2006; Leuthardt et al., 2004). However, when 17 ALS patients (all on respirators) were asked to choose between surgical implantation and noninvasive BCI control, 16 of the 17 chose the slower and higher error performance of the noninvasive BCI (Birbaumer, 2006). This points BCI research in a noninvasive direction and challenges researchers to improve noninvasive control. There are several forms of noninvasive BCI control, slow cortical potentials, Mu and Beta rhythms, and P300 (Birbaumer et al., 1999; Birbaumer et al., 2000; Farwell & Donchin, 1988; McFarland, Lefkowicz, & Wolpaw, 1997). The P300 BCI speller has shown the most promise due to its paradigm eliciting a driven response, in other words it requires little to no training to use (Guger et al., 2009; Townsend et al., 2010). Several decades of research have shaped the design on the P300 BCI. The following sections summarize a few P300 BCI basics and design advancements.

Event-Related Potential

Event-related potentials (ERPs) represent paradigm or task specific activity of neuronal generators that “sum and volume conduct to scalp electrodes” (Kayser & Tenke 2003, p. 2307). ERPs are collected from EEG recordings. EEG is “a recording of the difference in electrical potential between various points on the surface of the scalp” (Hugdahl, 1995, p. 234). A typical ERP is a recorded window of EEG data, following or preceding the stimulus, defining the window recording as “time-locked” to the stimulus event. The window is usually between 500-1500 ms in duration. A time-locked window of EEG data is taken each time the stimulus is presented. Time-locked windows are then averaged together. Averaging increases the signal to noise ratio, therefore making the components of the ERP more salient (Fabiani, Gratton, & Coles, 2000). However, when averaging a signal some features can be lost due to the variability of the signals (e.g. the peak of a positive deflection at 100 ms can be shifted later by another positive peak at 125 ms or even canceled out by negative deflection at 100 ms from another time-locked window). Time locking the ERP’s to a stimulus allows for an in-depth temporal analysis of electrical brain activity in response to a stimulus. A series of positive and negative waves make up the ERP, each wave is a component. Each component reflects the activity of underlying neural generators’ summed response to a stimulus (Kayser & Tenke 2003; Naatanen & Picton, 1987). ERP components are named by their polarity (“P” or “N”) and latency (time after the stimulus) or by order of appearance. Therefore, N400 or N4 is a negative deflection around 400 ms post stimulus.

The P300 ERP Component

The P300 has been the subject of research for over 45 years. The reliability of P300 eliciting paradigms has been well defined. Fabiani, Gratton, Karis, and Donchin (1987) describe the P300 component as having a positive polarity with latency longer than 275 ms, with maximum amplitude at the parietal and central locations. The P300 is elicited by task relevant stimuli. A common method used to elicit the P300 is referred to as an oddball paradigm. Donchin and Coles (1988) describe the four conditions that must be met in this paradigm: one, random stimuli must be presented; two, rules on how to categorize the stimuli are presented; three, the rules must be implemented by the participant; four, one category of stimuli must occur less often that the others. The infrequent stimuli elicit a P300.

The P300 component of the ERP was discovered by Sutton, Braren, Zubin, and John (1965). In their experiment stimuli were delivered in pairs. A cue followed by a test stimulus with a 3 to 5 second delay between the cue and test stimuli. This set of stimuli was presented in two types of groups. The first group had a consistent test stimulus of always a light or always a sound that followed the cue (the certain group). In the second group the test stimulus was inconsistent; it would either be a light or a sound that followed the cue (the uncertain group). When the ERPs were compared, the uncertain stimuli had larger positive amplitude, especially around 300 ms (see Figure 1). This increase in amplitude was reflected across all participants. A second experiment had two groups but both groups were uncertain of the test stimulus. The first group had 33% sound and 66% light stimuli. The second had 33% light and 66% sound. All of the stimulus waveforms had a positive deflection around 300ms, but the less common occurrence stimulus had larger amplitude in both groups. In a final experiment the participants had to guess whether they were going to receive a light or sound stimulus; however, the light and sound stimulus were presented an equal amount of times. When the participants guessed wrong they had higher amplitude than when they were correct. This positive peak at 300ms became known as the P300.

Figure 1.

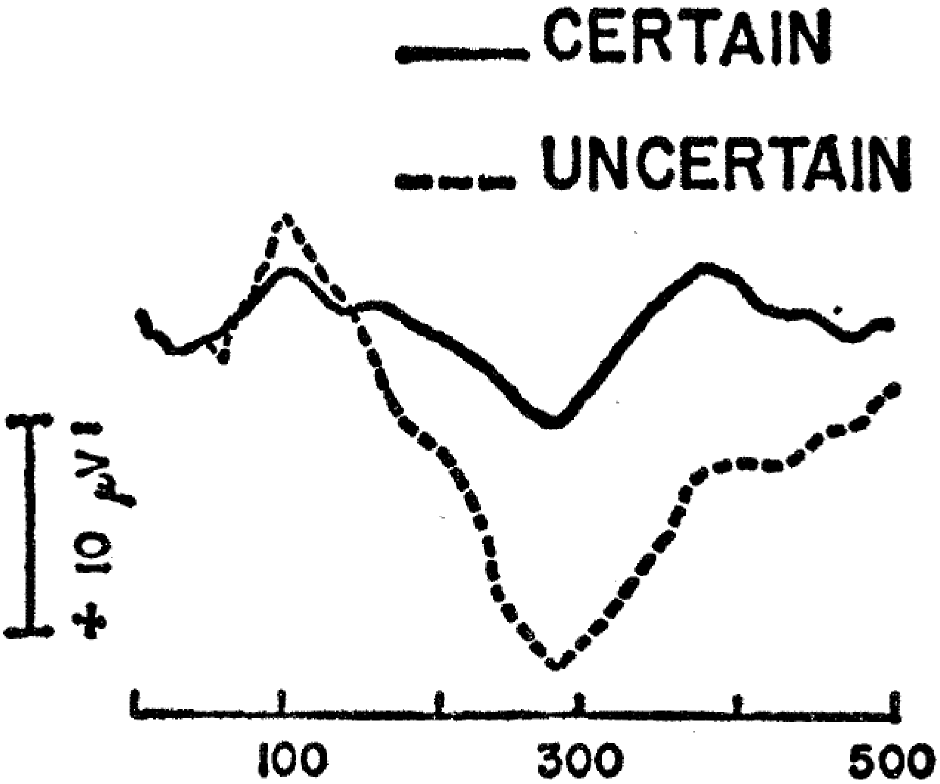

Figure 1. Certain and Uncertain waveforms adopted from the Sutton et al. (1964) study. Note that positive is plotted down. The P300 is in the uncertain dotted line.

<u>Effects of Averaging and Target Probability</u>

Cohen and Polich (1997) examined two different techniques of averaging 40 trials of auditory and visual stimuli with two different probabilities of targets (.20 and .80) and its effects on the amplitude and latency of the P300. The first technique (single-trial averages) averaged two trials together (i.e. 1&2, 3&4, 5&6,…39&40), resulting in 40 averages for each condition. The second technique (called successive averages) added trials to the average in blocks of two (i.e. 1-2, 1-4, 1-6,…1-40). The single-trial averages revealed little difference across trials. However, auditory stimuli had a larger amplitude and shorter latency compared to visual stimuli. Probability condition resulted in larger amplitude and longer latency for the .20 condition across modality. Successive averages revealed a decrease in P300 amplitude as trials were added to the average with blocks 1-19. As trials 20-40 were added there was no change in amplitude. Peak latency did slightly increase as trials were added. However, a post-hoc examination of latency revealed that only two pairs out of 190 trials were significantly different, suggesting that latency is not affected by adding trials. Similar to the single-trial averaging, the auditory P300 has larger amplitude and shorter latency than visual stimuli and the .20 probability has a larger amplitude and longer latency than the .80 condition across modality.

Habituation Effects

Ravden and Polich (1998) examined the habituation effects of a visual P300. The target stimulus has a probability of .50 and was presented in 10-trial blocks with a 10-minute interval between each trail. Three electrodes were recorded; Fz, Cz, and Pz with a linked earlobes reference. Comparing earlier trials with later trials, there was a significant decrease in P300 amplitude in later trials on electrode Fz, a smaller decrease at Cz, and no decrease on Pz. P300 amplitude increased from frontal to partial electrodes. There were no habituation effects on amplitude within trial blocks and no effects on latency across all trials. Habituation is further addressed in Channel Selection under Methods.

The P300-BCI

Using a 6x6 grid of letters and numbers, Farwell and Donchin (1988) modified the oddball paradigm to use the P300 as a virtual typing or spelling device (See Figure 2). The P300 speller flashes the rows and columns of the 6x6 matrix in a random order and the participant attends to the character (or target) they wish to select or “type.” When the row or column containing the target flashes, a P300 is elicited. By flashing each row and column several times an average of the EEG response was created for each row and column. A stepwise discriminant analysis examined the responses and determined which character the participant intended to select with accuracy levels high enough for effective communication.

A major advantage of the P300 BCI is that it requires minutes of training as compared to other systems that require weeks of training. This is because the P300 is stimulus driven; it is elicited in response to a rare or meaningful stimulus.

Figure 2.

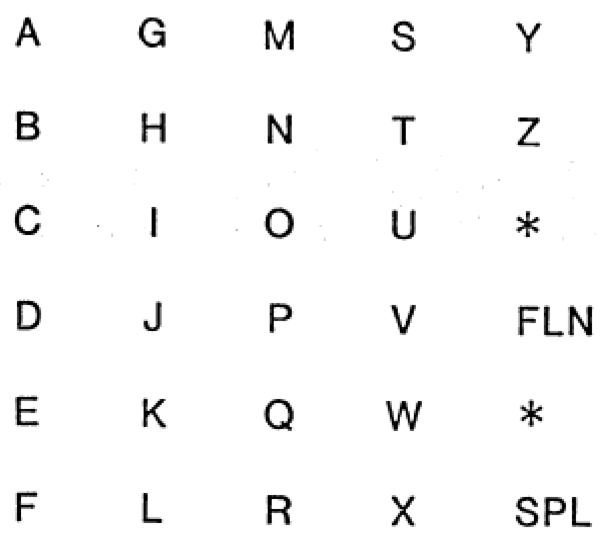

Figure 2. An example of the speller matrix used in the Farwell and Donchin (1988) study. The P300 speller flashes the rows and columns of the 6x6 matrix in a random order and the participants attend to the character they wish to select. A P300 is elicited when the row or column containing the target flashes.

