Introducing the Edges Paradigm: A P300 Brain-Computer Interface for spelling written words.

Obeidat, Qasem

2015

Obeidat , Q , Campbell , T A & Kong , J 2015 , ' Introducing the Edges Paradigm: A P300 Brain-Computer Interface for spelling written words. ' IEEE Transactions on Human-Machine Systems , vol. 45 , no. 6 , pp. 727-738 . https://doi.org/10.1109/THMS.2015.2456017

http://hdl.handle.net/10138/173803
https://doi.org/10.1109/THMS.2015.2456017

Introducing the Edges Paradigm: a P300 Brain-Computer Interface for spelling written words

Qasem Obeidat, Tom Campbell, and Jun Kong

Abstract—P300-based brain computer interface spellers employ the P300 component, which is derived from scalp measured electroencephalogram (EEG) during the brain's electrical response to a flash denoting an attended target character. The most popular P300 speller, the row column paradigm (RCP), displays characters in a matrix within which rows and columns of characters are flashed eliciting P300 responses when the illuminated row or column contains the attended target character. Despite being a longstanding successful approach, this RCP faces several challenges, including the adjacency and crowding problems. A new P300 speller is introduced – the edges paradigm (EP). Distinct from existing P300 spellers, the EP presents a square adjacent to each column or row in the outer boundary of the matrix. By replacing each flash of a row or column with that square, this EP exhibited attenuated influences of crowding and adjacency – problems known to perturb the RCP. In the copy-spelling mode, 14 neurologically normal participants demonstrated an improved accuracy of 93.3 ± 2.0% for the EP relative to 81.7 ± 2.8% for the RCP, alongside a faster communication rate. Subjective ratings also indicated that the EP caused significantly less fatigue, while increasing alertness and comfort.

Index Terms—P300-based speller, Brain-Computer Interface, Crowding, Edges Paradigm, Visual Event-Related Potentials

I. Introduction:

Research into brain-computer interfaces (BCIs) has, over the last two decades, emerged as a burgeoning field, offering modest improvements in quality of life to paralyzed individuals with minimal voluntary muscular control [1]. These individuals affected by a severe neuromuscular disease such as amyotrophic lateral sclerosis (ALS), have remained unable in any conventional manner to directly access many forms of information and communication technology such as computers and mobile phones. As a substitute for traditional communication channels (e.g., a keyboard, mouse, touch screen, or voice recognition), BCI has enabled users to control external devices by providing a direct real-time communication channel between the user's brain and an external device. For example, studies have designed and used BCI for the selection of commands to control a wheelchair [2], [3]. This visual wheelchair interface has enabled paralyzed individuals to control wheelchair movement to specific locations and directions by translating the selected target into motor commands. Other successful BCI applications have included brain-controlled internet browsers [4] and controlling mobile robots [5]. Further, a "NeuroPhone" system [6] allows neural signals to control mobile phone applications, such as calling a contact number from a phone address book by selecting a target flash contact image. This BCI approach has potential for mobile digital communication via text for spelling written words, the focus of the present work.

These aforementioned BCI applications have utilized a high amplitude component of the brain's electrical response to visual stimulation [7], the P300, that is derived from electroencephalogram (EEG) measured via electrodes attached to the scalp – a component elicited during the processing of an attended target yet not by a to-be-ignored non-target stimulus [8]. Solutions to the electromagnetic inverse problem [9] have indicated that this scalp-measured P300 component is a consequence of neurocognitive processes [8], [10], [11] affecting multiple source generators in the temporal and parietal lobes of the cerebral cortex of neurologically normal individuals [12], [13].

Of such BCIs, the P300-based BCI speller, introduced by Farwell and Donchin [14], is an extensively investigated approach [5], [15], [16], [17], [18], [19], [20], [21], [22]. The long-lasting P300 is characterized by a high-amplitude positive peak component of the event-related potential (ERP); a component that is maximal over the parietal scalp with a peak latency of around 300 ms after the stimulus onset. Farwell and Donchin's speller (the row-column paradigm (RCP), also called the matrix speller [14]) consisted of a 6-by-6 matrix of 36 alphanumeric characters displayed on a screen in front of the user. The rows and columns are flashed alternately in a randomized order, while the user focuses on a target character that is infrequently displayed and silently counts how many times the target character has flashed. Once the row or column containing a target character is flashed, the P300 component is elicited. A classification algorithm is then applied to the EEG data to determine the row and column that elicited the largest P300 amplitude. The intersection of the identified row and column indicates the target character. Though the RCP has been widely used, the paradigm has faced several challenges, namedly the adjacency, crowding, and fatigue problems. Non-targets surrounding targets, "flankers", hinder the speller's classification [23], [24], and flankers can hamper perceptual identification of a parafoveal target [25], [26], in accordance with Bouma's law [26]. This law states that the identification of a stimulus is improved as a function of the spatial separation between the target stimulus and flanking non-target stimuli. The central thesis of this work is that Bouma's law is intimately intertwined with the crowding problem of multiple similar objects in a display impeding speller performance, alongside the adjacency problem whereby the proximity of objects also adversely affects performance. These problems are considered to be causal of the associated fatigue problem experienced by BCI users. Problems have been identified. The RCP is still considered as the benchmark against which new versions of the P300 speller concept have to be evaluated. With a view to devise an improved visual interface and flashing technique for a P300-based speller, each of these problems is considered here in turn. The motivation of this investigation is to improve the performance and user experience with P300 BCIs.

The small distance between adjacent row or column flashes has been identified as the major factor affecting accuracy [23], i.e., the adjacency problem. Flashes are assumed to distract the user more when a character close to the target character is flashed and the user is attempting to focus upon that target character. Accordingly, P300 elicitation is affected by evoking a P300 component in response to the non-target character flashes rather than to the target character flash, leading to a recognition error that is termed an adjacent error. Fazel-Rezai [23], Townsend et al. [24], and Obeidat et al. [27] found, respectively, that 60%, 41%, and 42% of these errors were such adjacent errors.

The number of errors, especially adjacent errors, is assumed to increase when the target object and that object's neighboring objects have a similar pattern and contours because this similarity leads to confusion between the target and non-target objects [25], i.e., the crowding problem. Crowding refers to the phenomenon that the identification of an object is hampered if that object is surrounded by similar objects. For instance, visual discrimination of the target character is difficult with more surrounding non-targets [28]. By reducing the number of neighboring characters, the zigzag paradigm has yielded better P300 classification performance than the RCP [27], and has exposed this approach to be effective in attenuating the influence of the crowding problem. Another problem that has been identified for the RCP is fatigue. After typing a number of characters using the RCP, which required many row and column flashes, a user often becomes tired, sleepy, or loses concentration, adversely affecting the discriminability of signals generated by the brain, and in turn, rendering the target character identification difficult.

This investigation introduces a distinct visual interface and flashing technique to address the aforementioned RCP problems. This new P300 speller is termed the edges paradigm (EP) (Fig. 1). The EP is intended for disabled people without any eye impairment (i.e., this EP is an overt speller). A key difference between the EP and the RCP is that a gray edge point is displayed to the left of every odd row, to the right of each even row, below every odd column, and above each even column. In order to reduce the user distraction between the target and non-target flash edge points, the color of the characters is white.

The basis of the EP's flashing technique and mode of use is as follows: only one edge point at-a-time exhibited a luminance increment rather than flashing the entire row or column as in the RCP. A character is selected in two stages. That is, in the first stage, a user focused on the edge point that is paired with the row including the target character, as shown above in Fig. 1(a). Then, in the second stage, the user shifted the gaze to refocus upon the edge point that is paired with the column containing the target character, as illustrated in Fig. 1(b). The EP is intended to: 1) reduce the adjacency problem by increasing the distance between adjacent flash objects [23], [24], [27] (i.e., edge points); 2) reduce the crowding problem by decreasing the number of flash objects surrounding any target object; 3) reduce the crowding problem by placing a spatial separator, the character matrix, between edge points upon opposite sides of the matrix; and 4) reduce fatigue by minimizing the flash illumination size from flashing an entire row or column by an edge point.

