

ACCEPTED MANUSCRIPT

## Faces, locations, and tools: a proposed two-stimulus P300 brain computer interface

To cite this article before publication: Marissa Rae Jones *et al* 2019 *J. Neural Eng.* in press <https://doi.org/10.1088/1741-2552/aaff22>

### Manuscript version: Accepted Manuscript

Accepted Manuscript is “the version of the article accepted for publication including all changes made as a result of the peer review process, and which may also include the addition to the article by IOP Publishing of a header, an article ID, a cover sheet and/or an ‘Accepted Manuscript’ watermark, but excluding any other editing, typesetting or other changes made by IOP Publishing and/or its licensors”

This Accepted Manuscript is © 2018 IOP Publishing Ltd.

During the embargo period (the 12 month period from the publication of the Version of Record of this article), the Accepted Manuscript is fully protected by copyright and cannot be reused or reposted elsewhere.

As the Version of Record of this article is going to be / has been published on a subscription basis, this Accepted Manuscript is available for reuse under a CC BY-NC-ND 3.0 licence after the 12 month embargo period.

After the embargo period, everyone is permitted to use copy and redistribute this article for non-commercial purposes only, provided that they adhere to all the terms of the licence <https://creativecommons.org/licenses/by-nc-nd/3.0>

Although reasonable endeavours have been taken to obtain all necessary permissions from third parties to include their copyrighted content within this article, their full citation and copyright line may not be present in this Accepted Manuscript version. Before using any content from this article, please refer to the Version of Record on IOPscience once published for full citation and copyright details, as permissions will likely be required. All third party content is fully copyright protected, unless specifically stated otherwise in the figure caption in the Version of Record.

View the [article online](#) for updates and enhancements.

Faces, Locations, and Tools: A Proposed Two-Stimulus P300 Brain Computer Interface

M.R. Jones and E.W. Sellers

East Tennessee State University

Marissa R Jones, East Tennessee State University, [kellicut@etsu.edu](mailto:kellicut@etsu.edu)

Eric W. Sellers, East Tennessee State University, [sellers@etsu.edu](mailto:sellers@etsu.edu)

**Abstract**

Brain Computer Interface (BCI) technology can be important for those unable to communicate due to loss of muscle control. Given that the P300 Speller provides a relatively slow rate of communication, highly accurate classification is of great importance. Previous studies have shown that alternative stimuli (e.g., faces) can improve BCI speed and accuracy. The present study uses two new alternative stimuli, locations and graspable tools. Functional MRI studies have shown that images of familiar locations produce brain responses in the parahippocampal place area and graspable tools produce brain responses in premotor cortex. The current studies show that location and tool stimuli produce unique and discriminable brain responses that can be used to improve offline classification accuracy. Experiment 1 presented face stimuli and location stimuli and Experiment 2 presented location and tool stimuli. In both experiments, offline results showed that a stimulus specific classifier provided higher accuracy, speed, and bit rate. This study was used to provide preliminary offline support for using unique stimuli to improve speed and accuracy of the P300 Speller. Additional experiments should be conducted to examine the online efficacy of this novel paradigm.

## Brain Computer Interfaces

Brain Computer Interfaces (BCIs) involve the measurement of neural signals produced by the electrical activity of the brain, a method or algorithm applied to decode these signals, and a systematic method for applying the decoded signals to a behavior (Sajda, Müller, & Shenoy, 2008). The uses of these recorded signals to operate BCIs can range from controlling external devices such as a robotic arm to creating works of art (MünBinger, et al., 2010; Velliste, Perel, Spalding, Whitford, & Schwartz, 2008). These systems can be useful methods of communication for individuals who lose their ability to communicate due to amyotrophic lateral sclerosis (ALS), brainstem stroke (Sellers, Ryan, & Hauser, 2014), or severe traumatic brain injury (Sellers, Krusienski, McFarland, Vaughan, & Wolpaw, 2006). The P300 Speller BCI has been shown to be a promising non-invasive method of alternative communication, however there is still room for improvement to make the P300 Speller more accessible and functional for in-home use (Vaughn, et al., 2006). Speed and accuracy of word selection, as well as making the system more user friendly continue to be the focus of numerous research efforts.

The P300 Speller is a modified oddball task that displays a matrix of letters, numbers, and computer commands, like that of a computer keyboard. Groups of characters in the matrix are intensified or 'flash' at random intervals. In most standard P300 Spellers, the 'flash' can consist of changing from grey to white, change from a different color to white, or will disappear and reappear. To make a character selection from the matrix, the participant attends to the letter or character he or she wishes to select. Each time the character of interest flashes, the participant keeps a mental count of the character flash. When the participant attends to each individual flash of the desired character, a P300 ERP is elicited. The P300 Speller detects these P300 responses,

## FACES, LOCATIONS, AND TOOLS: TWO-STIMULUS PRESENTATION

4

and then discriminates between target characters versus non-target characters (i.e., letters the participant is trying to select versus letters the participant is not trying to select).

In recent years there has been research investigating the flashing of alternative stimuli, such as images of familiar faces, instead of matrix characters themselves (Kaufmann, Schulz, Gruzinger, & Kubler, 2011; Zhang, Zhao, & Jin, 2012; Kaufmann, Schulz, et al., 2013; Kaufmann & Kubler, 2014; Geronimo & Simmons, 2017; Kellicut-Jones & Sellers, 2018). This method of altering stimulus presentation is used to evoke different ERPs in addition to the P300 component. For example, two negative components, N170 and N400, have been shown to occur when participants recognize and process facial information. The N170 occurs in response to observing faces at lateral temporal electrode positions and occurs approximately 170ms following stimulus presentation (Eimer, 2000; Bentin, 1996). The N400 occurs approximately between 200ms and 600ms (Kutas, & Federmeier, 2011) over the right hemisphere electrode positions. Both of these components have been observed using unaltered facial images, inverted facial images, and even line drawings of faces (Jin., Daly, Zhang, Wang, & Cichocki, 2014; Chen, Jin, Wang, & Cichocki, 2015; Geronimo & Simmons, 2017).

Kaufmann, Schulz, Gruzinger, and Kubler (2011) first implemented faces as P300 Speller stimuli. It was proposed that components elicited by facial stimuli provide additional ERP information to augment the P300 ERP. Thus, the paradigm should increase signal-to-noise ratio through the addition of the N170 and N400 ERP components. The additional information would create a more robust and detectable response, resulting in improved overall P300 Speller performance. Kaufmann et al., (2011) superimposed the familiar, famous image of Albert Einstein sticking his tongue out over characters within the BCI matrix. In each sequence of

1  
2  
3 character flashes, the image itself would flash over the characters in the matrix, as opposed to the  
4  
5 matrix characters themselves flashing.  
6

7  
8 Kaufmann and Kubler (2014) introduced a paradigm that implemented a simultaneous  
9  
10 presentation of two very different stimuli in the four quadrants of the matrix. The image of  
11  
12 Einstein was presented in the top left and bottom right quadrants, and a yin-yang symbol was  
13  
14 presented in the top right and bottom left quadrants. The two-stimulus presentation was  
15  
16 compared to the standard row-column. The results showed that the two-stimulus paradigm was  
17  
18 able to make selections more quickly than the one stimulus paradigm, despite a decrease in  
19  
20 accuracy. This suggests that a two-stimulus paradigm could increase speed compared to the more  
21  
22 common single stimulus paradigm.  
23  
24  
25