<u>System Errors</u>

Systematic errors typically occur in the P300-based BCI. Changing the presentation could improve performance by reducing common systematic errors. Two common errors are related to attention being attracted away from the desired item (e.g. flash of nearby stimuli, eliciting a P300 response to the nontarget), or fatigue related to the high rate of stimulus presentation and/or prolonged duration of stimulus presentation (e.g. a high flash rate for a long duration) as described in Fazel-Rezai (2007). The current proposal examines novel stimulus presentation paradigms in an effort to attenuate such errors.

Not an error, but a serious system limitation is the speed of P300 BCI communication. The current maximum character selection rate is approximately four selections per minute in P300 BCIs (Lenhardt, Kaper, & Ritter, 2008; Ryan et al.,2011; Townsend et al., 2010). The absolute best speed of the system (i.e. running at the minimum target flashes needed) would still take 3 seconds for one selection. This limitation is one of the major challenges for researchers who develop BCIs. This slow speed is taxing on the user as well as to the person the user is trying to communicate. Most improvements made to any BCI system are to increase the rate of accurate communication.

In most studies the same basic format introduced by Farwell and Donchin (1988) is still employed today; however, there have been improvements in several areas from signal processing to stimulus presentation. A number of these improvements are covered in the following sections.

Channel Selection

Prior to the Krusienski et al. (2008) study the majority of BCI research used a full range of electrodes (from 3 to 64). The authors examined the possibility of expanding the electrodes used for classification. Using a stepwise liner discriment analysis (SWLDA, described in Methods) classifier for online and offline analysis of 64-channel data referenced to the right earlobe. Online analysis refers to participants using the classifier in real time to make selections. Offline refers to a program predicting what selections would be made based on the participant's data. Seven participants had a task of spelling provided words that totaled 36 characters. This study examined 19 channels (Fz, FCz, Cz, C3, C4, CPz, Pz, P3, P7, P4, P8, POz, PO3, PO7, PO4, PO8, O1, Oz, and O2). In an online test Fz, Cz, Pz, PO7, PO8, and Oz provided the best performance.

In an offline test different decimation factors along with common average reference (CAR) were examined. Decimation is the process of passing a signal through a low pass filter (this takes out some of the high frequency) and then reducing the sample rate; a decimation factor is the ratio of input rate to output rate. That is, a signal that has a sample rate of 100 Hz (100 samples a second) is reduced to a 75 Hz (75 samples a second). Krusienki et al. (2008) examined the decimation factors of 6, 12, and 24 to sample rates of 40, 20, and 10 Hz, and found decimation factors of 6 and 12 performed better than 24 but with no statistical difference. Common average reference (CAR) is done by averaging the electrical signal from all the electrodes and this average is used as a reference for each individual electrode. CAR showed no significant difference from the right ear lobe reference.

Classification

There have been several studies examining P300 BCI classification techniques. A brief list includes: 1) Independent components analysis (ICA) examined by Li, Sanka, Arbel, and Donchin (2009) revealed 76% accuracy when classifying single P300 responses. Serby, Yom-Tov, and Inbar (2005) performed an online ICA study and found it performed at 79%. 2) Support vector machines (SVMs) examined by Thulasidas, Guan, and Wu (2006) revealed high accuracy and Olison, Si, Hu, and He (2005) used SVMs to classify single unit recording in rats in a discrete directional task. 3) Stepwise linear discriminant analysis (SWLDA) showed promise in patients with ALS in a P300 four-choice paradigm (Sellers & Donchin 2006) and a tactile P300 BCI (Brouwer & van Erp, 2010). 4) Fisher's linear discriminant (FLD) revealed good classification of rhythmic finger movements (Nazarpour, Praamstra, Miall, & Sanei, 2009) and high accuracy rates for disabled and able-bodied P300 BCI users (Hoffmann, Vesin, Ebrahimi, & Diserens, 2008).

Krusienski et al. (2006) used the same data set to examine five types of classification methods: Pearson's correlation method (PCM), Fisher's linear discriminant (FLD), stepwise linear discriminant analysis (SWLDA), linear support vector machine (LSVM), and Gaussian support vector machine (GSVM). The performance of each classifier was evaluated by the number of intensifications needed for accurate classification and accuracy from a subsequent testing condition. Improvements in classification or performance would result in an increased bit rate. Sixty-four channels where collected, but only 8 channels where used for classification (Fz, Cz, Pz, P3, P4, PO7, PO8, and Oz). Eight participants were included in this study. PCM had the lowest accuracy. FLD had superior performance to PCM. Two support vector machines were tested, LSVM and GSVM. While the LSVM performed well the GSVM over-fitted the training data, resulting in poor performance. Over-fitting is when an accurate model is created from the training data but is too specific (does not allow for variance in response) so the model does not fully represent the test data. Overall FLD and SWLDA provided the best results. The authors state that SWLDA could be more advantages because of its ability to eliminate insignificant features that could cause over-fitting. SWLDA was the method used for classification in this study and is explained further in the Methods section.

Stimulus Presentation

Performance of the P300 speller can also be improved by using modified stimulus presentation paradigms to increase the signal-to-noise ratio between target and nontarget responses. Increased target response amplitude allows the components (e.g. P300) to be more salient than the nontarget response, thus, improving signal-to-noise ratio. An increase in matrix size from the 6x6 (36 items) used by Farwell and Donchin (1988) to an 8x9 (72 items) matrix has shown an increase in P300 amplitude (Sellers, Krusienski, McFarland, Vaughan, & Wolpaw, 2006). This increase in amplitude is due to the reduction in the probability of the target stimulus occurring (Allison & Pineda, 2003; Cohen & Polich 1997; Sellers et al., 2006). The target probability in a 36 item matrix is 1 in 36 versus 1 in 72 in a 72 item matrix. Polich, Ellerson, and Cohen (1996) examined the effects of increasing the intensity of the stimuli (auditory and visual) on P300 amplitude and latency. A correlation of increasing intensity with increased amplitude was only found when auditory and visual ERP results were combined, no significant difference was found when a modality was examined individually. Hong, Guo, Liu, Gao, and Gao (2009) examined a visual motion onset N200 based BCI speller. The stimulus flashed entire rows and columns of small vertical bars that moved across a box below a character. The stimulus for each character was a randomly selected color, redundant colors were controlled for in each row. This 'N200 speller' showed comparable results to the P300 BCI speller. Takano, Komatsu, Hata, Nakajima, and Kansaku (2009) sought to improve accuracy by changing the way the characters flashed with three different paradigms; a white-to-gray pattern (luminance condition), a green-to-blue isoluminance pattern (chromatic condition), and a green-to-blue luminance pattern (luminance chromatic condition). Of the 10 participants, 4 had a significant increase in accuracy in the chromatic condition and 5 had a significant increase in the luminance chromatic condition. The authors took advantage of the fact that large groups of neurons in the parietal, occipital, and temporal areas are involved in color processing, and the occipital and parietal areas are involved in luminance processing. Presumably, this additional activity enhanced the EEG signal and provided a stronger response to the target items (Takano et al., 2009).

Until recently the previous P300 BCI studies have used the "row/column" presentation paradigm proposed by Farwell and Donchin (1988) described above. Guger et al. (2009) compared the row/column to a single characters flash in which each character flashes individually. Even though the single character flash had higher P300 amplitude, the row/column method yielded higher accuracy and communication rate. Townsend et al. (2010) has presented a novel paradigm referred to as the "checkerboard paradigm" (CBP). Instead of flashing the rows or columns, quasi-random groups of 6 characters flashed. This controlled for adjacent flashes (i.e., adjacent items could not flash at the same time), which can cause errors (Fazel-Rezai, 2007). When compared to the row/column, the CBP had higher accuracy (92%) than row/column (77%) as well as higher information transfer rate (23 bits per min verses 17 bits per min).

A recent study used the CBP and added a predictive speller program (Ryan et al., 2011). The predictive speller program takes each character as it is selected and populates a list of the seven most probable words. Each of these words was numbered and if the desired word appeared on the list the participant could select the corresponding number from the speller matrix. The predictive speller would then type the remaining characters of the word and provide a space afterward saving the participant several selections. Although there was a decrease in accuracy and P300 amplitude, there was an increase the number of output characters per minute from 3.76 to 5.28. In this 58 selection error correcting task (the task was not complete until all errors had been corrected) the participants without the predictive speller took an average 7.43 minutes longer to complete the task.

The addition of each item flashing a unique color stimulus would aid in the reduction of adjacent items (nontargets) eliciting a P300 response. The Townsend et al. (2010) checkerboard paradigm controls for double flashes and four of the eight adjacent nontarget flashes that surround the target (i.e. above, below, left and right). The remaining four adjacent nontarget flashes (each diagonal item) would be controlled by the addition color stimuli, similar to Takano et al. (2009). By defining each item in the matrix a unique color flash (one of nine colors), instead of a blue to green stimulus, no matter where the target happens to fall on the matrix it will be a different color than all adjacent stimuli.

Human Color Processing

Humans have trichromatic vision, the ability to see three photo pigments: blue, green, and red (King, 2005). This gives humans a wide range of color distinction, which is important in recognizing edible food and avoiding dangers (King, 2005). The role and importance of color in object detection has been the subject of many studies that incorporate visual search tasks, most of which examine theories proposed by Treisman and Gelade (1980). Additional studies have shown that changes in color can be attended to selectively within multi-feature stimuli (Anllo-Vento, Luck, & Hillyard, 1998).

The human retina has two general types of photoreceptors, rods and cones. Rods outnumber the cones, roughly 120 million to 6 million, and are located all over the retina except for one spot called the fovea. The fovea is a concentration of cones directly behind the lens at 0^0. A few degrees in either direction moves outside the fovea and the number of cones decreases dramatically, with an abundance of rods. Rod pigment has peak at 500nm (blue-to-green) in the light spectrum. There are three types of cones, each with its own pigment peak: 419nm (dark blue), 531nm (green-to-yellow), and 558nm (yellow-to-red) (Goldstein, 2010). This means that the focus point of vision, the fovea, is sensitive to a broad light spectrum, while our periphery is less sensitive to the full spectrum. In a color P300 speller, this translates to fewer distractions from color items flashing in the periphery compared to white flashes.

The color vision pathway starts at the retina then travels to the lateral geniculate nucleus, where the parvocellular layers (3-6) process color information from each retina. Through the optic radiation the color pathway leads to V1, the most posterior area of the occipital lobe. The blobs of V1 are the first area of the cortex to process color vision. From V1 the color pathway follows the ventral (or “what”) pathway toward the temporal lobe. The ventral route leads through the thin strips of V2, then to V4. V4 is where the majority of color processing takes place. Additional color processing is associated with the fusiform gyrus. Functional brain imaging studies (listed below) have shown the processing of color information is associated with the color processing pathway.