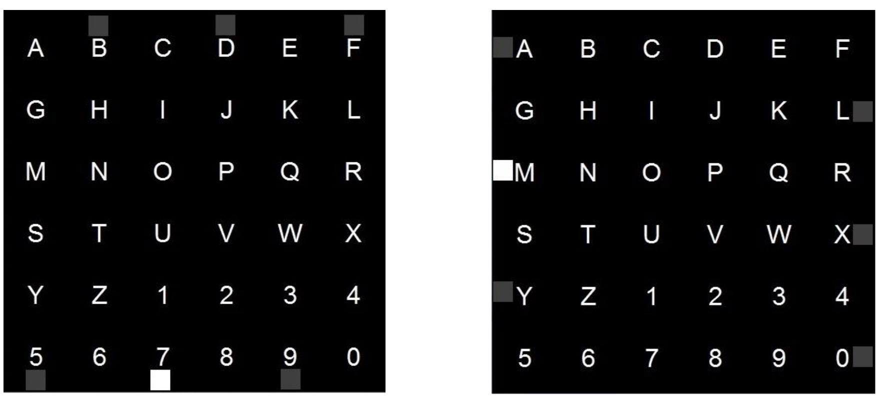


Fig. 1. The Edges Paradigm (EP).

If the influence of the adjacent and crowding problems for P300-based spelling is reduced by the EP, its use is envisaged to exhibit improvements upon the online classification performance demonstrated with the RCP. Similarly, if the influence of the fatigue problem is reduced by the EP, using the EP is predicted to cause less subjectively rated fatigue than the corresponding RCP.

The remainder of the paper is organized as follows: the related work is discussed in Section II; the methods are discussed in Section III; the results of the user study and the discussion are presented in Sections IV and V, respectively, and the conclusions are in Section VI.

II. Related Work:

A. P300-based Approaches to Matrix Spellers

Turning to alternatives for the traditional character matrix stimulus (i.e., flashing characters), several studies have implemented new visual stimulus presentation techniques. These techniques included combining the P300 component with motion-onset visual evoked potentials [29], flashing familiar faces transparently superimposed on characters [30], and facial motion and emotional expression [31]. Those novel stimulus techniques were intended to augment the user's attention, in turn eliciting stronger ERPs, to improve the classification accuracy. [29], [30], and [31] revealed that the classification accuracy was increased significantly, but no significant difference was found between the amplitudes of ERPs, as compared with the standard character flashes. In the EP, the physical distance between adjacent flash objects (i.e., squares) was doubled, which was expected to reduce the fatigue problem and reduce the distracting effects of non-target adjacent flashes on the target. In addition, the EP is expected to be more applicable to smaller screens, such as that of a mobile device. Tangermann et al. examined the influence of stimulation parameters upon ERP paradigms and revealed that a visual masking effect outperforms the highlighting methods comprising rotation, scaling, and change of brightness [32]. With the objective of increasing the spelling speed, Kaufmann and Kübler developed a two-stimulus paradigm, which displays two different stimuli (a face and a symbol) at the same time [33]. This two-stimulus paradigm achieved twice the maximum speed of the one stimulus paradigm but the accuracy decreased compared with the face paradigm.

Since traditional visual ERP paradigms have required good gaze control, auditory BCIs, independent of the visual domain, have attracted interest. Höhne et al. found that the use of syllables improves both the users' ergonomic ratings and classification performance, compared with artificially generated tones [34]. Kaufmann et al. compared the tactile, auditory, and visual modality for BCIs and demonstrated that the tactile modality was superior to the visual and auditory modality in a patient with the classical symptoms of locked-in-syndrome [35]. Hiyoshi-Taniguchi et al. investigated multimodal stimuli to clarify the EEG correlates of human emotional judgments [36]. Since these lines of inquiry into novel visual stimulus techniques and auditory approaches have offered some promise for those without gaze control (for other spellers centered on covert attention, see [37] and [38]), the focus, here, was rather to improve upon a traditional matrix speller by introduction of the EP, an approach intended for users with minimal voluntary muscular control yet still retaining eye movements.

B. Flashing Techniques

Concerning the flashing technique, studies have investigated various visual stimuli for replacing the RCP traditional stimulus (i.e., a flash of the entire row or column of characters). Guger et al. introduced the single character paradigm (SCP) that flashes each character individually in a random manner [22]. The single character flash was intended to increase the P300 amplitude thus attaining a higher overall accuracy than the RCP. However, such improvements in accuracy were not obtained, and, of more concern, the communication rate (i.e., the number of characters selected per minute) was reduced. Townsend et al. introduced the checkerboard paradigm (CBP), with 6 non-adjacent characters flashing simultaneously [24]. The CBP significantly improved accuracy relative to the RCP, but still also slowed down the communication rate. Other extended approaches were intended to enhance the CBP, such as preventing characters surrounding targets from flashing during the offline session [39], reducing the total number of flashes [19], or even using a hybrid spelling approach that combined electro-oculogram (EOG) with EEG [17]. While those extensions improved the communication rate, online classification accuracy was not improved over the performance demonstrated with the CBP. Based on Bouma's law [26] and the results from Felisberti et al. [40], the EP, introduced here, utilized a novel flashing technique; flashing an edge point rather than one or multiple characters. This edge point flashing method increased the distance between the target edge point and the flanking edge point, thus reducing the number of surrounding edge points. Consequently, this design presented here was predicted to minimize effects of adjacency and crowding. Further, compared with multi-character flashing techniques, a single edge point flash reduces the illumination on the screen, which potentially reduces a user's fatigue.

Concerning the flash-by-flash temporal characteristics, the stimulus-onset asynchrony (SOA) (i.e., the time between the onsets of the two successive flashes) has been shown to critically influence both the speed and accuracy of the speller. A short SOA of less than 200 ms commonly used in different spellers [15], [17], [24], [27], [41] has engendered a higher data transfer rate. A shorter SOA has also been shown to produce a higher online accuracy [8], [20]. Accordingly, the EP used a short SOA of 120 ms comprised by a brief yet supraliminal flash duration of 70 ms followed by a short inter-stimulus interval (ISI) of 50 ms, the time intervening between the flash termination and the onset of the next flash. In auditory ERP BCIs, Höhne and Tangermann found an individually optimized SOA preferable to fixed values [42]. Accordingly, this principle was extended from the auditory to the visual domain as an individually optimized SOA embodied within the EP in the present investigation.

Concerning the longer-term temporal characteristics of the flashing technique, an iteration is constituted by 12 flashes of the 6-by-6 matrix (i.e., 6 row flashes and 6 column flashes, all permuted in a random order), an iteration typically repeated several times over for each character such that the target character may be identified [14]. That is, while Serby et al. dynamically adapted the number of iterations per character for each individual user [41], several investigations have confirmed that larger number of iterations increased classification accuracy [21], [43], [44], [45], [46]. The EP thus employed a high number of iterations, i.e., 12 iterations.

C. Visual Layout

Tangermann et al. [47] investigated a pseudo-randomized layout in a BCI photobrowser application – a principle feasibly extendible to BCI spellers – yielding roughly comparable classification accuracy to the equivalent RCP photobrowser. Accordingly, perceptual separation of flashes is not a sufficient condition to attenuate crowding. That attenuation of crowding was bolstered by the effect of an approach using complex highlighting composed of brightness enhancement, rotation, enlargement, and a trichromatic grid overlay of flashed visual items. That approach proved more effective at attenuating crowding. That attenuation is thus postulated to rely upon the perceptual grouping of the target flashed objects being better segregated by dissimilarity from non-targets thus reducing the influence of crowding. Accordingly, the effect of perceptual grouping was more potent when the flashed items are grouped into rows and columns of the RCP photobrowser, as perceptually distinct from non-target row and columns, rather into than pseudo-randomized groups. That is, grouping visual items into a “Gestalt” serves to breakdown crowding [25] in a manner more effective than the simple spatial separation attempted with the pseudo-randomized flashing layout [47]. Accordingly, the approach to the crowding of the EP was to completely differentiate perceptually the flashing edge square from the group of characters. That approach did so in terms of shape and flashing character in a manner also promoting the perceptual segregation of the neighboring spatially segregated unflashed edge square. That is, each flashed square of the EP becomes a perceptual group of one item, which can be confused with no other item within that group of one visual item; an object segregated from other groups of visual items perceptually.

Turning to the visual layout of the speller, the number of different alphanumeric characters in the matrix has been examined in several investigations [15], [20], [48]. Yet the only statistically reliable result has been Sellers et al.’s report [20] that a 3-by-3 matrix produced significantly higher accuracy than the 6-by-6 matrix, particularly with a shorter ISI. Accordingly, a 6-by-6 matrix size is adopted in the EP, otherwise being a standard and widely-used successful matrix size considered to be the benchmark in the field. In a distinct approach to investigating the visual layout of the interface, Obeidat et al. reduced the influence of adjacency and crowding problems by shifting every second row in a character matrix to the right (i.e., the zigzag paradigm or ZP) [27]. The results showed that the ZP significantly increased the online accuracy and decreased the fatigue effect compared with the RCP. However, a drawback for use on devices with small screens was that the ZP increased overall width of the matrix.