### 26 27 **Facial Fusiform Area and Parahippocampal Place Area** 28

29  
30 In addition to EEG research, several different neuroimaging techniques, such as positron  
31  
32 emission tomography (PET) and functional magnetic resonance imaging (fMRI), have supported  
33  
34 the idea that recognition and perception of different types of stimuli elicit different cognitive  
35  
36 responses. There has been sufficient evidence to indicate that the processing of facial stimuli and  
37  
38 object stimuli, activate distinct brain regions (Kanwisher, McDermott, & Chun, 1997). The  
39  
40 fusiform face area (FFA), which is comprised of the region in the mid-fusiform gyrus, is shown  
41  
42 to be strongly activated by the viewing of faces compared to the viewing of objects (Kanwisher  
43  
44 et al., 1997; McCarthy, Puce, Gore, & Allison, 1997; Tong, Nakayama, Vaughan, & Kanwisher,  
45  
46 1998; Sergent, Ohta, MacDonald, 1992; Haxby et al., 1991;).  
47  
48  
49  
50

51  
52 While neuroimaging studies indicate that the FFA responds selectively to facial stimuli,  
53  
54 research has also demonstrated activation to images of buildings and scenes depicting locations  
55  
56  
57  
58  
59  
60

## FACES, LOCATIONS, AND TOOLS: TWO-STIMULUS PRESENTATION

6

1  
2  
3 in space in the parahippocampal gyrus referred to as the parahippocampal place area (PPA)  
4  
5 (Malach, Levy, & Hasson, 2002; Epstein, Harris, Stanley, & Kanwisher, 1999; Agguire, Zarahn,  
6  
7 & D'Esposito, 1998). The PPA, located in the ventromedial surface of the temporal lobe, has  
8  
9 been shown to respond selectively to houses and places, but not to objects or faces (Epstein &  
10  
11 Kanwisher, 1998). The strongest activation of the PPA was shown to occur in response to the  
12  
13 viewing of complete images or photographs of scenes that depicted places, or even in images that  
14  
15 showed empty landscapes with few discrete objects. Epstein et al. (1999) suggests that the spatial  
16  
17 layout information of a scene may be itself be enough to activate the PPA, as the PPA may play a  
18  
19 role in perceptual coding.  
20  
21  
22  
23

**Present Study**

24  
25  
26  
27 The current study was used to determine if two-stimulus paradigms can increase P300  
28  
29 Speller performance. In a two -stimulus paradigm, it could be beneficial to utilize a classifier for  
30  
31 each stimulus type. For example, one classifier would be specific to one type of stimulus (e.g.,  
32  
33 face) and another classifier would be specific to another type of stimulus (e.g., location). The  
34  
35 classifiers would compete in a 'race' to determine which stimulus type is the desired choice.  
36  
37 Having two stimulus-specific classifiers operating simultaneously could potentially discriminate  
38  
39 the distinct features produced by the each unique stimulus. Presently, a simultaneous two -  
40  
41 classifier paradigm has not been developed and the current study uses an offline analysis  
42  
43 conducted on data collected from an able-bodied sample to provide evidence to support the need  
44  
45 for the development of a simultaneous two-classifier system.  
46  
47  
48  
49  
50

51 The study consisted of two experiments. In Experiment 1, faces and locations were used  
52  
53 as stimuli. We hypothesized that a facial classifier would produce higher performance when  
54  
55 applied to the facial stimuli, and a location classifier would produce higher performance to the  
56  
57  
58  
59  
60

location stimuli. In contrast, when each classifier is applied to the different class of stimuli performance would be reduced. In Experiment 2, locations and graspable object stimuli were used as stimuli. In this case it was hypothesized that the unique spatially distant locations activated by the two types of stimuli would result in more distinct ERPs, which could further increase performance over the performance observed in the face-location stimuli used in Experiment 1.

These experiments may provide a rationale for how and why a two-stimulus paradigm may be effective, and may also provide further evidence that the P300 Speller may detect features that are specific to very different types of stimuli. Both experiments consisted of two phases. Phase I was used to obtain training data. Phase II was conducted online and the stimulus specific classifiers were applied. In other words, the classifier for the face stimuli was only used to classify face stimuli and the location classifier was only used to classify location stimuli. Subsequent offline analyses applied each classifier to the opposite type of stimulus (e.g., face classifier/location stimuli and location classifier/face stimuli). Accuracy, selections per minute, and bit rate were calculated to indicate whether each stimulus specific classifier would lead to increased performance when presenting corresponding stimuli on the P300 Speller matrix.

### Experiment 1

Two stimuli producing distinct ERPs could be used to improve upon current BCI classification methods. For example, a matrix presenting two types of images, which convey different types of information could be created for each stimulus. If simultaneous dual-classifiers were created and implemented, unique classifiers could potentially be used to identify target characters, based on the notion that these images produce different enough ERPs for the BCI to detect. By superimposing an image of a face on half of the matrix characters, and an image of a



location on the other half of the characters, two different classifiers could be made specifically for each image type. One classifier could detect the face-specific ERPs and the other classifier could detect location-specific ERPs. If such a simultaneous dual-classifier was developed, the BCI system could potentially discriminate targets from non-targets more quickly by eliminating half of the characters in the matrix as potential targets. This is the first step in providing a rationale for developing a simultaneous dual-classifier.

## Experiment 1 Methods

### Participants

Ten able-bodied participants (4 men, 6 women; age range 19-31) were recruited from East Tennessee State University. Four of the participants had prior BCI experience; all of the other participants were naïve to BCI use. The study was approved by the East Tennessee State Institutional Review Board and each participant gave informed consent.

### Data Acquisition and Processing

Electroencephalograph (EEG) was recorded using a cap (Electro-Cap International, Inc.) embedded with 32 tin electrodes. Only eight electrodes were used for online classification. The eight electrodes were subject-specific and determined by the jumpwise algorithm (Colwell, et. al. 2014). The EEG was digitized at 256 Hz and bandpass-filtered to [0.5 Hz, 30 Hz] by two 16-channel g.tec g.USBamp amplifiers, before the classification coefficients were derived the data were down-sampled to 20Hz. Data collection and stimulus presentation was performed by the BCI2000 open-source software suite (Schalk, McFarland, Hinterberger, Birbaumer, & Wolpaw, 2004). Before the session, the impedance of each channel was reduced to below 40k $\Omega$ .

Participants were seated approximately 90cm away from a computer monitor that displayed an 8x9 matrix of letters and numbers.

### **Classification**

The classification technique known as Stepwise Linear Discriminate Analysis (SWLDA) as described by Draper and Smith (1981) is a commonly used method to determine classification coefficients, which has been shown to be an efficient method of classification for BCI research (Farwell & Donchin, 1988; Sellers & Donchin, 2006; Krusienski et al, 2006; Krusienski et al, 2008; Colwell Ryan, Throckmorton, Sellers, & Collins, 2014).

To improve upon classification performance, multiple electrodes at various locations distributed over the scalp are used. A filter method known as jumpwise selection is used to improve upon classification through optimal channel selection (Colwell, et al., 2014). Jumpwise selection uses a variant of SWLDA that selects electrodes instead of electrode specific features. The advantage of jumpwise selection is that it reduces to the feature space to a unique set of electrode locations that are optimized for each individual participant. Once the eight electrodes that account for the most variance are selected, a SWLDA analysis is conducted on the eight electrodes to determine the spatio-temporal features that account for the most unique variance.