CHAPTER 2

BRAIN IMAGING

EEG/ERP

Liu and Guo (2002) examined the effects of different color checkerboard patterns had on the P1 (or P100) component. Four patterns were presented at 0.8 Hz; black-white, red-white, green-white, and red-green. The significant difference between each pattern for P1 latency (from short to long) was: red-white, black-white, red-green, green-white. Amplitude of P1 was higher for the black-white pattern than all color patterns, and there was no amplitude difference between color patterns. This study does not seem to support the idea of a color P300 speller. However, it is not representative of a P300 speller because it does not examine a meaningful stimulus. Rather, only a response to a color pattern, and only one component was analyzed. Although the P300 speller is based on one component, the entire ERP (800 ms) is used for classification. Therefore, any additional activity during the 800ms post stimulus could be used by the classifier.

Anllo-Vento et al.(1998) examined the ERPs of selective attention to a color stimulus. The stimuli were random checkerboard patterns of red-grey or blue-grey. A button press was required when the assigned attended color was dimmer. Thirty-two channels were recorded from 16 participants and referenced to the right mastoid. There was no difference in reaction time or accuracy to either color. Specific ERP components were isolated by inverse dipole modeling. The software Brain Electrical Source Analysis (BESA) provided the models of activity and were applied to magnetic resonance images (MRI) of six participants. BESA provides the estimated dipole location and orientation of underlying neurogenerators by comparing the scalp distribution to a dipole model. Using electrodes O1/O2, IN3/IN4, T5/T6, TO1/TO2, P3/P4, PO1/PO2, the dorsal extrastriate area showed activation at 100 ms. Using electrodes O1/O2, IN3/IN4, T5/T6, TO1/TO2 , the collateral sulcus showed activation at 160 ms. Using electrodes F3/F4, F7/F8, C3/C4, CT5/CT6, T3/T4, CP1/CP2 , the premotor area began at 190 ms. The authors explain that the activation of the premotor area was motor preparatory activity for the button press of target detection. The authors go on to state that premotor activity has been found in previous positron emission tomography studies (e.g. Corbetta et al., 1991; Gulyas et al., 1994). Using all 32 electrodes (F3, F4, F7, F8, C3, C4, P3, P4, O1, O2, T3, T4, T5, T6, CP1, CP2, CT5, CT6, PO1, PO2, TO1, PO2, IN3, IN4, Fz, Cz, Pz, IPz, INz, LM, & RM) the fusiform gyrus became active at 240 ms. The activity of these areas could be used by the classifier in a color P300 BCI.

Allison et al. (1993) examined the localization of color processing by implanting electrodes in 13 patients with epilepsy. The authors used red or blue checkerboard stimuli and determined the time course of color processing: starting in the medial lingual gyrus (at 180 ms), followed by the lateral lingual gyrus, then the posterior fusiform gyrus (at 275 ms), and ending in the inferior temporal gyrus. This activation is also seen in the in the functional imaging studies mentioned below (see Other Imaging Techniques).

Anllo-Vento et al. (1998) and Allison et al. (1993) all show activity within the 800ms ERP time window, thus providing additional features to be entered in the classifier allowing for improved performance. The authors also claim to show data of human color processing. However, they provide no control (i.e. monochromatic stimulus). Electrophysiological studies that compare color to monochromatic stimuli are limited; this suggests an opportunity for this study to provide much needed information on the electrophysiology of color versus monochromatic processing.

Other Imaging Techniques

Positron emission tomography (PET) studies had shown the color center of the human brain was in the lingual (inferior occipital lobe) and fusiform gyri (inferior occipitotemporal gyrus), these areas had shown the largest increase in blood flow when shown color stimuli compared to monochrome (Lueck et al., 1989). This activation was later isolated to the fusiform gyrus (Zeki et al., 1991).

McKeefry and Zeki (1997) examined human visual color processing with functional magnetic resonance imaging (fMRI). An fMRI measures the blood oxygen level dependent (BOLD) response, a change in magnetization directly correlated to the increased use of oxygen in the brain. This change was measured at a resolution of 3x3x3 mm cubes, or voxels. A chromatic Mondrian (an abstract scene with no recognizable objects) image comprised of eight colors and achromatic Mondrian image comprised of the same image only in gray scale were presented on a monitor to 12 participants. When the color image was compared to the grayscale image, the participant's pattern of additional activation fell into three different patterns. All of these patterns included activation in the ventral occipitotemporal cortex either 1) bilaterally, 2) bilaterally with activation in V1/V2, or 3) only in the occipitotemporal left hemisphere.

Lee, Hong, Seo, Tae, and Hong (2000) examined the effects of electrical cortical stimulation on visual perception. Twenty-three patients with epilepsy participated in this study; all had subdural electrodes placed over occipital cortices. The participants were asked to describe what they saw after electrical stimulation of different areas. They found that stimulation of the basal temporo-occipital area, lingual gyrus, and inferior occipital gyri (suggesting V4) were all associated with color illusions (color perception). Activation of other occipital areas resulted in visual illusions of white spots or movement, but none of these illusions had color.

All of these functional imaging studies support additional activation in response to a color stimulus. The majority of fusiform gyrus activation is also associated with color processing and can be seen in both hemispheres but consistently seen in the left hemisphere

(McKeefry & Zeki 1997; Zeki et al., 1991). In the color P300 speller this additional activation will be present as an increase in amplitude on the electrodes over the occipital and parietal lobes, with a higher increase in the left hemisphere (Oz, O1, O2, POz, PO3, PO7). Increased activation in the left hemisphere is already expected due to the right mastoid reference.

CHAPTER 3

CURRENT STUDY

The traditional BCI visual presentation is a character matrix that has grey characters and each character flashes white to present a stimulus (Grey to White, GW; Figure 3). The present study examined the traditional and two novel visual presentation paradigms and their effects on BCI performance. All presentations used the CBP.

Figure 3.

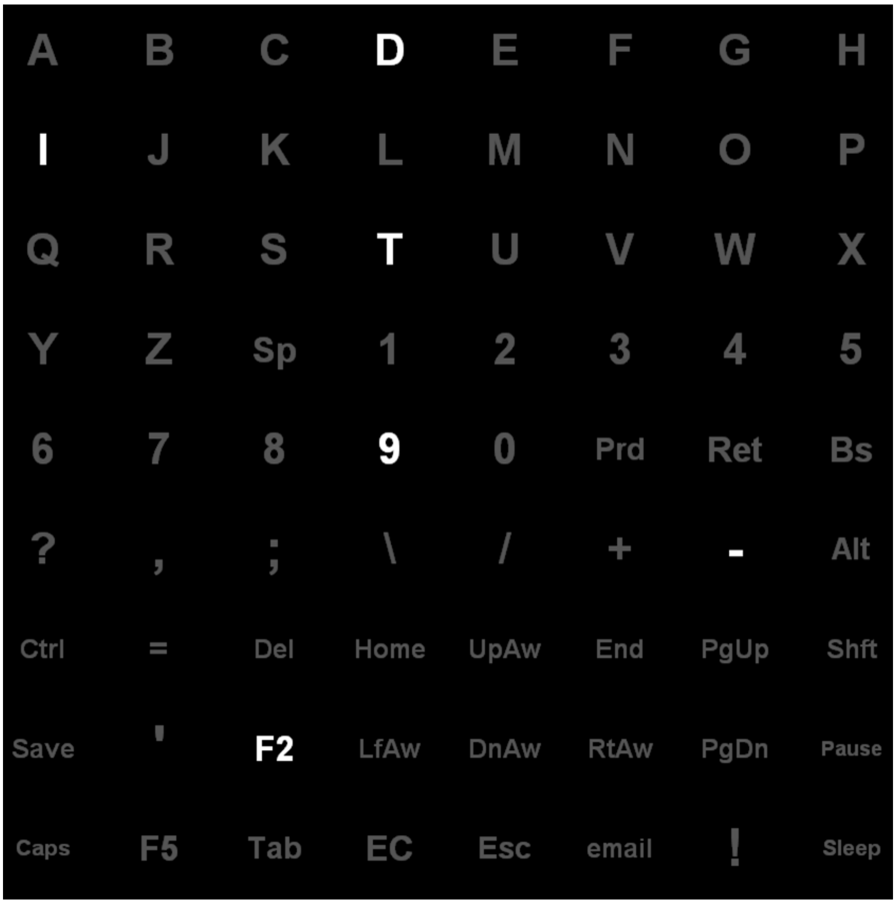

Figure 3. 8x9 matrix with grey characters with white flash stimulus in CB paradigm. Source; Ryan et al. (2011).

The first presentation was a color to intensified color (CI) character matrix on a black background (see Figure 4). The character matrix was made up of nine different colors so that no adjacent characters have the same color. Each character intensified its assigned color to be presented as a stimulus (e.g., Figure 4, red 'C' [stimulus off] to bright red 'F' [stimulus on]).

Only eight other characters, throughout the matrix, had the same color as the target. A colored flash that was distinguished from all adjacent flashes should allow the participant to focus easily on the desired target, instead of all adjacent flashes being the same as the target (traditional stimulus). I hypothesize that an easily distinguished target will lead to higher accuracy classification due to less distraction from nontargets.

Figure 4.

Figure 4. 8x9 matrix in color intensification (CI) condition. Each item color intensifies for stimulus (e.g. dark red "C" compared to bright red "F"), the items are assigned a color (1 of 9 colors) so that no item is the same color as adjacent items.

In the second type of presentation the characters were grey but flashed an assigned color (Grey to Color [GC], Figure 5) that was distinct from all adjacent flashes, similar to the first paradigm. Fazel-Rezai's (2007) study examined how adjacent flashes in P300 BCI spellers contributed to incorrect selections by the classifier. Expanding on the Takano et al.

(2009) findings on enhanced P300 performance with luminance and chromatic change, presumably due to additional EEG activity, I hypothesize that the distinct change from a grey character to a color will increase brain activity, resulting in higher amplitude ERP response.

Figure 5.