In order to increase the distance between flashing objects, several new paradigms have clustered characters into different groups and derived a target character through two successive stages [15], [16], [49]–[51]. The first stage was used to identify the group that included the target character. Then, the second stage was used to recognize the target character from the selected group. Compared with the RCP, those two-stage paradigms improved the accuracy. However, these paradigms placed an additional memory load upon the user to memorize the location of a character in the first and second stages. Further, these two-stage paradigms slowed down the spelling process, caused by moving from the first-stage window to the second-stage window, which required a longer inter-stage interval. As an advance upon these two-stage approaches, the EP rather adopted a single-screen approach, just as the RCP has, making a selection within one window. Accordingly, distinct from these two-stage approaches, the EP was intended to improve accuracy without compromising communication rate.

D. Classification

Farwell and Donchin [14] found that the accuracy of a classification algorithm was affected by different factors, including the ISI, ERPs, the shape of the time course of P300, and the application of the speller. Farquhar and Hill concluded a simple method including spectral filtering, spatial whitening and regularized classification achieved near optimal performance for more than 90% of the evaluated datasets [52]. In [21], the Fisher’s linear discriminant analysis (FLDA) algorithm produced the best performance over four well-known BCI classifiers (i.e., Pearson’s correlation method, stepwise linear discriminant analysis (SWLDA), linear support vector machine, and the Gaussian kernel support vector machine. The Bayesian linear discriminant analysis (BLDA) algorithm (i.e., an extension of FLDA) has been compared with FLDA [53], with SVM, LDA, and regularized LDA [54], and with FLDA, SWLDA, SVM, neural network, and nonlinear SVM [55]. The results showed that BLDA, in general, produced the highest accuracy. Therefore, the BLDA was the classification algorithm applied in the EP.

III. Methods:

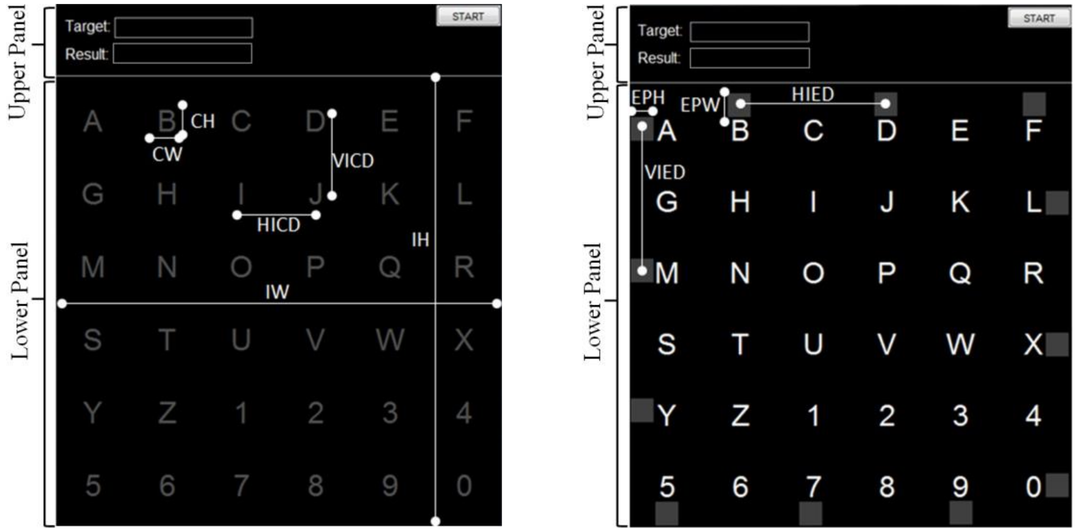
A. Visual Interface Design

The RCP and EP visual interfaces are shown in Fig. 2. See Table I for the dimensions and the distances between objects in the two interfaces. Both interfaces were divided into a small upper panel and a larger lower panel. The upper panel in both interfaces consisted of the input and output text boxes and a start button to run the speller. The lower panel in the RCP, depicted in Fig. 2(a), included a 6-by-6 matrix of 36 gray alphanumeric characters. The corresponding lower section of the EP, as illustrated in Fig. 2(b), differed from that of the RCP in two respects: (1) the alphanumeric characters had a white color and (2) a gray edge point was displayed adjacent to each row or column.

In the RCP, each character was surrounded by 3, 5, or 8 characters, whereas each edge point in the EP was surrounded by 1 or 2 edge points. The EP implemented a different flashing technique from the RCP. That is, the EP only flashed the edge point rather than the entire row or column, so the distance between two adjacent flash objects was doubled. Those designs in the EP potentially reduce the adjacency and crowding issues.

B. Visual Stimulus Design

The visual stimulus of interest was a flash in both interfaces. As shown in Fig. 3, when selecting a target character, there were two stages in the randomized sequence of flash stimuli, which included a total of 144 events (flashes) with 72 row events in the first stage followed by 72 column events in the second stage. A flash-free inter-stage interval lasted for 2 seconds, as in [18]. Row and column events were grouped into 24 iterations (i.e., 12 row iterations and 12 column iterations). Specifically, each iteration consisted of 6 row or 6 column events, and the same row or column was prevented from flashing successively in order to address the double flash issue [41], which would have occurred when the target character flashed successively. The target row and column that contained the target character evenly flashed 24 times (rarely; once per iteration), and the non-target rows and columns flashed 120 times (frequently; 5 times per iteration). The EP flashing technique was the same as the RCP flashing technique described above, with the exception that only the edge point was flashed rather than the entire row or column.



(a) (b)

Fig. 2. (a) The RCP visual interface, (b) The EP visual interface. Annotations use abbreviations in Table I.

TABLE I
THE OBJECTS' DIMENSIONS AND DISTANCES BETWEEN OBJECTS FOR THE RCP AND EP (CM).

Dimensions and Distances	RCP	EP
Character height (CH)	0.68	0.68
Character width (CW)	0.68	0.68
Edge point height (EPH)	—	0.68
Edge point width (EPW)	—	0.68
Horizontal inter-character distance (HICD)	2.13	2.13
Vertical inter-character distance (VICD)	2.13	2.13
Horizontal inter-edge point distance (HIED)	—	4.26
Vertical inter-edge point distance (VIED)	—	4.26
Interface height (IH)	12.7	12.7
Interface width (IW)	12.7	12.7

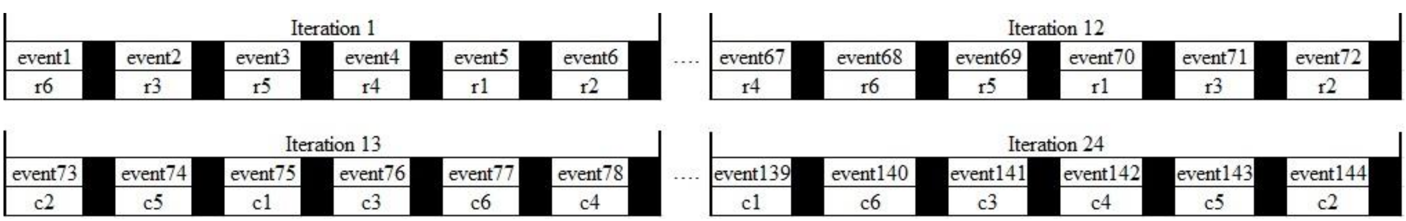


Fig. 3. The flashing technique for the RCP or EP. (r: row or row edge point, c: column or column edge point).

The SOA duration in both spellers was 120 ms, which consisted of 70 ms of flash and 50 ms of inter-stimulus interval (ISI). Thus, each iteration's duration was 120 ms × 6 events = 720 ms, and each stage lasted 720 ms × 12 iterations = 8640 ms. Overall, 2000 ms + (120 ms × 144 events) = 19280 ms were needed to select one target character.

C. Participants

Seventeen neurologically normal university students and employees, who did not suffer from paralysis, voluntarily gave their informed written consent to participate in this investigation. Three participants were excluded from the study due to having long, coarse, or dense hair insulating the connection between the scalp and the saline electrodes [27], [56]. The remaining 14 participants (aged 20-35 years; mean: 27 years; Two females) all reported English as their first language and normal or corrected-to-normal vision.