### **Experiment Stimuli, Procedure, and Design**

## FACES, LOCATIONS, AND TOOLS: TWO-STIMULUS PRESENTATION

10

Two types of images were used. The face stimulus was the famous image of Albert Einstein sticking out his tongue; the image has been used in previous BCI studies (Kaufmann et al., 2011; Kaufmann et al., 2013; Kaufmann & Kubler, 2014). The location stimulus was an image of the White House. The White House image was used because it includes a familiar famous landmark and additional landscape information.

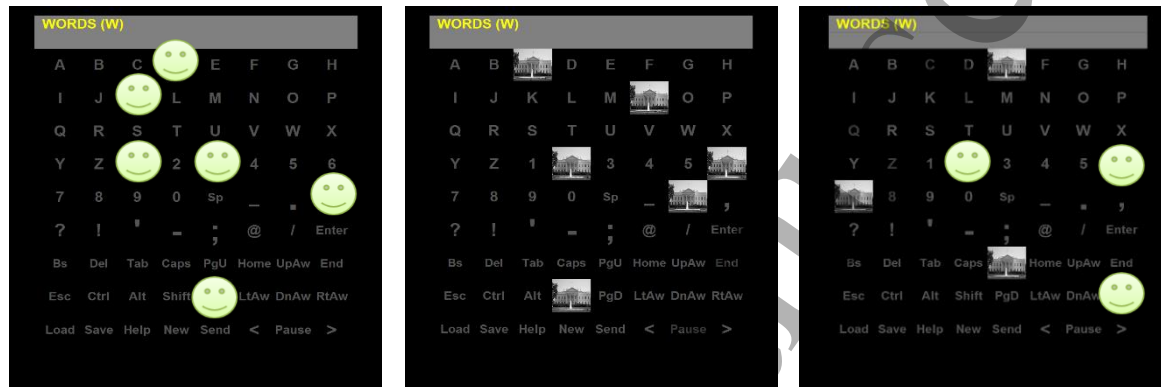


Figure 1a (left), 1b (middle), and 1c (right). Examples of matrices of the three stimulus presentation conditions. (The picture of Einstein was used as the stimulus in the face conditions. The picture is not used in the present figure due to copyright restrictions. The White House image used was available in the public domain and not subject to copyright.)

Each participant completed one experimental session consisting of two calibration phases and one copy spelling phase. Participants were fitted for an electrode cap, then an 8x9 matrix of letters and characters was presented on the computer monitor. For the calibration phase, participants were asked to focus their attention on a specific character in the matrix and count how many times it changed to one of the two images. For example, as shown in Figure 1, the top left side of the display would show a word (e.g., WORDS) and the letter they should attend to is shown in parentheses at the end of the word. After a predetermined amount of flashes of each character (in this case 14) the matrix would stop flashing. After a 4-second pause the letter in parentheses would change to the next letter in the word (e.g., (O)).

1  
2  
3 The session consisted of two calibration phases, counter-balanced, in which the  
4 participant made selections from a matrix presenting only the face image (Figure 1a) or only the  
5 location image (Figure 1b). Each participant spelled three six-letter words, 18 total characters,  
6 for each calibration. Following each calibration phase (i.e., training data collection), the  
7 jumpwise channel selection algorithm and a subsequent SWLDA analysis were conducted to  
8 derive channel specific classification coefficients for each stimulus.  
9  
10  
11  
12  
13  
14  
15  
16  
17

18 Following calibration, participants completed an online copy-spelling task. The matrix  
19 presented face images over half of the matrix characters and location images over the other half  
20 of the matrix characters (Figure 1c). In the online phase, 14 flashes of each character in the  
21 matrix were presented, corresponding to the calibration phase of the experiment. There were two  
22 conditions, counter-balanced. In each condition, 18 character selections were made. In one  
23 condition, the face classifier was applied and the 18 targets were facial stimuli. In the other  
24 condition, the location classifier was applied and the 18 targets were location stimuli. Although  
25 we were primarily interested in the offline performance, it was necessary to provide the  
26 participants with feedback; thus, we used the congruent stimulus classifier in phase II of the  
27 experiment. Afterward, offline analyses were conducted to examine how well the face classifier  
28 performed when applied to the location data, and how well the location classifier performed  
29 when applied to the face data.  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48

### 49 **Offline Analysis**

50  
51 The offline analysis was used to determine how many flashes would be necessary for  
52 classification. In the online phase of the experiment 14 flashes of each target were presented  
53  
54  
55  
56  
57  
58  
59  
60

before the classification decision was made. This number of flashes is sufficiently high to produce a ceiling effect for accuracy. The offline analysis simulated the number of flashes necessary to make an accurate response. The SWLDA classification coefficients were applied to every character after each flash of the matrix and the number of flashes necessary to make an accurate selection was calculated. If an accurate selection was not made after 14 flashes, the selection was marked as inaccurate. There was not a cross-validation procedure; in contrast to a cross-validation procedure, the coefficients were applied to each flash as it was presented in the online phase of the experiment. With each flash of a stimulus, the mean ERP for each specific stimulus was updated. Therefore, the number of flashes varied from one character selection to the next.

## Experiment 1 Results

### Statistical Analyses

A two-way repeated measures analysis of variance (ANOVA) was used to examine the effects of classifier type (Face or Location) and the effects of stimulus type (Face or Location). Analyses were performed on predicted accuracy, target flashes, selections per minute, and bitrate. Offline accuracy is expressed as the percentage of correctly selected characters. Offline selections per minute are the estimated number of correct character selections made in one minute. Offline, predicted bitrate is calculated using the formula described by Wolpaw et. al. (2002):

$$\text{Bitrate} = \log_2 N + P \log_2 P + (1-P) \log_2 [(1-P) / (N - 1)]$$

Paired sampled t-tests were used to examine the differences in waveforms between the face and location stimuli. To control the false positive error rate for performing multiple

comparisons, the Benjamini-Hochberg (B-H) procedure was used to determine the critical p value (Thissen, Steinburg, & Kuang, 2002). Waveform analyses were conducted on the calibration data to maintain a consistent amount of data in each condition.

## Results

### Offline Performance

The means and standard deviations examining offline accuracy, target flashes, selections per minute, and bitrate produced by each classifier type applied to each stimulus type are shown in Table 1. Electrode locations used in the jumpwise-SWLDA classification algorithm are shown in Table 2. The table shows the locations that were used by at least fifty percent of the participants. The ANOVA examining offline accuracy indicated no significant differences between the four conditions  $F(3, 27) = 1.48, p = .240$ . The interactions for the ANOVAs examining offline target flashes produced by each classifier type applied to each stimulus type, offline selections per minute, and bit rate were all significant ( $F(3, 27) = 3.059, p = .045$ ;  $F(3, 27) = 3.619, p = .026$ ; and  $F(3, 27) = 3.992, p = .018$ , respectively). Post-hoc tests indicated no significant simple effects in any of the three ANOVAs. Thus, indicating cross-over interactions where the face classifier performed better on face stimuli than it performed on location stimuli and the location classifier performed better on location stimuli than on face stimuli.