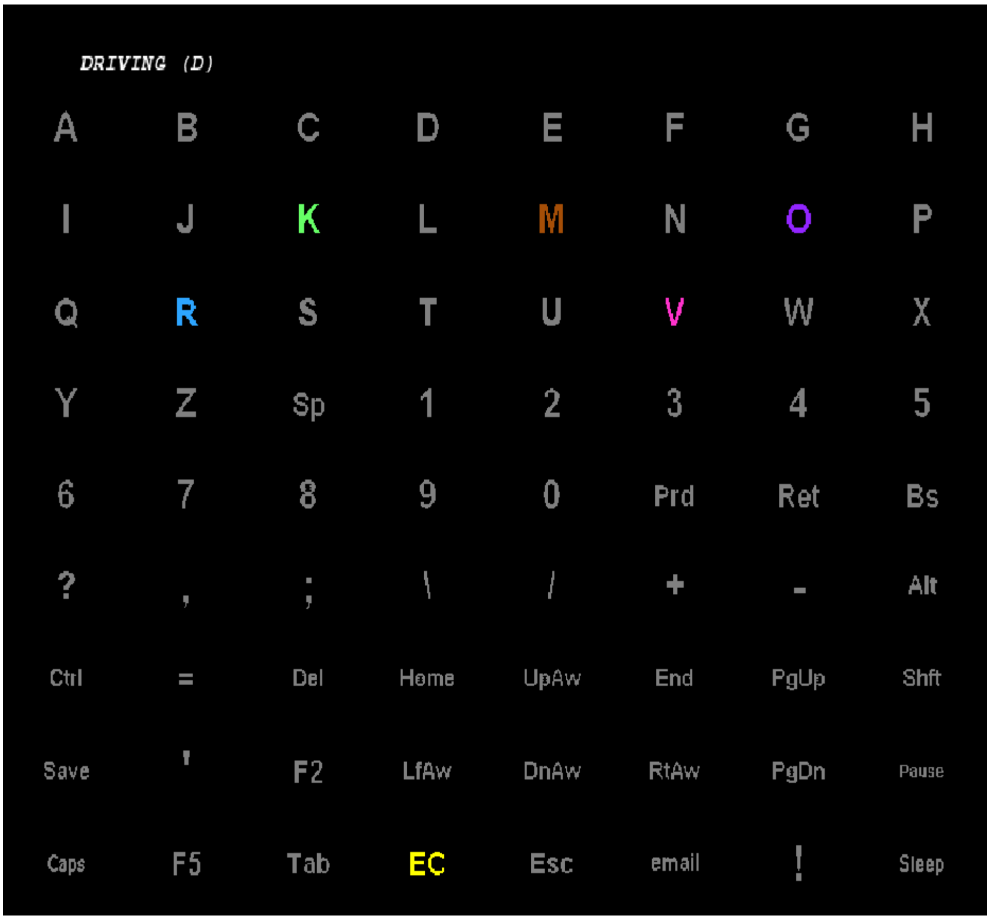

Figure 5. 8x9 matrix in grey to color (GC) condition. Each item flashes its assigned color (1 of 9 colors) so that no item flash is the same color as adjacent flashes.

With these changes to the visual presentation, an increase in accuracy and a decrease in participant eye strain are hypothesized. To measure eye strain, a self-report measure was administered at the beginning and at the end of each session on a scale of 1 to 5 (with a score of 1 indicating no eye strain, and a score of 5 indicating very strained eyes), the difference between the before and after scores provided a level of eye strain caused by each type of presentation.

The color matrices add one more distinguishing characteristic to each item in the matrix. The participant has location of the target character within the matrix, identification of the character (e.g. the target is “A”, “A” is identified from the other characters in the matrix), and a specific target color different from adjacent colors to increase the participant’s abilities to attend to the target character. In the CI condition all of the aforementioned matrix qualities remain constant, whether flashing or not, it is expected that it will become easier for the participant to stay focused on the intended target character.

It is unlikely that P300 amplitude decreased due to the decreased flash intensity (Polich, Ellerson, & Cohen, 1996). In fact, additional brain activity related to color processing (V4 & fusiform gyrus) may enhanced the P300 response (Takano et al., 2009). In conjunction with the lack of peripheral color sensitivity of the retina, it is hypothesized that the P300 target response will be larger with the color matrix and the amplitude of the nontarget response will be reduced, providing more unique target features for the classifier. Thus, the color matrices produce higher accuracy and faster communication.

CHAPTER 4

METHODS

Participants

Twenty-one participants, 8 male and 13 female (mean age= 21.29, age range= 19-25, 6 had previous BCI experience), were recruited from the participant pool at ETSU. Following provision of informed consent, participants were seated in a chair approximately 1m from a computer monitor that displays the 8x9 matrix. All participants were given the Ishihara colorblindness test and no color deficiencies were found. The study was approved by the East Tennessee State University Institutional Review Board.

Presentation paradigm was pseudorandom order; each participant was randomly assigned to one order of the three visual presentations: GW, CI, and GC. The order of the sessions used a Latin square. Each session consisted of two parts. Part one was used to collect calibration data for the classifier. Part two was an online measure of classification accuracy of the BCI.

Stimuli and Materials

In part one of the study, the participant was given a word to spell and prompted to attend to each letter of the word in sequential order (copy spelling task). Stimuli were presented in groups of six (randomized by the CBP), each group intensified for a duration of 62.5 ms. Each flash was followed by a 62.5 ms inter-stimulus interval. This provides a flash every 125 ms. Data from five words (five runs, 36 total selections) were collected and processed offline using a stepwise linear discriminate analysis (SWLDA; described in Classification) that generated a set of classification coefficients (or feature weights) specific to the individual. The resulting set of coefficients was then used for online classification of each character selection in part two of the session. In part two, the participant was provided with feedback after each character selection that indicates whether or not the classifier (or

BCI system) was able to correctly recognize the character to which the participant was attending. In two subsequent sessions, the same procedure was followed for the remaining two stimulus presentation paradigms. Thus, each participant experienced all three matrix paradigms.

EEG Acquisition and Processing

The EEG was recorded with a 32-channel electrode cap using tin electrodes (Electro-Cap International, Inc.). All channels were grounded to the left mastoid and referenced to the right mastoid. Two g.tec (Guger Technologies) 16-channel USB biosignal amplifiers were used to amplify the minute electrical activity recorded from the scalp. The electrical signal from the 32 channels was amplified (+/- 2V before ADC), digitized at 256 Hz, high-pass filtered at 0.5 Hz, and low-pass filtered at 30 Hz. Only electrodes Fz, Cz, P3, Pz, P4, PO7, PO8, and Oz (Sharbrough, Lesser, Lüders, Nuwer, & Picton, 1991) were used for BCI operation (Krusienski et al., 2006). All channel impedances (electrical resistance) were reduced below 10.0 kΩ before recording. The software package BCI2000 (Schalk, McFarland, Hinterberger, Birbaumer, & Wolpaw, 2004) was used to control stimulus presentation, data collection, and online processing.

Classification

The SWLDA algorithm (as described in Krusienski et al., 2006) performs forward and backward partial regression procedures to select the spatiotemporal features (i.e., features determined by the combination of electrode location and specific time points during the recording epoch) that account for the most unique variance. Initially, the single feature that accounts for the most significant variance was added to the model (forward regression, $p<0.1$). After each feature was added, the least significant features were removed from the model through a backward stepwise analysis (backward regression $p>0.15$). This forward and backward process continued until the model includes the maximum number of features (set to

60 in this study) or until no additional features reach the criteria for entry ($p<0.1$) or removal ($p<.15$) from the model. Krusienski et al. (2008) found the maximum of 60 features in the model was optimal (over 60 features did not increase accuracy).

Habituation was a potential problem given the habituation of the P300 response on frontal electrodes. However, the majority of electrodes used for classification are posterior (parietal and occipital). SWDLA is not required to use features on frontal electrodes. This allows SWLDA to select features that do not habituate.

<u>Written Symbol Rate</u>

Online target flashes were optimized for each participant, using the same techniques in Townsend et al. (2010). To make the features of the target P300 response more salient, each item was flashed 10 times during calibration (10 responses per selection). From the calibration data (36 selections) two classifiers were generated and tested offline, one from the first 21 selections then tested (runs 1,2, &3) on the last 15 (runs 4 &5), and a second classifier generated from the last 22 selections then tested (runs 3,4, &5) on the first 14 (runs 1 &2). From this offline test a maximum written symbol rate (WSR) was determined for each participant from his or her own calibration data. WSR estimates the number of selections that can be made by taking into account the accuracy of the classifier and error correction. That is, for each error there is a need for two more correct selections (one to delete the erroneous item and another to make the correct selection). If a classifier was less than or equal to 50% accurate the WSR was zero, and the participant was not able to convey a meaningful message. However, if the classifier was accurate WSR estimated the optimal number of flashes to obtain about 90% accuracy. A participant may see only five flashes of the target item for the classifier to determine a correct response, while another participant with a lower WSR would require eight flashes of the target to obtain the same accuracy.

Optimal Channel Selection

An offline analysis was conducted with a channel selection algorithm, with custom software developed at Duke University in Dr. Collins's BCI lab. This algorithm works similar to the classification algorithm SWLDA. However, instead of selecting significant features from the classification channels, the algorithm selects channels by examining the features of a channel as a whole. The algorithm then selects the eight channels that contribute to the most variance by the significant features contained within each channel. A classifier was generated with the resulting channels to obtain offline performance results for each participant in each condition. The channel selection algorithm indicated the channels that perform best in the given condition.

CHAPTER 5

RESULTS

Accuracy, bit rate, and theoretical bit rate were all taken from the second portion of the session for analysis and comparison across the three paradigms. Here the term "theoretical" is applied to measures that have time between selections removed. This provides a measure easily comparable with other BCI studies. Waveform analysis was performed on the first portion (calibration) due to the variability in the number of flashes (e.g. WSR) performed for the second online session. Statistical comparisons were done with repeated measures ANOVA and planned contrasts with use a post-hoc Bonferroni. Performance analysis consisted of percentage correct, selections per minute, theoretical selections per minute, information transfer rate (ITR), and theoretical information transfer rate (tITR). GC yielded higher ITR than CI, $F(2, 40)=3.909$, $p=.017$. GC also had a higher tITR than CI, $F(2, 40)=3.546$, $p=.018$ (Figure 6). No statistical differences were found in performance measures of GW and the two color conditions. There was a trend of GC having a higher ITR and tITR than GW ($p=.11$, $p=.15$ respectively). There were no statistical differences in additional measures, flashes per selection, selections per minute, and theoretical selections per min (Figure 7). However, GC did have a trend of higher percent correct ($p=.15$), fewer flashes per selection ($p=.18$), more selections per minute ($p=.22$), and more theoretical selections per min ($p=.26$). These three measures reflect a higher WSR, the trend that the classifier needed fewer flashes to make a correct selection in GC.

Figure 6.