D. Apparatus

This investigation used the Emotiv "Research Edition" EEG wireless headset to collect bioelectric signals via 14 saline electrodes positioned on the scalp according to the International 10-20 system of electrode locations [57] at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 at a sample rate of 128 Hz, in a 0.16-43 Hz bandpass within the Emotiv device. In passing, it has been shown that the montage of this commercial system is not optimal for the RCP P300 speller [58]. While the saline electrodes of the Emotiv device may also be considered sub-optimal for EEG recording, the electronics including amplification have proved effective for the purposes of deriving event-related potentials, even when walking [56].

Analysis of P300 speller accuracy and information transfer rate has revealed that the wireless Emotiv amplifier performed as well as a wired laboratory EEG system [59]. While improved performance may be obtainable with higher cost electrodes [56], the poorer signal obtained via saline electrodes has sufficed for previous comparisons of P300 speller interfaces [27]. This current investigation laid the groundwork for evaluations of several P300 spellers implemented on mobile devices for which the quality of data recorded through Emotiv's low-cost saline electrodes using a wireless amplifier has already sufficed to yield P300 speller accuracies exceeding 80%. Such accuracies still did not approach ceiling, as would have otherwise obscured the influences of user interface on performance. The P300 speller systems considered here, the EP and the RCP, were implemented on a PC using custom routines and EEG data simultaneously acquired onto the same computer via the Emotiv EEG Headset Toolbox [60]. All presentation and acquisition software was written in MATLAB 7.14.0.739.

The hardware and software framework of the P300-based EP speller is illustrated in Fig. 4. For each single character, the EEG signals were acquired simultaneously with the presentation of visual stimuli. Then, the raw EEG data were preprocessed and recorded with a suitable format for the classifier. Finally, based on the classification result, the application interface displayed the target character on the computer screen as feedback to the user.

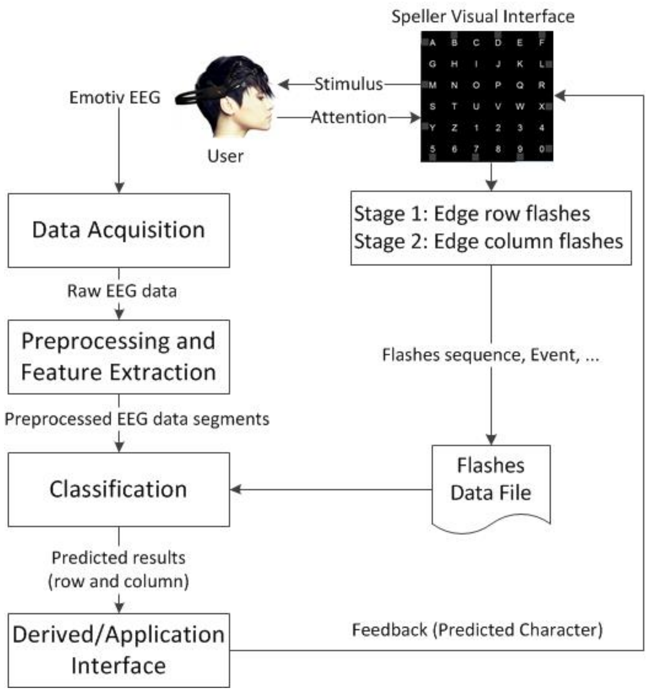


Fig. 4. The framework of the P300-based EP speller.

E. Procedure

The participant sat in front of the speller presented on a computer screen at a distance of about 90 cm. For the RCP, participants were instructed to focus attention on a given character in the separate stages of row and column flashing. With the EP, participants were instructed to focus attention on the edge point corresponding to the row that contains the target character in the first stage, and then to shift visual focus, during the inter-stage interval, to the corresponding column edge point. In both spellers, participants were required to silently count the number of times the target object (character or edge point) flashes and to minimize blinking and muscle movements during that flashing. The experiment for the current target was repeated once the participant made noticeable muscle movements, where these movements would have otherwise generated strong electrical potentials contaminating the electrophysiological measurements.

Each participant completed an experimental session with the RCP and another experimental session with the EP on separate days. The order of the presentation of spellers was counterbalanced. Each experiment was divided into a calibration or "offline" session, which lasted approximately 40 minutes – inclusive of consent procedure, EEG preparation, and 8.4 minutes of calibration data collection (144 flash × 120 ms × 29 offline characters = 501 seconds = 8.4 minutes) – followed by 20 minutes for the "online" session. Pre-investigation and postinvestigation questionnaires were filled out by the participant before and after each experiment. Participants rated subjective fatigue on a scale 1 to 10 (1: no fatigue, 10: severe fatigue). The difference in the fatigue ratings was used as an index of the increase in the fatigue level, caused by using the speller. In the post-investigation questionnaire, the participants were also asked to rate comfort level (1: uncomfortable, 10: comfortable) and alertness (1: drowsy, 10: alert) felt during the experiment while using the speller.

In the offline session for both spellers, each participant spelled 29 alphanumeric characters organized into 6 words and a number (i.e., LAP, ROD, BAND, FLAG, DRINK, MINUTE, and 9253). The calibration data recorded in the offline session was used to train the classifier to identify the classification coefficients for each individual user (i.e., the classification model). Afterwards, based on the classification model, each participant spelled 16 alphanumeric characters distributed into 3 words and a number (i.e., SUM, LAMP, BUNCH, and 7492) in the online session. The above words and numbers were derived from the MRC psycholinguistic database [61] on the basis of having similar, relatively early, Age-Of-Acquisition norms [62].

In the offline and online sessions, the input text box contained one word or a number. The current target character was highlighted in red for 2 seconds within the matrix before the first and second stages, which allowed the participant to shift attention to fixate on the target object (character or edge point). In addition, specifically for the EP, a row (or column) guide arrow (0.05 × 0.68 cm) temporarily appeared 0.09 cm above (or to the right of) each character before the first (or the second) stage and then disappeared during each stage. The orientation of those arrows directed a user to the location of the corresponding edge point. The row (or column) edge points were displayed only during the first (or the second) stage.

F. Preprocessing and Classification

The recorded signals included noise caused by different artifacts (eye movement, muscle and body movement, respiration, cardiac signals, and scalp skin sweating) [23], [63], [64], which could obscure the EEG signal of interest. Prior to classification, a sequence of four pre-processing steps were used. Firstly, the high cutoff of digital filtering within a chip of the recording device attenuated the effects of high frequency electrical noise (50-60Hz), and brain responses of high frequency neuronal oscillations in the high gamma-band [65], [66]. This digital filtering also had a low cut-off as could remove slow potentials, such as those caused by sweating [64], and infra-slow oscillations [67]. The remaining EEG contribution to the recorded signal was in the frequency range typically used in ERP analysis. Secondly, artifacts present at all electrodes were removed by subtracting the time series of potentials from the average of all electrodes from each electrode. This was accomplished by subtracting an average of the time series at all electrodes from the time series of potentials at each electrode. Such Common Average Referencing is effective in attenuating artifacts such as those induced in the body by electrical sources including power cables. The remaining electrical currents were thus caused by the flow of volume currents within the head to the scalp from bioelectric electromagnetic sources within the brain, and electro-ocular, muscular, and cardiac sources. The expression of electromagnetic sources on the scalp via the flow of such volume currents has a geometry with a scalp distribution, less characteristic to induced currents. A third "epoching" process segmented the data into segments from 0-600 ms post-flash onset (Fig. 5). During such segments, participants fixated a character in the RCP or an edge square in the EP. This epoching thus removed, amongst other periods contaminated by electro-ocular artifact, the aforementioned inter-stage interval of the EP during which participants made eye movements between edge squares. This epoching accordingly attenuated the influence of electro-ocular artifact on the signal of interest. Finally, the remaining artifacts such as blinks tend to produce extreme values that were removed by a mathematical process known as Winsorizing excluding such extreme values prior to classification [53].

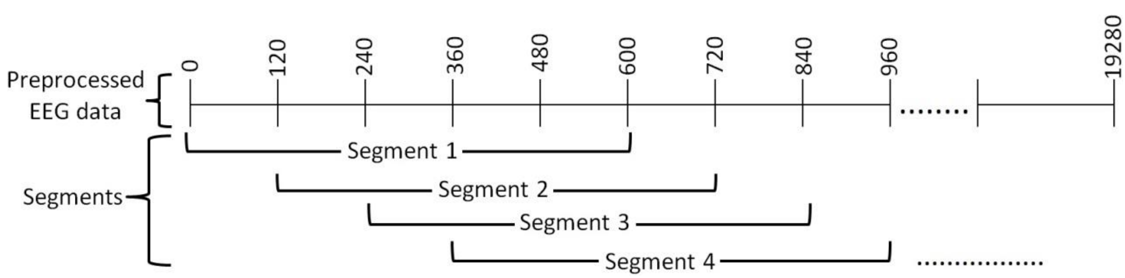


Fig. 5. Feature extraction (Segmentation). The flash segment is the EEG data recorded for 600 ms after flash onset, where there are 144 flashes to select one single character with one flash every 120 ms (SOA).