**Table 1**

*Offline means and standard deviations (in parentheses) for performance measures for each classifier applied to each stimulus type for Experiment 2.*

	Accuracy	Target Flashes	Selections per Minute	Bitrate
Face Classifier				
Face	99.4 (1.89)	2.50 (0.70)	4.31 (0.77)	28.30 (7.88)

## FACES, LOCATIONS, AND TOOLS: TWO-STIMULUS PRESENTATION

14

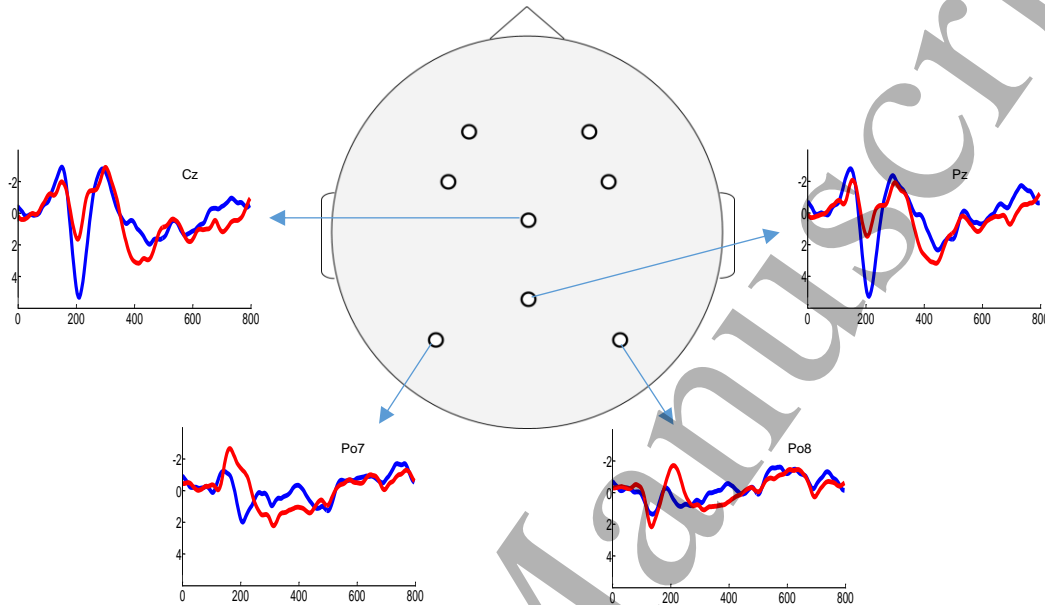
Location	96.6 (8.4)	2.70 (0.67)	4.06 (0.74)	21.53 (7.87)
Location Classifier				
Face	100 (0)	3.10 (0.87)	3.71 (0.87)	20.07 (7.67)
Location	100 (0)	2.10 (0.87)	5.10 (1.6)	33.39 (11.02)

**Table 2***Experiment 1 Jumpwise Channels used by 50% or more of the participants*

Experiment 1							
Face Jumpwise Channels	Po8	Po7	P8	O1			
Participants	7	7	7	5			
Location Jumpwise Channels	Po8	Po7	P8	Oz	O2	Cp6	Pz
Participants	8	7	7	7	7	6	5

**Waveforms**

To determine whether differences in performance may be due to differences in ERPs produced by the two different stimulus types, a paired samples-t-test was used to examine ERPs. Figure 2 represents the waveforms averaged across all participants for each of the four conditions. The specified time windows examined for positive amplitudes and latencies were set to 150-320ms and 350-550ms, as well as 128-195ms for the N170 component, and 191-300ms for the N400 component. The time windows were determined by examination of the grand mean waveforms. Four electrode locations Cz, Pz, PO7, and PO8 were examined. Before producing the waveforms data were down-sampled to 20Hz and a moving average of 12 samples was applied. These waveforms were not baseline corrected.



*Figure 2:* Average waveforms for all ten participants for the two types of images, Face (blue line) and Location (red line) used in the BCI task for electrode locations Cz, Pz, PO7, and PO8.

In the positive time window of 150-320ms, the amplitude at electrode Cz was significantly higher in response to the face stimulus ( $M=5.9$ ,  $SD=1.2$ ) than to the location stimulus ( $M=2.0$ ,  $Sd=1.6$ ),  $t(9)=7.642$ ,  $p<.001$  (B-H critical value 0.001315789). Comparison of responses at electrode location Pz also indicated significantly higher amplitude in response to the face stimulus ( $M=5.9$ ,  $SD=1.6$ ) than to the location stimulus ( $M=2.2$ ,  $SD=0.3$ ),  $t(9)=6.059$ ,  $p<.001$  (B-H critical value 0.002631579). No significant differences in amplitude were observed in the time window of 150-300ms at electrode locations PO7 and PO8.

Comparison of latency in the positive time window of 150-320ms showed a significantly earlier response at electrode location PO7 in response to the face stimulus ( $M= 243$ ,  $SD= 42$ ),



1  
2  
3 than to the location stimulus ( $M= 288$ ,  $SD= 42$ ),  $t(9)= -3.259$ ,  $p = 0.00985$  (B-Hochberg critical  
4 value  $0.02237$ ). No significant differences in latencies were observed at the remaining electrode  
5  
6 locations.  
7  
8

9  
10  
11 The Comparison of the second positive time window 350-550ms amplitude at electrode  
12 location Cz indicated significantly higher amplitude in response to the location stimulus ( $M= 4.9$ ,  
13  $SD= 2.3$ ) than to the face stimulus ( $M= 3.6$ ,  $SD= 1.7$ ),  $t(9)= -3.476$ ,  $p = 0.00698$  (B-H critical  
14 value  $0.02368$ ). The remaining comparisons of second positive time window 350-550ms  
15  
16 amplitudes and latencies indicated no significant differences between the two conditions at Pz,  
17  
18 PO7, or PO8.  
19  
20  
21  
22  
23

24  
25 Comparison of amplitude in the negative time window of 191-300ms at electrode  
26 location PO8 indicated significantly higher amplitude in response to the location stimulus ( $M= -$   
27  $2.4$ ,  $SD= 1.2$ ) than to the face stimulus ( $M= -1.4$ ,  $SD= 0.8$ ),  $t(9)= 2.511$ ,  $p = 0.00958$  (B-H  
28 critical value  $0.02105$ ). The remaining comparisons of amplitudes and latencies indicated no  
29  
30 significant differences between the two conditions in the negative 191-300ms time window.  
31  
32  
33  
34  
35  
36

37  
38 Statistical analyses indicated no significant differences between amplitudes or latencies  
39 produced by either condition during time window 128-195ms at any of the four electrode  
40  
41 locations.  
42  
43  
44

### 45 **Experiment 1 Discussion**

46  
47  
48 Offline analyses were used to provide evidence that a stimulus specific classifier for each  
49 stimulus type results in better offline BCI performance. The interactions between classifier type  
50 (Location vs. Face) and data type (Location vs. Face) were significant for number of target  
51  
52 flashes, number of selections, and bit rate. Thus, evidence indicates that using two independent  
53  
54  
55  
56  
57  
58  
59  
60

1  
2  
3 classifiers, one for each stimulus type, could eliminate half of characters in the matrix as  
4  
5 potential selections.  
6  
7

8 The ERPs produced by the two stimuli differed in the amplitudes at the first positive  
9  
10 window for electrodes Pz and Cz. The only significant difference in negative amplitude was at  
11  
12 the second negative time window at electrode location PO8. These findings are consistent with  
13  
14 our previous findings (Kellicut-Jones et al., 2018) and the findings of Kaufmann et al., (2011;  
15  
16 2013; 2014).  
17  
18  
19

## 20 21 **Experiment 2**

22  
23 Experiment 1 examined the use of two types of stimuli, face and location, which have  
24  
25 been shown to produce distinct ERPs. This was done with the intent to provide a rationale for the  
26  
27 development of classifiers that identify specific stimuli in a two-stimulus matrix presentation. To  
28  
29 further investigate two-stimulus paradigms, Experiment 2 examined a third type of stimuli (i.e.  
30  
31 graspable objects) to determine if they would produce distinctly different ERPs from location  
32  
33 stimuli.  
34  
35  
36  
37