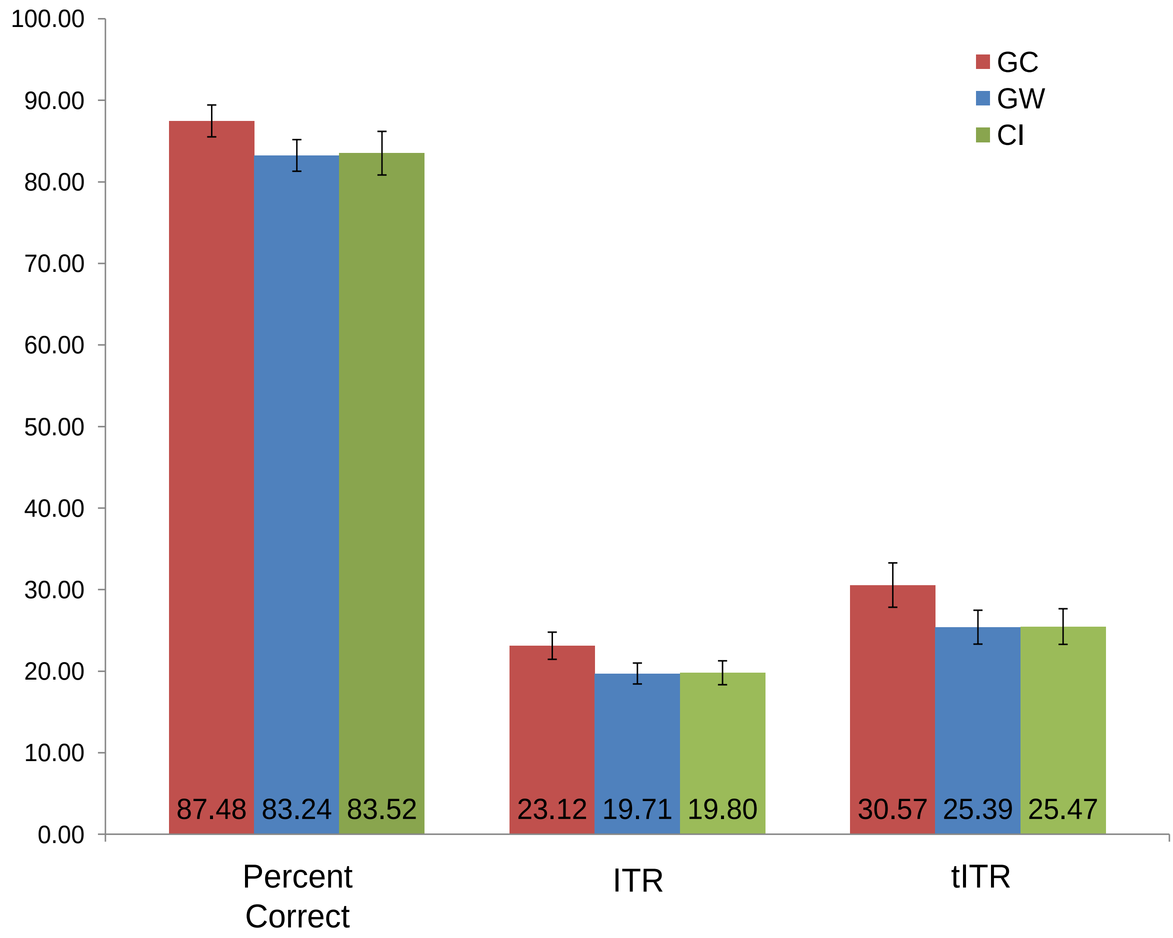

Figure 6. Accuracy, information transfer rate (ITR), and theoretical ITR. The term "theoretical" is applied to measures that have time between selections removed. GC yielded higher ITR than CI, $F(2, 40)=3.909$, $p=.028$. GC also had a higher tITR than CI, $F(2, 40)=3.546$, $p=.038$. No statistical differences were found in performance measures of GW and the two color conditions.

Figure 7.

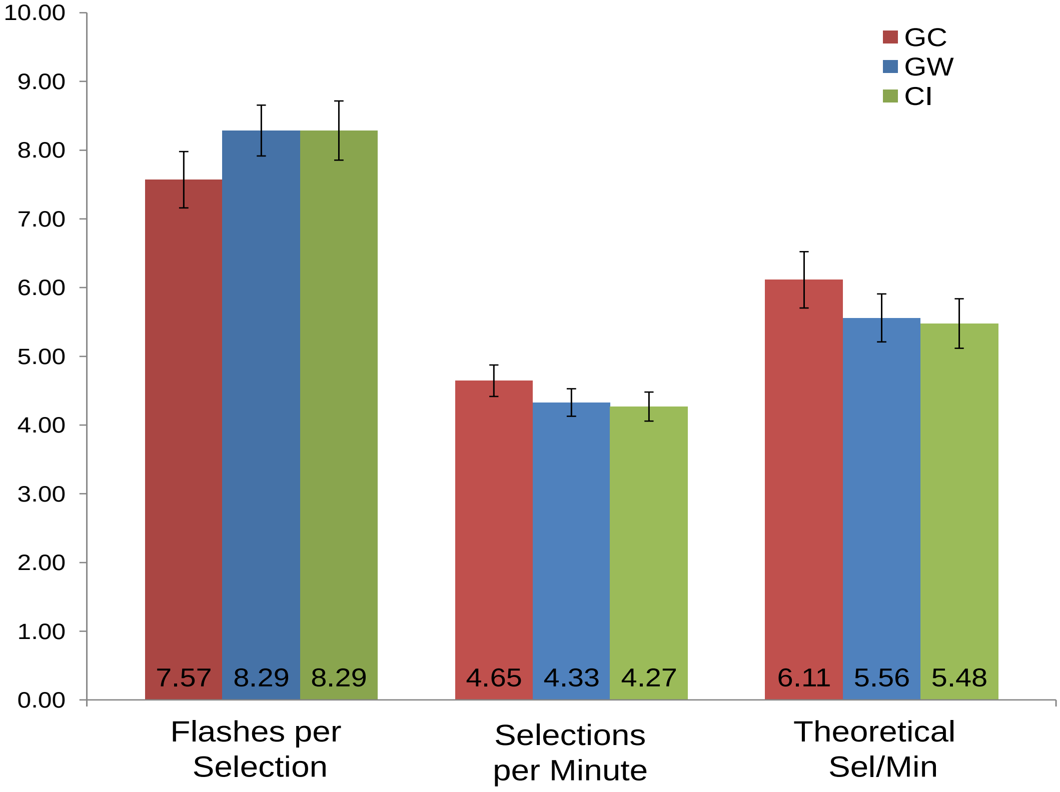

Figure 7. Flashes per selection, selections per min, and theoretical selections per min.

For waveform analysis all classification channels' (Fz, Cz, P3, Pz, P4, PO7, PO8, & Oz) target responses were averages together within condition (Figure 8). Analyses of positive and negative peaks were performed by examining time windows that overlapped peak amplitudes. Time windows were picked by a visual inspection of the averaged waveforms. Positive peak amplitude was analyzed in a time window of 113ms to 310ms poststimulus. No positive amplitude differences were found between conditions. Positive peak latency was analyzed in the same time window as positive peak amplitude. GC had a shorter latency than GW, $F(2, 40)=4.380$, $p=.014$. Negative peak amplitude was analyzed in a time window of 310ms to 515ms poststimulus. GC had a higher negative amplitude than CI, $F(2, 40)= 4.528$, $p=.035$. There were no differences for negative peak latency. There were no condition order effects.

Figure 8.

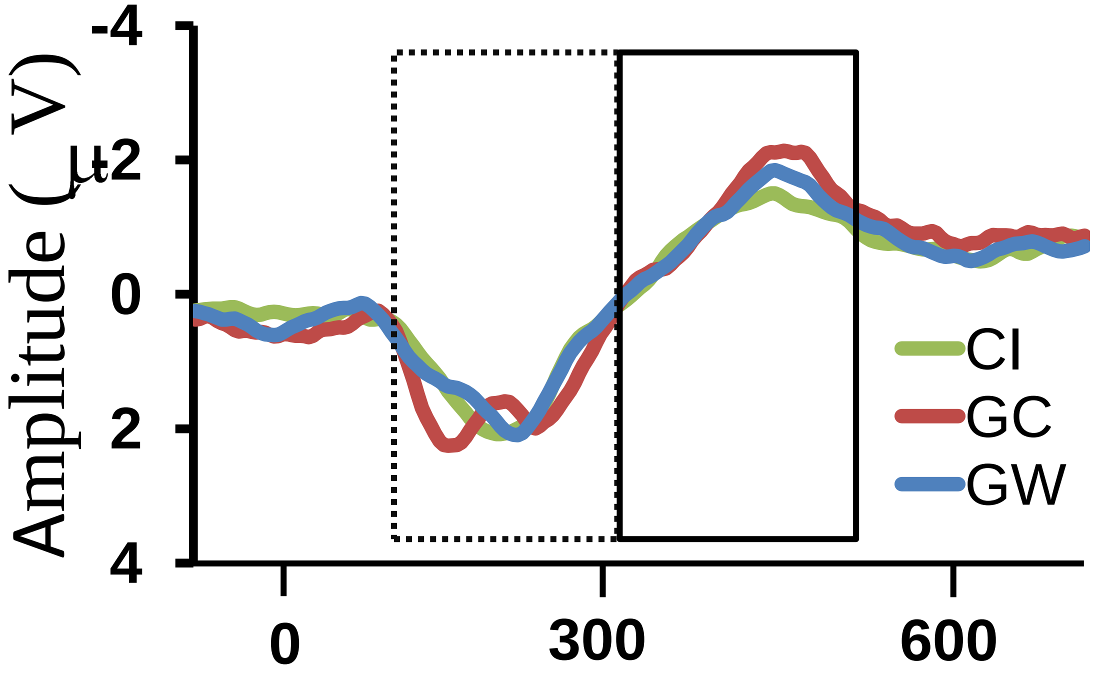

Figure 8. (Fz, Cz, P3, Pz, P4, PO7, PO8, & Oz) target responses were averages together within condition. Positive peak amplitude was analyzed in a time window of 113ms to 310ms (yellow window). Negative peak amplitude was analyzed in a time window of 310ms to 515ms (blue window). GC had a higher negative amplitude than CI, F(2, 40)= 4.528, *p*=.035. GC had a shorter latency than GW, F(2, 40)=4.380, *p*=.014.

Each participant's data were entered into a channel selection algorithm, and optimal channels were determined for each condition. This algorithm analyzes all 32 channels that were recorded and selects the eight channels that contain features that account for the most variance (Figure 9).