A digital 5^{th}-order sinc filter with a bandpass of 0.16 to 45 Hz was applied by the Emotiv EEG device. Common Average Referencing [68] was used to increase the Signalto-Noise Ratio by Common Mode Rejection, rendering the target signal simpler to identify. Specifically, the average of all 14 electrodes for each time point was subtracted from all electrode data at that time point. All pre-processed EEG data for each target character were epoched into 600 ms sections with a total of 144 segments (Fig. 5). This epoching excluded the time periods when eye-movements were made to and from the upper panel back to the lower panel to fixate on the relevant character and/or edge square, prior to the presentation of flashes denoting that character. This epoching also ensured the exclusion of the brief saccadic eye-movements that occurred during the inter-stage interval. Each segment corresponded to one flash (event) from the stimulus onset to the 600 ms post stimulus onset (i.e., 600 ms time frame) to identify if that flash evoked the P300 component. That is, each segment was an individual two-dimensional matrix structure containing EEG data recorded from 14 electrodes within 77 time points following each flash (segment size of 14-by-77), where the number of time points = ceil (0.6 s × 128 sample/s). Finally, during Winsorizing, 5% of the highest and lowest sample amplitudes (tail outliers) generated by artifacts for each electrode were reduced to the 95^{th} percentile amplitude value or increased to the 5^{th} percentile value, respectively [53].

Bayesian Linear Discriminant Analysis (BLDA) was applied to determine the target character. For each participant, the calibration EEG data of 144 × 29 = 4176 flashes (696 target and 3480 non-target flashes) were used to train the BLDA. Then, in the online classification, BLDA was performed after the EEG data were recorded and pre-processed for each single character (144 segments) to identify the target character. The BLDA ran on all of the 144 segments to classify each segment. Afterwards, the BLDA-calculated value for each segment corresponding to each row (row edge point) or column (column edge point) was averaged over the 12 iterations (12 segments). The row (row edge point) or column (column edge point) with the highest average was considered as the target row or column. See Equations 1 to 4:

$$AVG\_BLDA(r_i) = \left(\sum_{n=1}^{12} BLDA(r_i, n)\right) / 12 \quad (1)$$

$$Target\_Row = \{r_i \mid \max(AVG\_BLDA(r_i))\} \quad (2)$$

$$AVG\_BLDA(c_i) = \left(\sum_{n=13}^{24} BLDA(c_i, n)\right) / 12 \quad (3)$$

$$Target\_Column = \{c_i \mid \max(AVG\_BLDA(c_i))\} \quad (4)$$

Where a row or column segment is denoted by *r* or *c*, *i* represents the row or column number (1 to 6), *n* indicates the row iteration number (1 to 12) or the column iteration number (13 to 24), $\mathrm{BLDA}(r_i, n)$, and $\mathrm{BLDA}(c_i, n)$ describe the BLDA classification results of row *i* segment and column *i* segment respectively for iteration *n*. Finally, the character located at the intersection of the target row and column was selected as the target character.

G. Independent and Dependent Variables

The speller (i.e., RCP or EP) is the independent variable of interest. Three types of dependent variables are measured, i.e., accuracy, bit rate and user experience (see Table II).

Table II. DEPENDENT VARIABLES

Dependent Variable	Definition
Online classification accuracy	The percentage of characters correctly recognized in the online session
Bit rate	The transmitted information per unit of time
User experience	Subjective ratings on fatigue, comfort and alertness

The online classification accuracy is measured in terms of letter selection accuracy. Bit rate is the best-known measurement method to compare the communication performance of different interactive systems [41], [69]. The bit rate (R; bits/min) was computed using Equation 5 [69]:

$$\mathrm{R} = \frac{60}{t}(\log_2 N + P\log_2 P + (1-P)\log_2(\frac{1-P}{N-1})) \quad (5)$$

Where *t* is the time duration for one character selection; *N* is the number of possible selections in the matrix; P is the probability of the target selection. User experience is evaluated in terms of subjective ratings on fatigue, comfort and alertness. Paired *t*-tests are applied to compare the EP and RCP on accuracy and bit rate, and a repeated-measure ANOVA is used to analyze the effect of the number of iterations on cumulative accuracy and bit rate. Likert-scale user experience data are analyzed using Wilcoxon matched-pairs signed rank tests comparing the EP and RCP.

IV. Results:

Inferential statistical analysis adopted a critical α of 0.05 throughout.

A. Online Character-based Classification Accuracy

The mean online classification accuracy was improved with the EP, 93.3 ± standard error of the mean or s.e.m. 2.0%, relative to the RCP, 81.7 ± 2.8% (Fig. 6, overleaf). The performance improvement produced with the EP relative to the RCP was significant, $t(13) = 4.19$, $p = 0.001$, $\eta^2 = 0.575$.

ERP components such as a P300 elicited over multiple iterations can be approximated as a function of the number of events [70] in a nonlinear manner predicted to tend to also asymptote in a nonlinear manner. There could be related increases in accuracy with the number of iterations, with precedent in the literature [21], [43]–[46]. The question of this asymptote is of practical relevance when the relative value of accuracy improvement with each additional iteration, each of which has the drawback of prolonging the time required to identify a character. Given this rationale, we tested with the trend analysis technique the significance of linear and progressively higher order nonlinear trends until the first trend that was nonsignificant. No theoretical weight was placed on higher order trends. As predicted, accuracy increased with the number of iterations (i.e., up to 12 iterations). A repeated-measures ANOVA revealed that in both the EP ($F(1,11) = 108.6$, $p < 0.001$, $\eta^2 = 0.893$) and the RCP ($F(1,11) = 78.5$, $p < 0.001$, $\eta^2 = 0.858$), there was a significant main effect of the number of iterations used on this cumulative accuracy. There were subtle nonlinear tendencies indicating that each increment in the number of iterations had, on the whole, progressively slightly less effect on cumulative accuracy. That is, for the RCP, this main effect of number of iterations was revealed by a trend analysis to be primarily caused by a significant linear trend, $F(1,13) = 348.5$, $p < 0.001$, $\eta^2 = 0.964$, but there were also significant nonlinear tendencies including a significant quadratic trend, $F(1,13) = 15.6$, $p < 0.01$, $\eta^2 = 0.545$. Trends that were eighth-order, $F(1,13) = 6.2$, $p = 0.027$, $\eta^2 = 0.324$, and ninth-order, $F(1,13) = 6.4$, $p = 0.026$, $\eta^2 = 0.328$, were also significant. For the EP, the corresponding main effect of number of iterations was revealed by a trend analysis to be primarily caused by a linear trend, $F(1,13) = 416.0$, $p < 0.001$, $\eta^2 = 0.970$, but there were also significant nonlinear tendencies including a quadratic trend, $F(1,13)=14.5$, $p < 0.01$, $\eta^2 = 0.528$. Again, the cubic trend was not significant, $F < 1$.

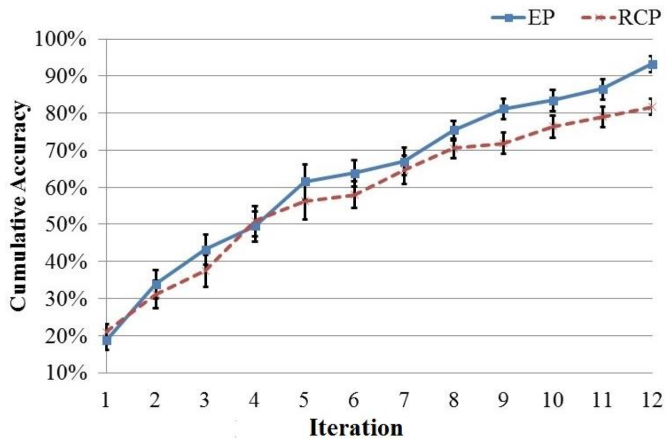


Fig. 6. Cumulative online classification accuracy as function of the number of iterations of 12 flashes used to calculate that cumulative accuracy (error bars denote standard error); N=14.