### 38 **Graspable Objects as Stimuli: Tools**

39  
40  
41 The results of Experiment 1 provide support for using a two-stimulus, two-classifier  
42  
43 paradigm. The main hypothesis was that these stimuli would produce significantly different  
44  
45 N170 and N400 components. However, this result was not observed. The observed differences  
46  
47 were in the P300 component. The rationale behind using face stimuli was based on previous  
48  
49 EEG studies, as well as neuroimaging evidence identifying facial processing in the FFA.  
50  
51 Similarly, location stimuli were chosen due to neuroimaging evidence showing distinct  
52  
53 activation in the PPA.  
54  
55  
56  
57  
58  
59  
60

Functional MRI studies can discriminate the FFA from the PPA due to the high spatial resolution produced by MRI. In our study, we hypothesized that these differences would also be observed in the scalp recorded EEG. We expect this result was not observed due to the close proximity of the PPA and FFA. The PPA is located at the medial portion of the fusiform gyrus, whereas the FFA is located at a nearby cortical region in the mid-fusiform gyrus. Therefore, Experiment 2 examined another possible stimulus, images of tools, which activate more frontal areas such as the premotor and motor cortex.

Neuroimaging studies have shown a unique cognitive response to graspable objects such as tools (Creem-Regehr, & Lee, 2005). Tools are considered a unique class of objects, due to the relationship between object recognition as well as the potential actions that can be performed with the object (Handy, Grafton, Shroff, Ketay, & Gazzaniga, 2003). Viewing images of tools has been shown to activate the premotor cortex, and research has suggested that the priming of visual systems by viewing tools also primes motor systems (Tucker & Ellis, 2004; Grafton, Fadiga, Arbib, & Rizzolatti, 1997).

## Experiment 2 Methods

### Participants

Twenty-four able-bodied participants (10 men, 14 women; age range 19-42) were recruited from East Tennessee State University. Seven of the participants had prior BCI experience, the remainder of participants were naïve to BCI use. The study was approved by the East Tennessee State Institutional Review Board and each participant gave informed consent.

### Data Acquisition, Processing, and Classification

Data acquisition, processing, and classification were identical to Experiment 1.

## Experimental Stimuli, Procedure, and Design

The experimental protocol used in Experiment 1 was also used in Experiment 2. The two experiments differed in the images presented to participants, and the instructions given to participants for “attending” to the stimuli used. The images were those of the location image (i.e., the White House) and a hammer. The experimental task for the location image was to focus attention on a specific character in the matrix and to count how many times the image appeared, while ignoring the images flashing over the other characters in the matrix. For the tool stimuli, the experimental task was to focus attention on a specific character in the matrix and imagine themselves using the object each time the image of the object flashes (i.e., swing a hammer). This was done to elicit a stronger response in the premotor cortex than simply counting the number of character flashes. Following each calibration phase, a SWLDA analysis derived classification coefficients specific to each stimulus type. Following calibration, participants completed an online copy-spelling task similar to the online-copy spelling task in Experiment 1 using the stimuli shown in Figure 3.



Figure 3: Example of one-stimulus matrix displaying the image of the location only (left) and one-stimulus matrix displaying the image of the tool only (right).

## Experiment 2 Results

## Statistical Analyses

A two-way repeated measures analysis of variance (ANOVA) was used to examine the effects of classifier type (Location or Tool) and stimulus type (Location or Tool) on accuracy, number of flashes, selections per minute, and bit rate. Waveform analyses were conducted on the calibration data to maintain a consistent amount of data in each condition. Paired sampled t-tests were used to examine the differences in waveforms between the tool and location stimuli. To control the false positive error rate for performing multiple comparisons, the Benjamini-Hochberg (B-H) procedure was used procedure was used to determine the critical p value (Thissen, Steinburg, & Kuang, 2002).

## Results

### Offline Performance

The means and standard deviations examining offline accuracy, target flashes, selections per minute, and bitrate produced by each classifier type applied to each stimulus type are shown in Table 3. Electrode locations used in the jumpwise-SWLDA classification algorithm are shown in Table 4. The table shows the locations that were used by at least fifty percent of the participants. The ANOVAs examining offline accuracy, number of target flashes, selections per minute, and bit rate all yielded significant differences ( $F(3, 33) = 8.42, p < .001$ ;  $F(3, 33) = 22.21, p < .001$ ;  $F(3, 33) = 19.93, p < .001$ ; and,  $F(3, 33) = 26.094, p < .001$ , respectively). Table 2 shows a summary of the means and standard deviations for each measure. In all cases, the stimulus specific classifier provided higher performance. For example, the tool classifier applied to the tool data resulted in higher accuracy than the tool classifier applied to the location data.

## FACES, LOCATIONS, AND TOOLS: TWO-STIMULUS PRESENTATION

21

Pairwise comparisons indicated there was no significant difference in the comparisons of each stimulus specific classifier applied to the corresponding stimulus.

**Table 3**

*Offline means and standard deviations (in parentheses) for performance measures for each classifier applied to each stimulus type for Experiment 2.*

	Accuracy	Target Flashes	Selections per Minute	Bitrate
<b>Tool Classifier</b>				
Tool	97.79(3.34)*	3.04(1.12)*	4.74(1.13)**	28.30(7.88)***
Location	93.42(8.9)	4.00(1.10)	3.83(0.98)	21.53(7.87)
<b>Location Classifier</b>				
Tool	89.79(14.5)	4.04 (0.99)*	3.74(0.80)	20.07(7.67)
Location	99.08(3.1)*	2.58(1.13)	5.46(1.7)***	33.39(11.02)***

\* significant at  $p < 0.05$ ; \*\* significant at  $p < 0.005$ ; \*\*\* significant at  $p < 0.001$ .

**Table 4**

*Experiment 2 Jumpwise Channels used by 50% or more of the participants*

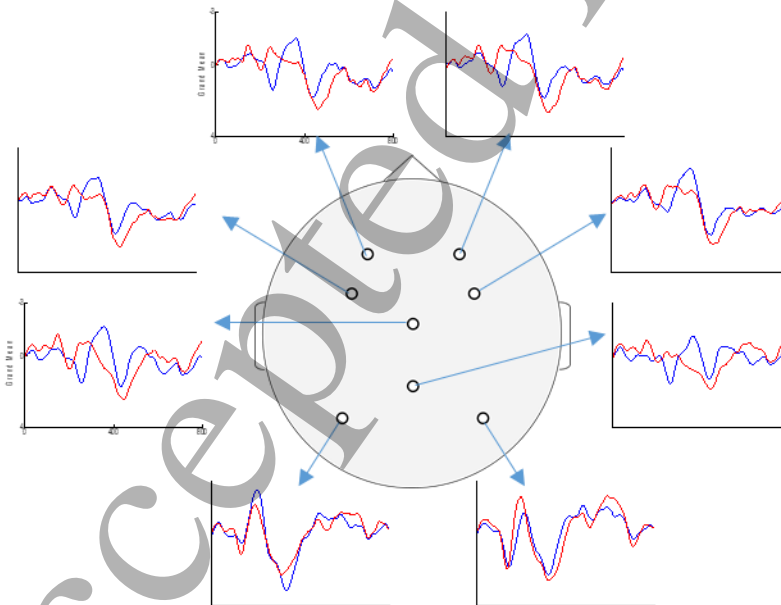
Experiment 2									
Tool Jumpwise Channels	O2	Po8	Po7	Oz	Cp6	Cp5	P8	O1	
Participants	18	16	16	16	15	15	13	12	
Location Jumpwise Channels	Po8	Oz	P8	O2	Po7	O1			
Participants	21	18	16	16	15	15			

**Waveform Analysis**

## FACES, LOCATIONS, AND TOOLS: TWO-STIMULUS PRESENTATION

22

The specified time windows examined for positive amplitudes and latencies were 150-320ms and 350-550ms. The specified time windows to examine N170 and N400 amplitudes and latencies were sets to 128-195 for the N170 component, and 191-300 for the N400 component. Eight electrode locations Pz, Cz, PO7, PO8, F3, F4, FC5, and FC6 were examined (Figure 4). Paired samples t-tests were used to compare differences between the two types of stimuli.