Figure 9.

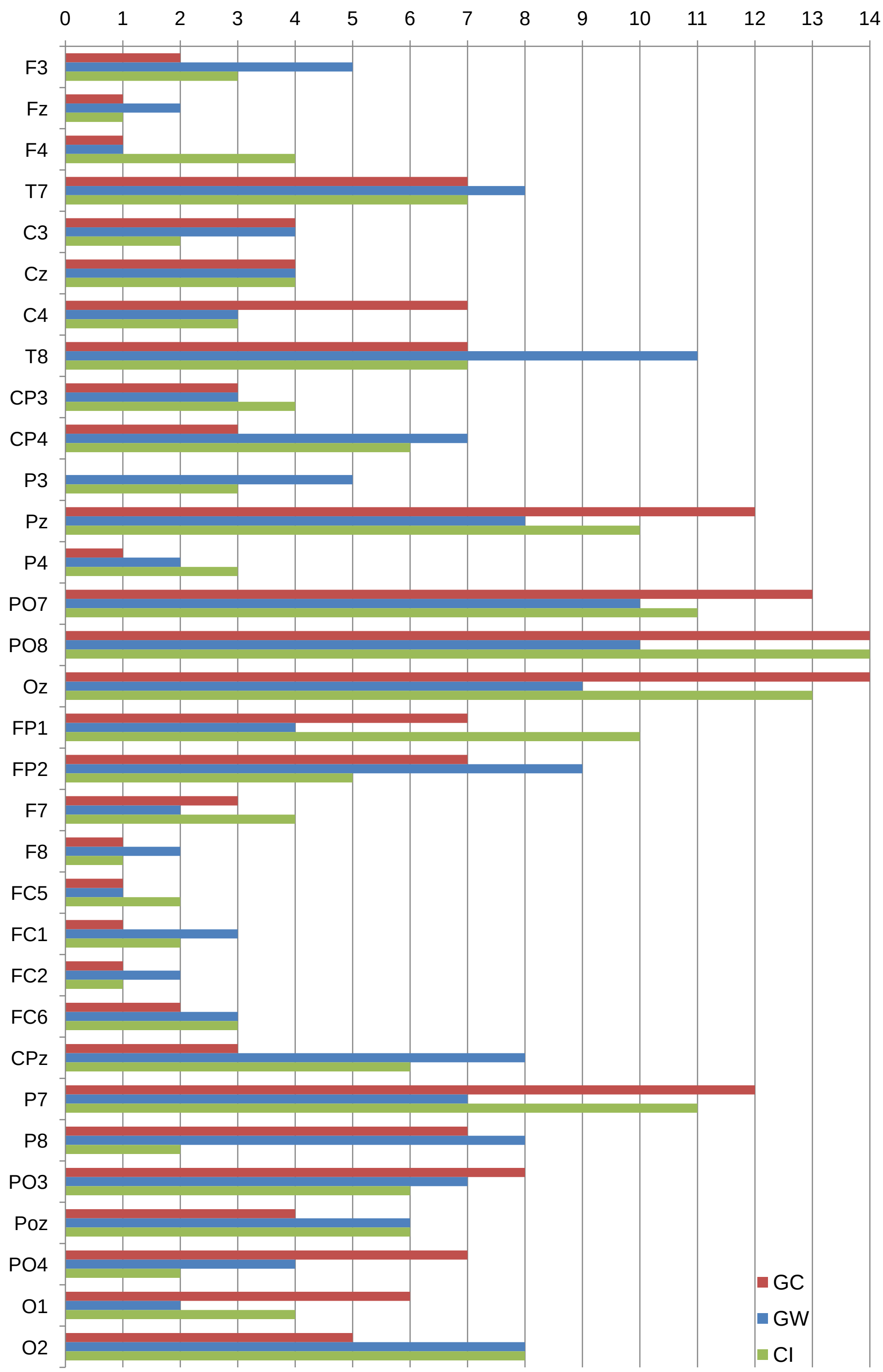

Figure 9. Frequency of channel selected (summed from all participants) across all conditions for the optimal channel set.

A subsequent offline performance analysis was carried out on the optimized channel sets (Figure 10). Two participants' data could not be entered into the offline analysis due to an error during online recording (which was required to predict offline performance, but did not affect online performance), reducing the total to N=19 for the offline analysis. A 2x3 repeated measures analysis using the three stimulus conditions (GC,GW, & CI) and the two channel sets, optimized and standard (channels selected by the algorithm and original classification channels), revealed no differences between conditions (GC,GW, & CI) or an interaction effect. However, there were significant differences between the two channel sets (optimal over standard) in percent correct, ITR, and tITR, $F(1,18$ (same for all tests))= 13.479, $p=.002$; $F=7.8$, $p=.012$; $F=5.504$, $p=.031$, respectively. Results suggest the importance of a optimal channel set for each individual.

Figure 10.

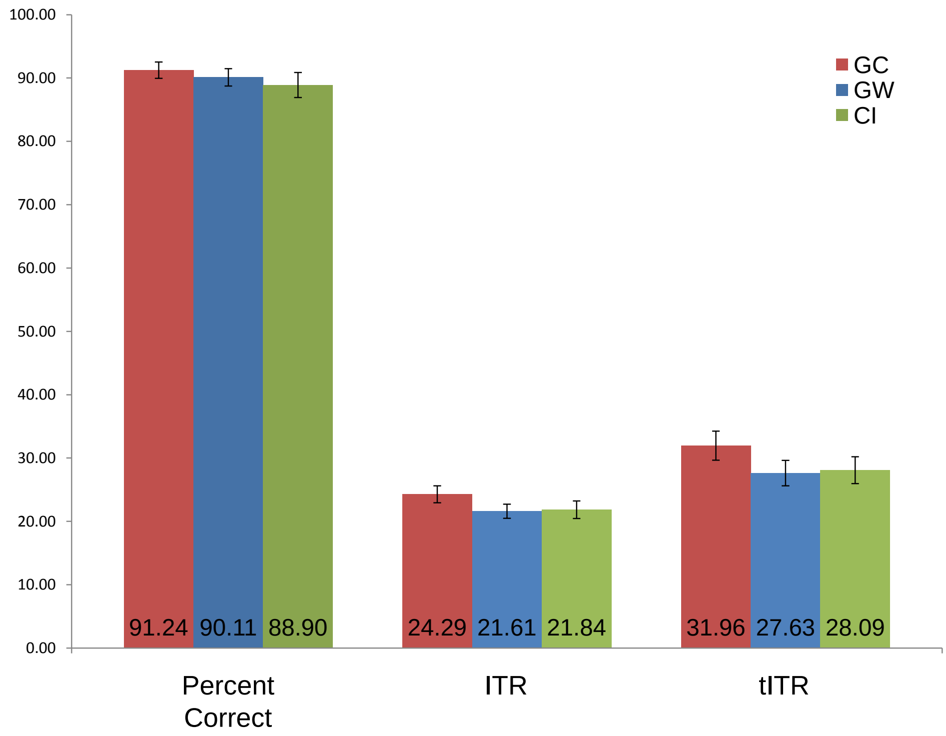

Figure 10. Offline performance results for the optimal channel set. Percent correct, Information transfer rate (ITR), and theoretical information transfer rate (tITR). All three measures were significantly improved over online performance.

Classification Features

A frequency analysis of top ranked feature (first feature) selected by SWLDA (i.e. the feature that accounts for the most variance, across all channels, entered into the classifier) revealed the channel and feature deemed most important for classification. The first feature was examined in the standard channel set and the optimal channel set for each condition. For a visual comparison of target responses for all conditions on all channels, see Figure 11. For GC in the optimal channel set (e.g. out of all of the 32 channels) Oz was selected most, five times or accounted for 23.8% of selections, and the feature that was selected most, seven times or 33.3% (regardless of channel), occurred between 136-183 ms (Figure 12, highlighted in blue). For GW in the optimal channel set PO7 was selected most, four times (19%), the same feature (136-183 ms) was selected six times or 28.6% (Figure 13, highlighted in blue). The channel selected most for CI in the optimal channel set was PO8, seven times (33.3%), with the same feature (136-183 ms) selected 10 times or 47.6% (Figure 14, highlighted in blue). For GC in the standard channel set (Fz, Cz, P3, Pz, P4, PO7, PO8, & Oz) PO7 was selected most, six times or 28.6% with the feature occurring at 136-183 ms selected six times or 28.6% (Figure12, highlighted in yellow). For GW in the standard channel set PO8 was selected eight times (38.1%) with the same feature selected nine times or 42.9% (Figure 13, highlighted in yellow). Interestingly, in the standard channels for CI channels PO7 and PO8 were both selected 10 times (47.6%) with the same feature (136-183 ms) selected eight times or 38.1% (Figure 14, highlighted in blue & yellow). Feature selection results suggest the importance of the feature at 136-186 ms on the channels Po7 and PO8. Further analysis is necessary to fully interpret this feature (see Discussion).

Figure 11.