B. Bit Rate

The mean online bit rate for the EP, 13.7 ± 0.6 bits/min, was higher than for the RCP, 10.8 ± 0.6 bits/min; a difference corroborated by the medians (EP: 14.0 bits/min > RCP: 10.9 bits/min) found to be significant by inferential statistical analysis with a Wilcoxon matched-pairs signed rank test, $W(12) = 77.0$, $p < 0.01$, $\eta^2 = 0.564$. The number of iterations has no significant effect on the cumulative bit rate. Fig. 7 illustrates the accumulative bit rate on these iterations. During the last 8 iterations, the bit rate is higher with the EP compared with the RCP. Fig. 7 also showed that the EP has the highest average bit rate in the 5th iteration, which indicates the best trade-off between speed and accuracy.

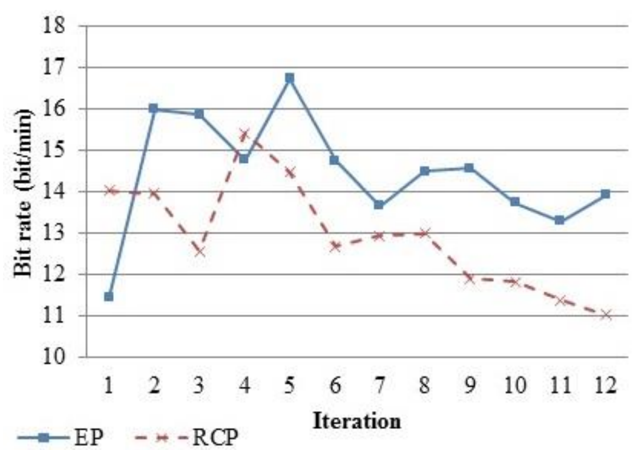


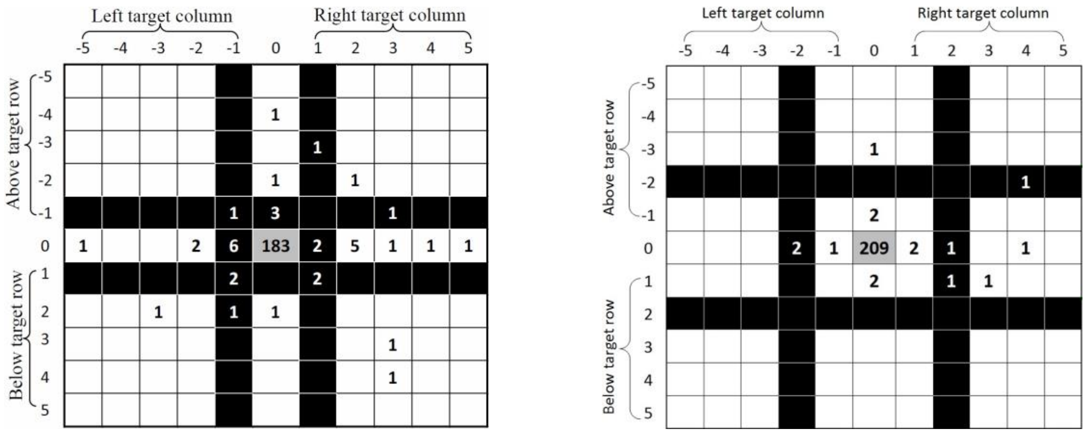
Fig. 7. A bit rate for each stimulation iteration accumulated based on online data

C. Flash Object-based Analysis of Errors

For each paradigm, the results for the 224 (16 characters × 14 participants) selected characters from the online sessions were summarized within confusion matrices of error distributions (Fig. 8). Given the error confusion matrix denoted by m, the number of correctly selected target characters is designated by the center cell $m(0, 0)$, as is highlighted in gray; the row '0' and column '0' representing the target row and target column, respectively. The frequency of erroneously selected characters relative to the target character is reflected by the values in the other cells. The difference in rows and columns between the erroneously selected character and the target character is signified by the cell position. If a participant selected a character with the speller, then the value at the cell position (selected row target row, selected column target column) within the error distribution matrix is incremented by one.

Further error analysis was computed based upon the flash objects to examine the effect of the adjacency problem in both paradigms. In Fig. 8, all adjacent error cells are highlighted in black. For the RCP, as shown in Fig. 8(a), the flash rows or flash columns adjacent to the target row or target column were indexed with '1' and '-1'. As depicted in Fig. 8(b), the adjacency for the EP was identified based on the flashing edge point, rather than the row or column flash. More specifically, the flashing row or column edge points adjacent to the target row or column edge point were indexed with '2' and '-2'.

The frequencies in these confusion matrices showed that the influence of the adjacency problem was reduced with the EP. Of 41 errors for the RCP, there were 28 adjacent errors (68.3%). Of 15 errors for the EP, there were only 5 adjacent errors (33.3%). The mean number of adjacent errors was significantly higher for the RCP, 2 ± 0.4, than for the EP, 0.4 ± 0.2, $t(13) = 4.10$, $p = 0.001$, $\eta^2 = 0.564$.



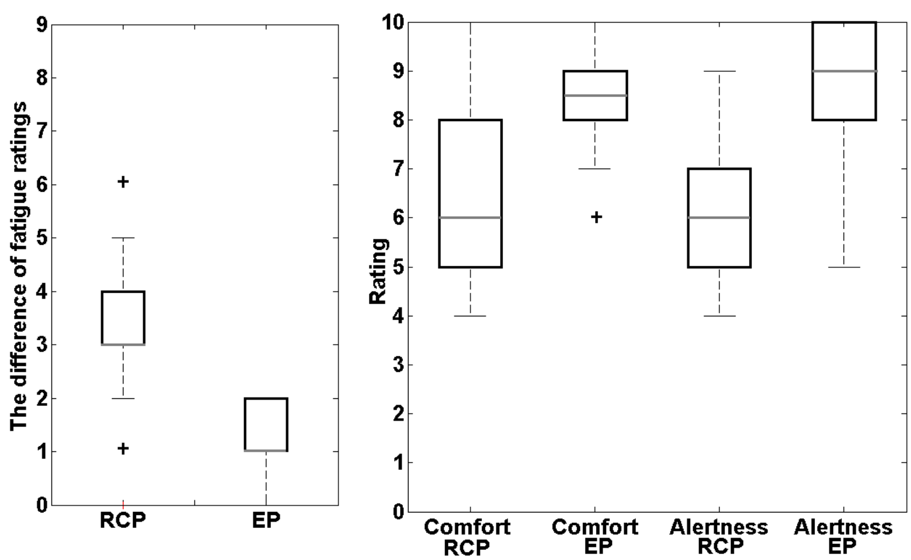
(a) (b)

Fig. 8. The error confusion matrix of all participants for 16 selected characters in the online session for the RCP (a) and EP (b); gray cell denoting the target; black cells denoting adjacent errors, where a neighboring flash was erroneously detected as denoting the row or column of the target.

D. User Experience

The user experience questionnaire data measured subjective ratings of fatigue, comfort, and alertness in both paradigms, corroborated by means and standard errors as well by the medians and the measures of dispersion depicted in Figure 9. As shown in Fig. 9(a), the EP, mean 1.14 ± 0.2, caused less fatigue than the RCP, 3.14 ± 0.4. The difference of fatigue ratings before and after the experiment ranged from 0 to 9, where 0 and 9 indicated the smallest and largest fatigue caused by using the speller, respectively. Also, participants reported that the EP, 8.3 ± 0.3, was more comfortable after the experimental session relative to the RCP, 6.4 ± 0.6, as well as feeling more alert during the experiment of the EP, 8.5 ± 0.4, relative to the RCP, 6.1 ± 0.4, as shown in Fig. 9(b), where 10 indicated the highest comfort and alertness level.

Wilcoxon matched-pairs signed-rank tests comparing the EP and RCP revealed a significant effect upon fatigue, $W(13) = 89.0$, $p = 0.001$, $\eta^2 = 0.683$, upon comfort, $W(14) = 75.5$, $p < 0.01$, $\eta^2 = 0.604$, and upon alertness, $W(12) = 100.0$, $p = 0.001$, $\eta^2 = 0.677$.



(a) (b)

Fig. 9. Subjective rating for all participants (a) Boxplots of the fatigue rating difference before and after the experiment (0:9). (0: lowest level of fatigue, 9: highest level of fatigue). (b) Boxplots of the comfort, and alertness rating (1:10). (1: lowest level of comfort and alertness, 10: highest level of comfort and alertness). Gray lines denote medians, black boxes interquartile range, whiskers the adjacent values, and black crosses outliers (N=14).