1  
2  
3 *Figure 4: Average waveforms for all 24 participants for the two types of images, Tool (blue line)*  
4 *and Location (red line) used in the BCI task for electrode locations Cz, Pz, PO7, PO8, F3, F4,*  
5 *FC5, and FC6.*

6  
7  
8  
9  
10  
11 Across all eight electrode locations no significant differences in latency were observed in  
12  
13 any of the four time windows.

14  
15  
16 In the positive time window 350-550ms significantly larger amplitude was observed at  
17  
18 electrode location PO7 to the tool stimulus ( $M= 3.8$ ,  $SD= 2.6$ ) than to the location stimulus ( $M=$   
19  $3.0$ ,  $SD= 1.5$ ),  $t(23)= 2.403$ ,  $p= 0.02472$  (B-H critical value 0.025). At the seven remaining  
20  
21 electrode locations, the location stimulus elicited a larger amplitude: Pz ( $t(23)= -4.813$ ,  $p<.001$ ;  
22  
23 B-H critical value 0.01842); Cz ( $t(23)= -4.858$ ,  $p<.001$ , B-H critical value 0.01711); PO8 ( $t(23)=$   
24  
25  $-5.946$ ,  $p<001$ ; B-H critical value 0.01579); F3, ( $t(23)=-2.931$ ,  $0.00751$ ,  $p=.008$ ; B-H critical  
26  
27 value 0.02368) ; F4, ( $t(23)=-3.57$ ,  $p= 0.00163$ ; B-H critical value 0.02105); FC3, ( $t(23)= -3.285$ ,  
28  
29  $p= 0.00325$ ; B-H critical value 0.02237); and, FC4, ( $t(23)= -4.375$ ,  $p<001$ ; B-H critical value  
30  
31 0.01974).

32  
33  
34  
35  
36  
37 In the negative time window of 128-195ms, amplitudes were significantly higher for the  
38  
39 location stimulus than to the tool stimulus at: Cz ( $t(23)= 3.253$ ,  $p = 0.00175$ ; B-H critical value  
40  
41 0.018421053); Pz ( $t(23)= 3.265$ ,  $p = 0.0017$ ; B-H critical value 0.017105263); and, PO8 ( $t(23)=$   
42  
43  $4.486$ ,  $p = 8.4E-05$ ; B-H critical value 0.015789474).

44  
45  
46  
47 Except for electrode location PO7, all amplitude comparisons in the negative time  
48  
49 window of 191-300ms were significantly larger for the location stimulus than the tool stimulus:  
50  
51 Pz ( $t(23)= 4.51$ ,  $p<.001$ ; B-H critical value 0.01579); Cz ( $t(23)=2.348$ ,  $p<001$ ; B-H critical value  
52  
53 0.02105); F3 ( $t(23)=2.939$ ,  $p= 0.00369$ ; B-H critical value 0.02368); PO8 ( $t(23)= 3.886$ ,  $p<.001$ ;  
54  
55  
56  
57  
58  
59  
60



1  
2  
3 B-H critical value 0.01711); F4 ( $t(23)=3.043$ ,  $p=.00289$ ; B-H critical value 0.02237); FC3  
4  
5 ( $t(23)= 3.619$ ,  $p<.001$ ; B-H critical value 0.01974); and, FC4 ( $t(23)= 3.86$ ,  $p = 0.0004$ ; B-H  
6  
7 critical value 0.01842).  
8  
9  
10  
11  
12

### 13 14 **Experiment 2 Discussion**

15  
16  
17 Experiment 2 provided offline evidence that a stimulus-specific classifier could produce  
18  
19 superior BCI performance in terms of accuracy, selections per minute, and bitrate. The classifier  
20  
21 applied to the same stimulus type (i.e., location-to-location or tool-to-tool) yielded better  
22  
23 performance than either classifier applied to the other stimulus type. These findings support our  
24  
25 hypothesis that a stimulus specific classifier applied to the corresponding stimulus can result in  
26  
27 improved BCI performance. By having two stimulus specific classifiers operating  
28  
29 simultaneously, using a two stimulus paradigm could potentially lead to increases in online BCI  
30  
31 performance. In addition, several differences in ERP components were observed (discussed  
32  
33 below).  
34  
35  
36  
37

### 38 **General Discussion**

39  
40  
41 Recent studies have shown that ERP components associated with facial stimuli can  
42  
43 improve BCI performance in a two-stimulus presentation paradigm (Kaufmann et al., 2014). The  
44  
45 present work extends these findings and incorporated two additional types of novel stimuli,  
46  
47 location and graspable objects. Prior to this study, ERPs produced by location and graspable  
48  
49 objects have not been examined; however, fMRI data has provided evidence that these stimuli  
50  
51 activate different brain regions. Thus, the purpose of the present study was to determine if  
52  
53  
54  
55  
56  
57  
58  
59  
60

1  
2  
3 location and graspable objects produce differential ERPs that can subsequently lead to an  
4 improvement in BCI speed and accuracy.  
5  
6  
7

8 Experiment 1, using facial and location stimuli, showed no differences in face specific  
9 components; nonetheless, other ERP differences were observed and the location stimuli  
10 produced slightly better performance than facial stimuli. Kaufmann et al. (2011) first examine  
11 facial stimuli in able-bodied subjects, based on their positive results, they extended the paradigm  
12 to people with severe speech and communication disorders and confirmed that facial stimuli  
13 produced higher speed and accuracy in this population as well (Kaufmann et al. 2011). The  
14 findings of our project indicate that location stimuli produce comparable performance to facial  
15 stimuli. Thus, we suggest that location stimuli may be beneficial for people with severe speech  
16 and communication disorders. This hypothesis should be tested in future studies.  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29

30 Functional MRI research indicating activation in the parahippocampal place area in  
31 response to visual processing of location stimuli (Malach et al., 2002; Epstein et al., 1999;  
32 Agguire, et al., 1998), as well as activation in the premotor cortex in response to stimuli such as  
33 graspable objects (Creem-Regehr, & Lee, 2005; Tucker & Ellis, 2004; Grafton et al., 1997),  
34 prompted the examination of parietal locations (PO7 and PO8) and frontal locations (F3, F4,  
35 FC5, and FC6) in addition to locations Pz and Cz. Due to lack of EEG research on the ERPs  
36 produced by these stimulus types, exploratory analyses were conducted. In Experiment 2,  
37 location stimuli were compared to graspable object stimuli. Our working hypothesis was that  
38 higher P300 amplitudes would be observed for the location stimuli than for the tool stimuli. The  
39 rationale for this hypothesis was due to the fact that participants were instructed to imagine  
40 swinging a hammer each time the target item appeared. The added cognitive demands of the task  
41 were, therefore, expected to reduce P300 amplitude and maximize the difference between the  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60