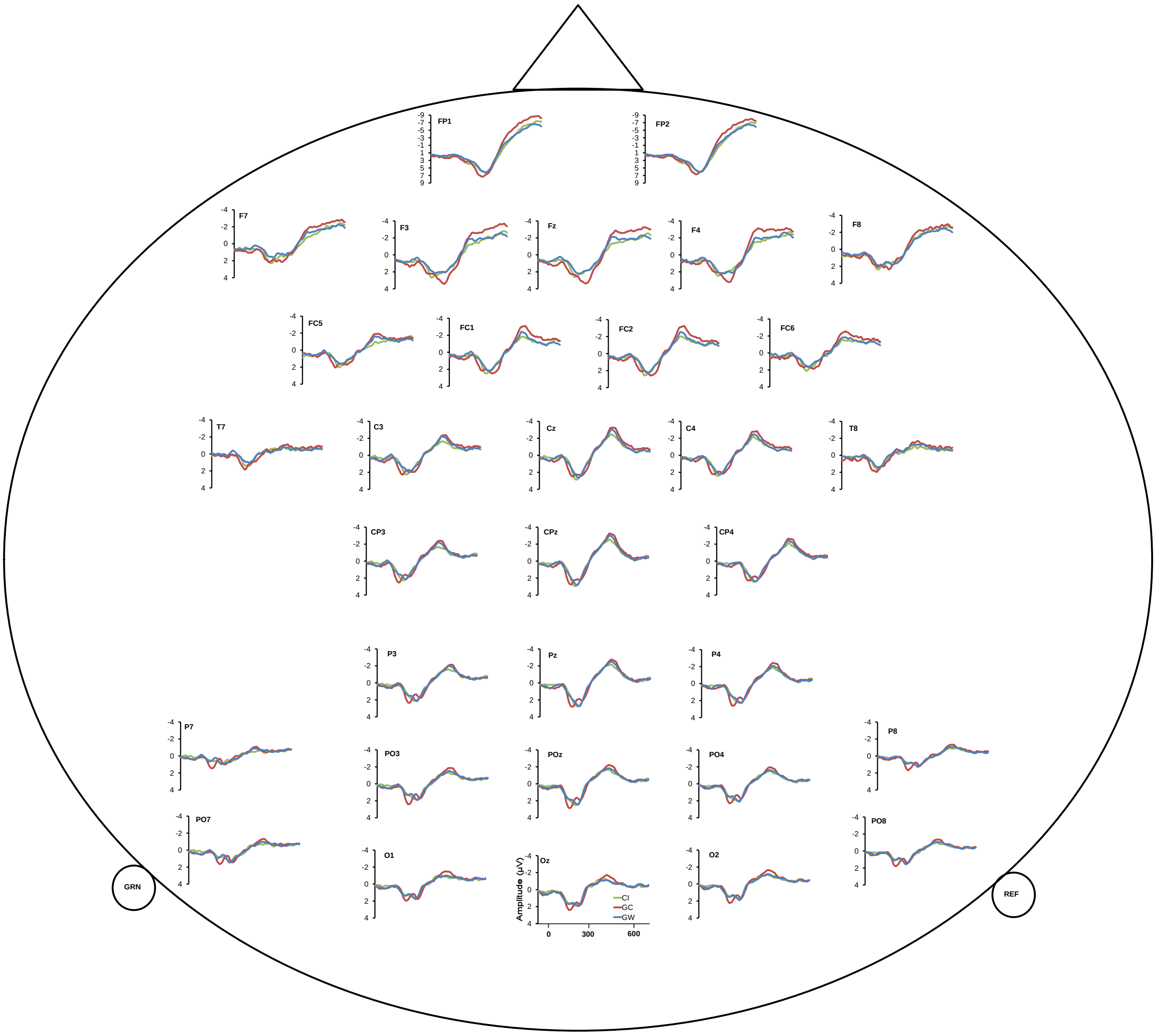

Figure 11. All target waveforms on all 32 electrodes for each condition, GC (red), GW (blue), CI (green).

Figure 12.

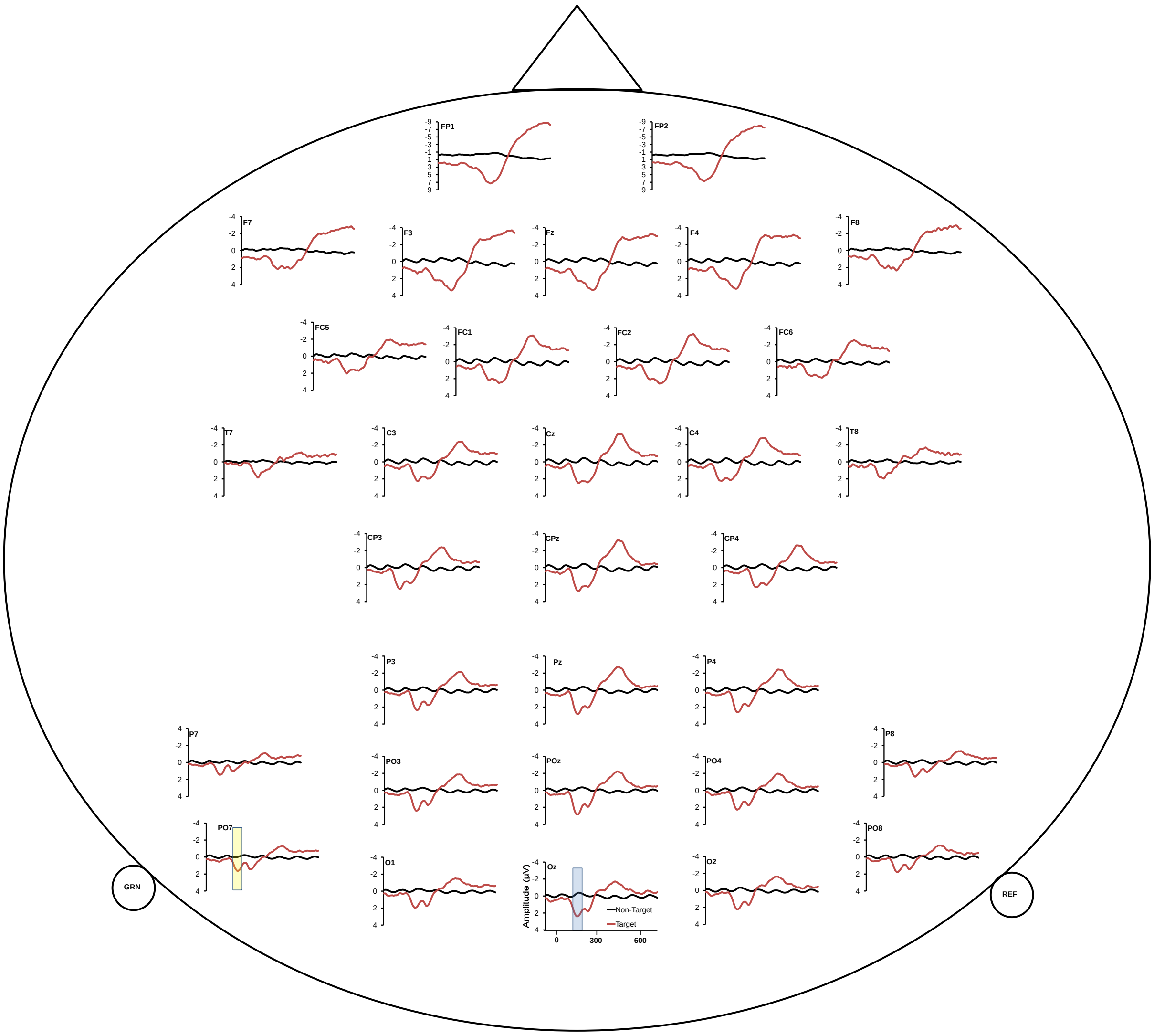

*Figure 12.*GC target (red) and nontarget (black) waveforms. The blue box marks the channel and feature selected most by SWLDA for optimal channel set. The yellow box marks the channel and feature selected most by SWLDA for standard channel set.

Figure 13.

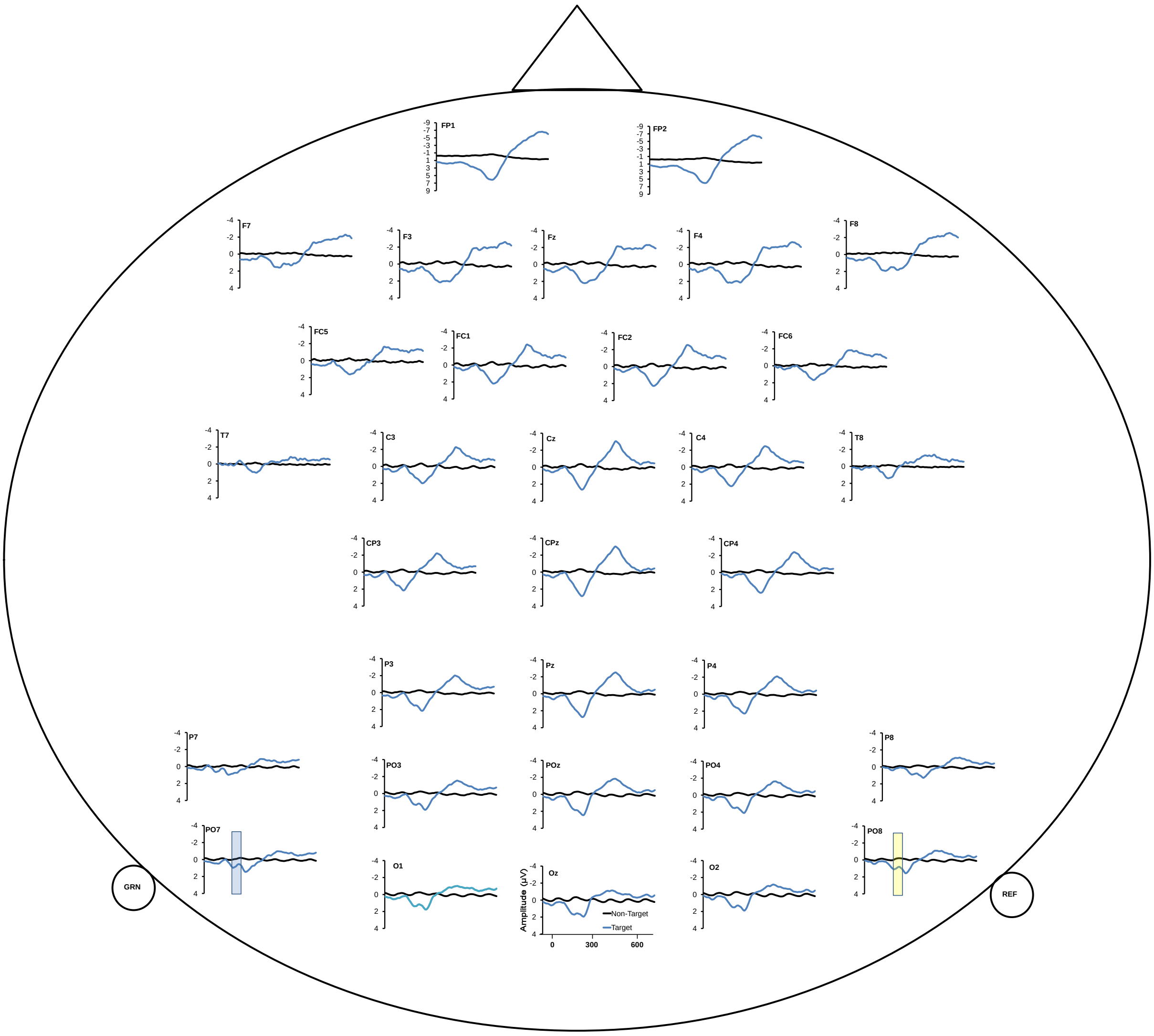

*Figure 13.*GW target (blue) and nontarget (black) waveforms. The blue box marks the channel and feature selected most by SWLDA for optimal channel set. The yellow box marks the channel and feature selected most by SWLDA for standard channel set.

Figure 14.