V. Discussion and Conclusion:

The results showed that the EP, relative to the RCP, led to significant increases in online classification accuracy and bit rate. Using the EP caused less fatigue than using the RCP, in a manner that also led to reliably enhanced levels of alertness and comfort. The results were thus consistent with the proposition that the design of the EP ameliorated the influence of adjacent, crowding, and fatigue problems.

Concerning the adjacency problem, a large proportion of the errors with the RCP were adjacent errors, as consistent with previous investigations [23], [24], [27]. The number of these adjacent errors was significantly reduced in the EP. This result was thus compatible with predictions of the introduction, whereby increasing the spatial separation between the target stimulus and flanking nontarget stimuli reduces the number of adjacent errors.

An additional outcome of this investigation was that, for either paradigm, increasing the number of iterations tended to improve overall accuracy – corroborative of the empirical precedent with the RCP [21], [43]-[46] – yet without affecting bit rate for either the EP or RCP up to a limit of at least 12 iterations. 12 or more iterations are typical for modern instances of the RCP [15], [70], [71]. Each increment in the number of iterations, here, showed progressively less of an improvement in accuracy, yet a clear asymptote was still not reached even within 12 iterations when mean accuracy was in excess of 80%. There thus appear to be practical benefits in increasing the number of iterations in terms of accuracy, as did not impact bit rate.

In summary, the EP improved user experience and online classification accuracy without compromising communication rate – even improving communication rate – by introducing edge points to replace flashing rows/columns. Especially, those edge points are displayed alternatively on opposite sides of a character matrix. This design of the visual layout increases the distance between adjacent flashing objects and reduces the number of surrounding objects. Consequently, the EP is suitable for mobile devices, which have a small screen. The EP outperforms the RCP [73], classification accuracy also suggesting an advance on the ZP's approach to crowding and adjacency [27]. The EP requires gaze control that moves the user's focus from one edge point to another. This requirement limits the applicability of the EP, which makes the EP only suitable for users with minimal voluntary muscular control yet retaining good eye gaze control. The eye tracking technique, which requires gaze control, has become a successful interacting means for disabled users [74]. However, the eye-movement problem for the target users of P300 BCI is well-known [50]. Versions of the EP on devices with a smaller screen than that employed here, such that inter-edge points are less than one degree of visual angle apart projecting on the macula, thus warrant evaluation to determine the relative utility of the EP for users not making such eye-movements.

Acknowledgment:

The authors would like to thank the volunteer participants in this investigation. This work is supported by NSF under grant CNS-1126570.

References:

[1] Z. Simmons, B. Bremer, R. Robbins, S. Walsh, and S. Fischer, "Quality of life in ALS depends on factors other than strength and physical function," Neurology, vol. 55, no. 3, pp. 388–392, 2000.

[2] I. Iturrate, J. M. Antelis, A. Kübler, and J. Minguez, "A noninvasive brain-actuated wheelchair based on a P300 neurophysiological protocol and automated navigation," IEEE Trans. Robot., vol. 25, no. 3, pp. 614–627, 2009.

[3] B. Rebsamen, E. Burdet, C. Guan, H. Zhang, C. L. Teo, Q. Zeng, M. Ang, and C. Laugier, "A brain-controlled wheelchair based on P300 and path guidance," in Proceedings of the First IEEE/RAS-EMBS International Conference on Biomedical Robotics and Biomechatronics, 2006, pp. 1101–1106.

[4] E. Mugler, M. Bensch, S. Halder, W. Rosenstiel, M. Bogdan, N. Birbaumer, and A. Kübler, "Control of an internet browser using the P300 event-related potential," Int. J. Bioelectromagn., vol. 10, no. 1, pp. 56–63, 2008.

[5] L. Bi, X.-A. Fan, and Y. Liu, "EEG-based brain-controlled mobile robots: a survey," IEEE Trans. Human-Mach. Syst., vol. 43, no. 2, pp. 161–176, 2013.

[6] A. Campbell, T. Choudhury, S. Hu, H. Lu, M. K. Mukerjee, M. Rabbi, and R. D. Raizada, "Neurophone: brain-mobile phone interface using a wireless EEG headset," in Proceedings of the second ACM SIGCOMM workshop on Networking, systems, and applications on mobile handhelds, 2010, pp. 3–8.

[7] S. Sutton, M. Braren, J. Zubin, and E. John, "Evoked-potential correlates of stimulus uncertainty," Science, vol. 150, no. 3700, pp. 1187–1188, 1965.

[8] J. Polich, "Theoretical overview of P3a and P3b," in Detection of Change. Springer, 2003, pp. 83–98.

[9] M. Hämäläinen, R. Hari, R. J. Ilmoniemi, J. Knuutila, and O. V. Lounasmaa, "Magnetoencephalography–theory, instrumentation, and applications to noninvasive studies of the working human brain," Rev. Mod. Phys., vol. 65, no. 2, pp. 413–497, 1993.

[10] E. Donchin, "Surprise! Surprise?" Psychophysiology, vol. 18, no. 5, pp. 493–513, 1981.

[11] J. Polich, "Updating P300: an integrative theory of P3a and P3b," Clin. Neurophysiol., vol. 118, no. 10, pp. 2128–2148, 2007.

[12] R. L. Rogers, S. B. Baumann, A. C. Papanicolaou, T. W. Bourbon, S. Alagarsamy, and H. M. Eisenberg, "Localization of the P3 sources using magnetoencephalography and magnetic resonance imaging," Electroencephalogr. Clin. Neurophysiol., vol. 79, no. 4, pp. 308–321, 1991.

[13] C. Bledowski, D. Prvulovic, K. Hoechstetter, M. Scherg, M. Wibral, R. Goebel, and D. E. Linden, "Localizing P300 generators in visual target and distractor processing: a combined event-related potential and functional magnetic resonance imaging study," J. Neurosci., vol. 24, no. 42, pp. 9353–9360, 2004.

[14] L. A. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials," Electroen. Clin. Neuro., vol. 70, no. 6, pp. 510–523, 1988.

[15] Y. Xu and Y. Nakajima, “A two-level predictive event-related potentialbased brain-computer interface.” IEEE Trans. Biomed. Eng., vol. 60, no. 10, pp. 2839–2847,2013.

[16] R. Fazel-Rezai and K. Abhari, “A region-based P300 speller for braincomputer interface,” Can. J. Elect. Comput. E., vol. 34, no. 3, pp. 81–85, 2009.

[17] C.-C. Postelnicu and D. Talaba, “P300-based brain-neuronal computer interaction for spelling applications,” IEEE Trans. Biomed. Eng., vol. 60, no. 2, pp. 534–543, 2013.

[18] E. Yin, Z. Zhou, J. Jiang, F. Chen, Y. Liu, and D. Hu, “A speedy hybrid BCI spelling approach combining P300 and SSVEP,” IEEE Trans. Biomed. Eng., vol. 61, no. 2, pp. 473–483, 2014.

[19] G. Townsend, J. Shanahan, D. B. Ryan, and E. W. Sellers, “A general P300 brain–computer interface presentation paradigm based on performance guided constraints,” Neurosci. Lett., vol. 531, no. 2, pp. 63–68, 2012.

[20] E. W. Sellers, D. J. Krusienski, D. J. McFarland, T. M. Vaughan, and J. R. Wolpaw, “A P300 event-related potential brain–computer interface (BCI): the effects of matrix size and inter stimulus interval on performance,” Biol. Psychol., vol. 73, no. 3, pp. 242–252, 2006.

[21] D. J. Krusienski, E. W. Sellers, F. Cabestaing, S. Bayoudh, D. J. McFarland, T. M. Vaughan, and J. R. Wolpaw, “A comparison of classification techniques for the P300 speller,” J. Neural Eng., vol. 3, no. 4, pp. 299–305, 2006.

[22] C. Guger, S. Daban, E. Sellers, C. Holzner, G. Krausz, R. Carabalona, F. Gramatica, and G. Edlinger, “How many people are able to control a P300-based brain–computer interface (BCI)?” Neurosci. Lett., vol. 462, no. 1, pp. 94–98, 2009.

[23] R. Fazel-Rezai, “Human error in P300 speller paradigm for braincomputer interface,” in Conf. Proc. IEEE Eng. Med. Bio. Soc., 2007, pp. 2516–2519.

[24] G. Townsend, B. LaPallo, C. Boulay, D. Krusienski, G. Frye, C. Hauser, N. Schwartz, T. Vaughan, J. R. Wolpaw, and E. Sellers, “A novel P300based brain–computer interface stimulus presentation paradigm: moving beyond rows and columns,” J. Clin. Neurophysiol., vol. 121, no. 7, pp. 1109–1120, 2010.