1  
2  
3 ERPs produced by each stimulus type. Waveform analyses comparing the ERPs produced by the  
4 two stimulus types showed higher amplitude produced by the location image than the tool image  
5 at each of the examined electrode locations, except for PO7 in positive time window 350-550ms.  
6  
7

8  
9  
10 Similar to Experiment 1, BCI performance was higher in the location stimulus condition.  
11  
12 These results support our hypothesis that stimulus-specific classifiers may provide higher  
13 performance, as compared to the current methodologies that rely on a single classifier. Future  
14 research will develop stimulus specific classifiers to be tested online in a two-stimulus  
15 presentation paradigm. The development of simultaneous, dual stimulus-specific classifiers  
16 could potentially allow the BCI to quickly eliminate half of the characters in the matrix as  
17 potential targets. Thus, having the potential to increase the speed with which selections can be  
18 made and decreasing the number of selection errors. The utility of two classifiers will be  
19 determined by the amount of variation in the ERPs produced by each class of stimuli. Thus, it is  
20 important to select stimuli that elicit significantly different ERPs.  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32

### 33 34 **Conclusion**

35  
36 P300 BCI technology has shown to be an effective method of communication; however,  
37 due to the relatively slow rate of communication improvements are necessary. The first online  
38 P300-based BCI study resulted in accuracy of 35 percent (Donchin, Spencer, & Wijesinghe,  
39 2000). Since this time, online accuracy is consistently near 100 percent. Nonetheless, further  
40 improvements are needed for the technology to rival assistive communication devices that rely  
41 on muscle movement. Therefore, novel classification techniques and paradigm modifications are  
42 necessary to provide people with severe speech and physical impairments more efficient BCI  
43 communication options after muscle control is lost.  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60

1  
2  
3 The goal of the current study, however, was to use offline analyses to investigate the  
4 efficacy of using unique categories of stimuli. Nonetheless, due to the early stages of this line of  
5 research, it would not be appropriate to test the current paradigm with people who have severe  
6 speech and physical impairments. As with most P300 BCI research conducted in laboratory  
7 settings, an inherent limitation to our study design is the use of able-bodied participants as our  
8 sample. Another limitation of the study design is that it did not afford us the opportunity to  
9 compare graspable object stimuli to facial stimuli. Further investigation comparing graspable  
10 object stimuli to facial stimuli may be beneficial to determine which would be more useful in the  
11 two-stimulus paradigm. In both experiments, the offline results suggest a two-stimulus dual-  
12 classifier paradigm can improve BCI performance. An online adaptation of the paradigm should  
13 be tested in future work.  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60

## REFERENCES

- 1  
2  
3  
4  
5  
6  
7  
8 Agguire, G.K., Zarahn, E., & D'Esposito, M. (1998). An area within human ventral cortex  
9 sensitive to “building” stimuli: Evidence and implications. *Neuron*, *21*, (2), 373-383.  
10  
11  
12  
13 Chen, L., Jin, J., Wang, X., & Cichocki, A. (2015). A survey of the dummy face and human face  
14 stimuli used in BCI paradigm. *Journal of Neuroscience Methods*, (239), 18-27.  
15  
16 <http://dx.doi.org/10.1016/j.jneumeth.2014.10.002>  
17  
18  
19  
20  
21 Creem-Regehr, S.H., & Lee, J.N. (2005). Neural representations of graspable objects: are tools  
22 special? *Cognitive Brain Research*, *22*, 457-469. doi:10.1016/j.cogbrainres.2004.10.006  
23  
24  
25  
26 Colwell, K.A., Ryan, D.B., Throckmorton, C.S., Sellers, E.W., & Collins, L.M. (2014). Channel  
27 selection methods for the P300 Speller. *Journal of Neuroscience Methods*, (232), 6-15.  
28  
29  
30  
31 Draper, N.R., & Smith, H. (1981) Applied regression analysis. 2. New York: Wiley.  
32  
33  
34 Donchin, E., Spencer, K.M., & Wijesinghe, R. (2000). The mental prosthesis: Assessing the  
35 speed of a P300-based brain-computer interface. *IEEE Transaction on Rehabilitation*  
36 *Engineering*, *8*(2), 174-179.  
37  
38  
39  
40  
41  
42 Donchin, E., & Coles M.G.H. (1988) Is the P300 component a manifestation of context  
43 updating? *Behavioral Brain Science*, *11*, 355-425.  
44  
45  
46  
47 Epstein, R., & Kanwisher, N. (1998). A cortical representation of the local visual environment.  
48 *Nature*, *392*, 598-601.  
49  
50  
51  
52 Epstein, R., Harris, A., Stanley, D., & Kanwisher, N. (1999). The parahippocampal place area:  
53 Recognition, navigation, or encoding? *Neuron*, *23*, 115-125.  
54  
55  
56  
57  
58  
59  
60

- 1  
2  
3 Fabiani, M., Gratton, G., Karis, D., & Donchin, E. (1987). Definition, identification, and  
4 reliability of measurement of the P300 component of the event-related brain potential.  
5  
6 *Advances in Psychophysiology*, 2, 1–78.  
7  
8  
9  
10  
11 Farwell, L., & Donchin, E. (1988). Talking off the top of your head: toward a mental prosthesis  
12 utilizing event-related brain potentials. *Electroencephalography and Clinical*  
13 *Neurophysiology* 70, 510-523. doi: 10.1016/0013-4694(88)90149-6  
14  
15  
16  
17  
18 Geronimo AM, & Simmons, Z. The P300 'face' speller is resistant to cognitive decline in  
19  
20  
21 ALS. *Brain-Computer Interfaces*. 2017. doi:10.1080/2326263X.2017.1338013  
22  
23  
24 Grafton, S.T., Fadiga, L., Arbib, M.A., & Rizzolatti, G. (1997). Premotor cortex activation  
25 during observation and naming of familiar tools. *Neuroimage*, 6, 231-236.  
26  
27  
28  
29 Handy, T.C., Grafton, S.T., Shroff, N.M., Ketay, S., & Gazzaniga, M.S. (2003). Graspable  
30 objects grab attention when the potential for action is recognized. *Nature Neuroscience*, 6  
31  
32 (4), 421-427. doi:10.1038/nm1031.  
33  
34  
35  
36  
37 Hillyard, S.A., & Kutas, M. (1983). Electrophysiology of cognitive processing. *Annual Review*  
38 *of Psychology*, 34, 33-61. doi: 0066-4308/83/0201-0033\$02.00  
39  
40  
41  
42 Kanwisher, N., McDermott, J., & Chun, M.M. (1997). The fusiform face Area: A module in  
43 human extrastriate cortex specialized for face perception. *The Journal of Neuroscience*,  
44  
45 17, (11), 4302-4311. doi: 0270-6474/97/174302-10\$05.00/0.  
46  
47  
48  
49  
50 Kaufmann, T. & Kubler., A. (2014). "Beyond maximum speed--a novel two-stimulus paradigm  
51 for brain-computer interfaces based on event-related potentials (P300-Bci)." *Journal of*  
52 *Neural Engineering* 11,(5). 056004. <http://dx.doi.org/10.1077/1741-2560/11/5/056004>  
53  
54  
55  
56  
57  
58  
59  
60