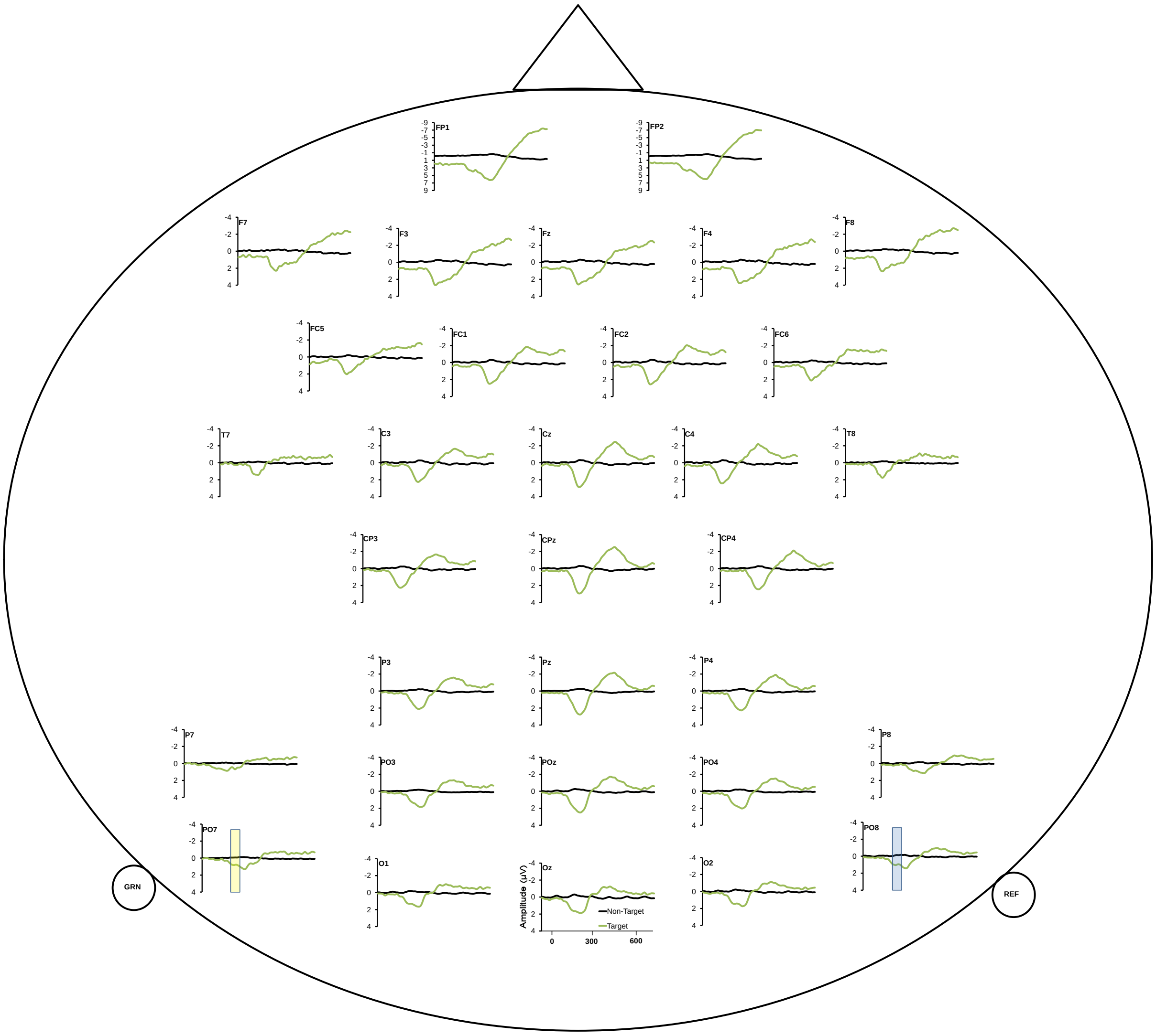

Figure 14. CI target (green) and nontarget (black) waveforms. The blue box marks the channel and feature selected most by SWLDA for optimal channel set. The blue and yellow boxes mark the channels and feature selected most by SWLDA for standard channel set.

There was no difference in the eye fatigue self-report. However, 19 participants preferred the GC condition, 1 preferred GW, and 1 preferred CI. Participants reported that in the GC condition was easier to focus on the target relative to the GW and CI conditions. That the change from grey to color of the target flash was what made the difference, and that being able to focus on the particular target color helped them ignore adjacent flashes.

CHAPTER 6

DISCUSSION

GC had a shorter latency than GW and higher amplitude than CI. The difference in latency suggests a faster perceptual process for GC that may provide more time for necessary target evaluation (indexed by the late negativity). The waveform differences could be due to underlying occipitotemporal activity. It is possible that the waveform differences are a result of lateral excitation. In the GC condition, color processing neurons receive mostly gray information with flashes of color. The color processing neurons have been inhibited by single color stimulus (e.g. stimulus off, gray), thus enhancing their response to a color stimulus (e.g. stimulus on, yellow). In the GW and CI conditions the color processing neurons are only processing a change in intensity of the same color, suggesting that habituation of color processing neurons in the GW and CI conditions and excitation in the GC condition resulted in a change in waveforms.

The GC stimulus was similar to the stimulus used in previously mentioned color processing studies, a black to color checkerboard was used in both Allison et al. (1993) and Anllo-Vento et al. (1998). The time window of this positive response (113-310 ms) overlaps the color processing activity described by Allison et al. (1993) and Anllo-Vento et al. (1998). This suggested that the activity of these areas processing color was the driving force behind GC's shorter latency compared to GW.

The color conditions (GC, CI) did not reveal any significant performance differences over the control (GW). However, there is a trend (higher mean) of increased accuracy and ITR of GC over GW. Lack of statistical power (i.e. small number of participants) and both GC and CI conditions having higher standard error than GW contribute to these trends not being significant. A minimum of 70% accuracy has been stated as the threshold of possible communication (Kubler et al., 2001). GC only had one participant below 70% (67%); GW and CI both had two total participants score below 70%.

The lack of activity in the CI condition (compared to GC) could be a result of habituation of the color processing neurons. Tailby, Solomon, Dhruv, and Lennie (2008) describe the habituation of V1 color processing neurons in single unit recordings of macaque monkeys after 30s of single color stimulus duration. The participants in CI would have to focus on a single color (target) for 15s for one selection, the duration of one item flashing 10 times prior to item selection. For this 15s duration the color processing neurons would be receiving only one color, the stimulus off (e.g. red) and stimulus on (bright red), there would only be a perceptual change in intensity. The extended exposure to one color could have habituated the corresponding color neurons enough to lower amplitude recorded at the scalp and provided fewer salient features and affected classification. CI did have lower ITR and tITR than GC. However, CI did not have lower performance than GW. The nontarget waveforms in the CI condition (see Figure 14) do not have the prominent 8Hz oscillation found in GW or GC (see Figure 12 and Figure 13). This lack of activity in response to nontargets could have compensated for the lower amplitude features of the targets. Future analysis including a signal-to-noise ratio examination would aid in clarifying this issue.

Channel Optimization

Figure 9 shows each channel and how many times it was selected for the optimal channel set for each condition. For both color conditions (GC & CI) the partial-occipital channels were selected most.

All conditions revealed higher accuracy, ITR and tITR in an offline channel optimization performance analysis compared to the channel set used for online results. The different type of stimulus (each condition was a different stimulus) activated different areas of the brain and optimizing the channels to capture this activity resulted in better performance. These results, particularly in the GW condition, suggest that an optimized channel set for each individual improves performance. Changes in individual participant responses vary across the scalp. A channel set built to capture the participant's more salient responses contributes to better performance.

GC was the only condition in which a channel was not selected, channel P3. However, it is expected that the GC condition, a color stimulus, would elicit a stronger response at this location in comparison to the other two conditions, GW and CI. Further analysis in classification feature selection is needed to address this issue.

Classification Features

The channel and feature ranked highest for each individual provides a glimpse of the criteria SWLDA has for selecting features. Across all conditions and channel sets (optimal and standard) PO7 and PO8 were the only channels ranked highest, with one exception of Oz in the GC optimal condition. Of the top ranked features the positive peak occurring at 136-183ms was selected the most regardless of channel. This suggests that the electrical activity recorded on the scalp at these locations was the most unique for target responses. Surprisingly, Oz was selected the most in the GC condition optimal channel set and not selected most in the standard channel set. A further analysis of each channel may provide more insight to feature selection.

Participants preferred the GC condition compared to traditional (GW) flash paradigms. Some participants said that the GW paradigm was "hard to use", while the GC paradigm was "easy to use"; some even said it was "fun". This suggests that a unique (to adjacent items) color stimulus was user friendly and participants considered GC a better BCI experience.

GC is easy to implement and can be readily combined with other techniques to improve performance. The enhanced ERP provides more salient features for target classification at no additional attentional costs to the participant while reducing the distraction of nontarget flashes.

Future Directions

Further analysis including blink correction and current source density can provide refined ERP differences in color and monochromatic responses. Current source density (CSD) can reveal nonreference bias information on location of surface activity (Tenke & Kayser, 2005). CSD is a form of standardizing the waveforms regardless of the recording reference. This is done by using a second special derivative of surrounding electrodes. If uncorrected, (i.e. non-CSD data) the recording only uses the electrical difference from the reference location that biases the recordings based on location of reference and recording channel (Tenke & Kayser, 2005). This corrected data would then be used to perform a principle component analysis (PCA). PCA would provide more information on the components and presumably the neurogenerators of color processing. Examining the corrected waveforms may reveal the N1 (N100) as the top ranked feature selected by SWLDA. However, there are limitations to CSD. One is that it requires the signal of surrounding electrodes; this poses a problem for electrodes at the edge of the montage. This would apply to electrodes P7, PO7, O1, Oz, O2, PO8, and P8. All of which are of particular interest due to their location over the occipital-parietal lobe. A further analysis of the features used by the classifier will provide more information on what a classifier selects as well as how to improve classification through stimulus and signal processing manipulation.

CHAPTER 7

CONCLUSION

The Gray to Color condition has shown promise as an easy to use paradigm that results in better performance over traditional gray to white flash paradigms. Results suggest the importance of maximizing neurophysiologically directed paradigm design, as evidenced by the parietal-occipital differences between the conditions. This enhanced response to color stimulus can be further improved upon when channels are optimized. Moreover, the performance results suggest that color paradigms provide more effective and user satisfying mode of P300 speller communication. This advancement will progress the usability of the P300 BCI speller thus, aiding those who depend on BCI to communicate.

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