- 1  
2  
3 Kaufmann, T., Schulz, S. M., Koblitz, A., Renner, G., Wessig, C. & Kubler, A. (2013). Face  
4 stimuli effectively prevent brain-computer interface inefficiency in patients with  
5 neurodegenerative disease. *Clinical Neurophysiology*, (124), 5. 893-900.  
6  
7 <http://dx.doi.org/10.1015/j.clinph.2012.11.006>  
8  
9  
10  
11  
12 Kaufmann, T., Schulz, S. M., Grunzinger, C., & Kubler, A. (2011). Flashing characters with  
13 famous faces improves ERP-based brain-computer interface performance. *Journal of*  
14 *Neural Engineering* (8), 5. 056016. <http://dx.doi.org/10.1088/1741-2560/8/5/056016>  
15  
16  
17  
18  
19  
20 Kellicut-Jones, M.R., & Sellers, E.W. (2018). P300 Brain-Computer Interface: Comparing Faces  
21 to Size Matched Non-Face Stimuli. *Brain-Computer Interfaces*, 5 (1), 30-39.  
22  
23  
24  
25 DOI:10.1080/2326263X.2018.1433776  
26  
27  
28 Krusienski, D. J., Sellers, E. W., McFarland, D. J., Vaughn, T. M., & Wolpaw, J. R. (2008).  
29 Toward enhanced P300 speller performance. *Journal of Neuroscience Methods*, (167),  
30 15-21. <http://dx.doi.org/10.1016/j.jneumeth.2007.07.017>  
31  
32  
33  
34  
35  
36 Krusienski, D.J., Sellers, E.W., Cabestaing, F., Bayouth, S., McFarland, D.J., Vaughan, T.M., &  
37  
38 Wolpaw, J.R. (2006). A comparison of classification techniques for the P300 Speller.  
39 *Journal of Neural Engineering*, (4), 3, 299-305. f  
40  
41  
42  
43 Kubler, A., Kotchoubey, B., Kaiser, J., Wolpaw, J. R., & Birbaumer, N. (2001). Brain-computer  
44 communication: Unlocking the locked in. *Psychological Bulletin*, 127, (3), 358-75.  
45  
46  
47 <http://dx.doi.org/10.1037//0033-2909.127.3.358>  
48  
49  
50  
51 Jin, J., Daly, I., Zhang, Y., Wang, X., & Cichocki, A. (2014). An optimized ERP brain-computer  
52 interface based on facial expression changes. *Journal of Neural Engineering*, 11(3), 1-12.  
53  
54  
55 <http://dx.doi.org/10.1088/1741-2560/11/3/036004>  
56  
57  
58  
59  
60

- 1  
2  
3 Malach, R., Levy, I., & Hasson, U. (2002). The topography of high-order human object areas.  
4  
5 *Trends in Cognitive Sciences*, 6, (11), 176-184.  
6  
7  
8 McCarthy, G., Puce, A., Gore, J.C., & Allison, T. (1997). Face-specific processing in the human  
9  
10 fusiform gyrus. *Journal of Cognitive Neuroscience*, 9, (5), 605-610.  
11  
12  
13 Mönninger, J.I., Halder, S., Kleih, S.C., Furdea, A., Raco, V., Hosle, A., & Kubler, A. (2010).  
14  
15 Brain painting: First evaluation of a new brain-computer interface application with ALS-  
16  
17 patients and healthy volunteers. *Frontiers in Neuroscience* 4, (182), 1-11.  
18  
19  
20  
21 Picton, T. W. (1992). The P300 wave of the human event-related potential. *Journal of Clinical*  
22  
23 *Neurophysiology*, 9, 456–79.  
24  
25  
26 Pierce, J.R. (1980). An introduction to information theory. Dover, New York, pp. 145-165.  
27  
28  
29 Sellers, E.W., & Donchin, E. (2006). A P300-based brain computer interface: Initial tests by  
30  
31 ALS patients. *Clinical Neurophysiology*, 117, 538-548.  
32  
33  
34 Sellers, E.W., Krusienski, D.J., McFarland, D.J., Vaughan, T.M., & Wolpaw, J.R. (2006). P300  
35  
36 event-related potential brain-computer interface (BCI): The effects of matrix size and  
37  
38 inter stimulus interval on performance. *Biological Psychology*, 73, 242-252.  
39  
40  
41  
42 Sellers, E.W., Ryan, D.B., & Hauser, C.K. (2014). Noninvasive brain-computer interface enables  
43  
44 communication after brainstem stroke. *Sci Transl Med*, 6(257), 1-16.  
45  
46 doi:10.1126/scitranslmed.3007801.  
47  
48  
49  
50 Sajda, P., Müller, K., & Shenoy, K.V. (2008, January). Brain-Computer Interfaces. *IEEE Signal*  
51  
52 *Processing Magazine* (25), 1, 16-17.  
53  
54  
55  
56  
57  
58  
59  
60



## FACES, LOCATIONS, AND TOOLS: TWO-STIMULUS PRESENTATION

32

1  
2  
3 Sutton S., Braren M., Zubin, J., & John, E. R. (1965). Evoked potential correlates of stimulus  
4 uncertainty. *Science*, *150*, 1187–8.

7  
8 Takano, K., Komatsu, T., Hata, N., Nakajima, Y., & Kansaku, K. (2009). Visual stimuli for the  
9 P300 brain-computer interface: A comparison of white/gray and green/blue flicker  
10 matrices. *Clinical Neurophysiology*, <http://dx.doi.org/10.106/clinph.2009.06.002>  
11  
12  
13  
14

15  
16 Tong, F., Nakayama, K., Vaughan, J.T., & Kanwisher, N. (1998). Binocular rivalry and visual  
17 awareness in human extrastriate cortex. *Neuron*, *21*, 753-759.

18  
19  
20  
21 Touryan, J., Gibson, L., Horne, J. H., & Weber, P. (2011) Real-time measurement of face  
22 recognition in rapid serial visual presentation. *Front Psychology* *2*, (42).  
23  
24  
25  
26 <http://dx.doi.org/10.3389/fpsyg.2011.00042>  
27

28  
29 Tucker, M. & Ellis, R. (2004). Action priming by briefly presented objects. *Acta Psychologica*,  
30  
31 *116*, (2), 185-203. <http://dx.doi.org/10.1016/j.actpsy.2004.01.004>  
32

33  
34 Velliste, M., Perel, S., Spalding, M.C., Whitford, A.S., & Schwartz, A.B. (2008). Cortical  
35 control of a prosthetic arm for self-feeding. *Nature*, *453*, 1098-1101.  
36  
37

38  
39 Vallabhaneni, A., Wang, T., & He, B. (2005). Brain-computer interface. *Neural Engineering*, *85-*  
40  
41  
42 *121*. doi: 10.1007/0-306-48610-5\_3  
43

44  
45 Wolpaw, J.R., Birbaumer, N., McFarland, D.J., Pfurtscheller, G., & Vaughn, T.M. (2002). Brain-  
46 computer interfaces for communication and control. *Clinical Neurophysiology*, *113*, 767-  
47  
48  
49 791.  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60

1  
2  
3 Zhang, Y., Zhao, Q., Jin, J., Wang, X., & Cichocki, A. (2012). A novel BCI based on ERP  
4 components sensitive to configural processing of human faces. *Journal of Neural*  
5  
6 *Engineering*, 2, (9), 1-13. 026018. <http://dx.doi.org/10.1088/1741-2560/9/2/026018>  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60