[25] D. Whitney and D. M. Levi, “Visual crowding: a fundamental limit on conscious perception and object recognition,” Trends Cogn. Sci., vol. 15, no. 4, pp. 160–168, 2011.

[26] H. Bouma, “Interaction effects in parafoveal letter recognition,” Nature, vol. 226, pp. 177–178, 1970.

[27] Q. Obeidat, T. Campbell, and J. Kong, “The zigzag paradigm: a new P300-based brain computer interface,” in Proceedings of the 15th ACM on International Conference on Multimodal Interaction, 2013, pp. 205–212.

[28] C. Feng, Y. Jiang, and S. He, “Horizontal and vertical asymmetry in visual spatial crowding effects,” J. Vision, vol. 7, no. 2:13, pp. 1–10, 2007.

[29] J. Jin, B. Z. Allison, X. Wang, and C. Neuper, “A combined brain– computer interface based on P300 potentials and motion-onset visual evoked potentials,” J. Neurosci. Meth., vol. 205, no. 2, pp. 265–276, 2012.

[30] T. Kaufmann, S. Schulz, C. Grünzinger, and A. Kübler, “Flashing characters with famous faces improves ERP-based brain–computer interface performance,” J. Neural Eng., vol. 8, no. 5, pp. 16–25, 2011.

[31] J. Jin, B. Z. Allison, T. Kaufmann, A. Kübler, Y. Zhang, X. Wang, and A. Cichocki, “The changing face of P300 BCIs: a comparison of stimulus changes in a P300 BCI involving faces, emotion, and movement,” PLoS ONE, vol. 7, no. 11, pp. 688–697, 2012.

[32] M. Tangermann, J. Höhne, M. Schreuder, M. Sagebaum, B. Blankertz, A. Ramsay, and R. Murray-Smith, “Data driven neuroergonomic optimization of BCI stimuli,” in Proceedings of 5th International BCI Conference, 2011, pp. 160–163.

[33] T. Kaufmann and A. Kübler, “Beyond maximum speed–a novel twostimulus paradigm for brain–computer interfaces based on event-related potentials (P300-BCI),” J. Neural Eng., vol. 11, no. 5, pp. 4–15, 2014.

[34] J. Höhne, K. Krenzlin, S. Dähne, and M. Tangermann, “Natural stimuli improve auditory BCIs with respect to ergonomics and performance,” J. Neural Eng., vol. 9, no. 4, pp. 3–14, 2012.

[35] T. Kaufmann, E. M. Holz, and A. Kübler, “Comparison of tactile, auditory, and visual modality for brain-computer interface use: a case study with a patient in the locked-in state,” Front. Neurosci., vol. 7:129, pp. 1–12, 2013.

[36] K. Hiyoshi-Taniguchi, M. Kawasaki, T. Yokota, H. Bakardjian, H. Fukuyama, A. Cichocki, and F. Vialatte, “EEG correlates of voice and face emotional judgments in the human brain,” Cogn. Comput., vol. 7, no. 1, pp. 11–19, 2015.

[37] F. Aloise, P. Aricò, F. Schettini, A. Riccio, S. Salinari, D. Mattia, F. Babiloni, and F. Cincotti, “A covert attention P300-based brain-computer interface: Geospell,” Ergonomics, vol. 55, no. 5, pp. 538–551, 2012.

[38] M. S. Treder, N. M. Schmidt, and B. Blankertz, “Gaze-independent brain-computer interfaces based on covert attention and feature attention,” J. Neural Eng., vol. 8, no. 6, pp. 3–14, 2011.

[39] G. Frye, C. Hauser, G. Townsend, and E. Sellers, “Suppressing flashes of items surrounding targets during calibration of a P300-based brain– computer interface improves performance,” J. Neural Eng., vol. 8, no. 2, pp. 24–28, 2011.

[40] F. M. Felisberti, J. A. Solomon, and M. J. Morgan, “The role of target salience in crowding,” Perception, vol. 34, no. 7, pp. 823–833, 2005.

[41] H. Serby, E. Yom-Tov, and G. F. Inbar, “An improved P300-based braincomputer interface,” IEEE T. Neur. Sys. Reh., vol. 13, no. 1, pp. 89–98, 2005.

[42] J. Höhne and M. Tangermann, “How stimulation speed affects eventrelated potentials and BCI performance,” in Conf. Proc. IEEE Eng. Med. Biol. Soc., 2012, pp. 1802–1805.

[43] S. Martens, N. Hill, J. Farquhar, and B. Schölkopf, “Overlap and refractory effects in a brain–computer interface speller based on the visual P300 event-related potential,” J. Neural Eng., vol. 6, no. 2, pp. 3–12, 2009.

[44] P. Brunner, S. Joshi, S. Briskin, J. Wolpaw, H. Bischof, and G. Schalk, “Does the ‘P300’ speller depend on eye gaze?” J. Neural Eng., vol. 7, no. 5, pp. 13–21, 2010.

[45] P. Brunner, A. L. Ritaccio, J. F. Emrich, H. Bischof, and G. Schalk, “Rapid communication with a “P300” matrix speller using electrocorticographic signals (ECoG),” Front. Neurosci., vol. 5:5, pp. 1–9, 2011.

[46] F. Aloise, F. Schettini, P. Aricò, F. Leotta, S. Salinari, D. Mattia, F. Babiloni, and F. Cincotti, “P300-based brain-computer interface for environmental control: an asynchronous approach,” J. Neural Eng., vol. 8, no. 2, pp. 25–34, 2011.

[47] M. Tangermann, M. Schreuder, S. Dähne, J. Höhne, S. Regler, A. Ramsay, M. Quek, J. Williamson, and R. Murray-Smith, “Optimized stimulation events for a visual ERP BCI,” Int. J. Bioelectromagnetism Volume, vol. 13, no. 3, pp. 119–120, 2011.

[48] B. Z. Allison and J. A. Pineda, “ERPs evoked by different matrix sizes: implications for a brain computer interface (BCI) system,” Trans. Neural Syst. Rehab. Eng., vol. 11, no. 2, pp. 110–113, 2003.

[49] B. Blankertz, M. Krauledat, G. Dornhege, J. Williamson, R. MurraySmith, and K.-R. Müller, “A note on brain actuated spelling with the Berlin brain-computer interface,” in Universal Access in HumanComputer Interaction. Ambient Interaction. Springer, 2007, pp. 759–768.

[50] M. S. Treder and B. Blankertz, “(C)overt attention and visual speller design in an ERP-based brain-computer interface,” Behav. Brain Funct., vol. 6, no. 1:28, pp. 1–13, 2010.

[51] G. Pires, U. Nunes, and M. Castelo-Branco, “Gibs block speller: toward a gaze-independent P300-based BCI,” in Conf. Proc. IEEE Eng. Med. Biol. Soc., 2011, pp. 6360–6364.

[52] J. Farquhar and N. J. Hill, “Interactions between pre-processing and classification methods for event-related-potential classification,” Neuroinformatics, vol. 11, no. 2, pp. 175–192, 2013.

[53] U. Hoffmann, J.-M. Vesin, T. Ebrahimi, and K. Diserens, “An efficient P300-based brain–computer interface for disabled subjects,” J. Neurosci. Meth., vol. 167, no. 1, pp. 115–125, 2008.

[54] X. Lei, P. Yang, and D. Yao, “An empirical bayesian framework for brain–computer interfaces,” Trans. Neural Syst. Rehab. Eng., vol. 17, no. 6, pp. 521–529, 2009.

[55] N. V. Manyakov, N. Chumerin, A. Combaz, and M. M. Van Hulle, “Comparison of classification methods for P300 brain-computer interface on disabled subjects,” Comput. Intell. Neurosci., vol. 2011:2, pp. 1–12, 2011.

[56] S. Debener, F. Minow, R. Emkes, K. Gandras, and M. Vos, “How about taking a low-cost, small, and wireless EEG for a walk?” Psychophysiology, vol. 49, no. 11, pp. 1617–1621, 2012.

[57] F. Sharbrough, G. Chatrian, R. Lesser, H. Lüders, M. Nuwer, and T. Picton, “American electroencephalographic society guidelines for standard electrode position nomenclature,” J. Clin. Neurophysiol., vol. 8, no. 2, pp. 200–202, 1991.

[58] D. J. Krusienski, E. W. Sellers, D. J. McFarland, T. M. Vaughan, and J. R. Wolpaw, “Toward enhanced P300 speller performance,” J. Neurosci. Meth., vol. 167, no. 1, pp. 15–21, 2008.

[59] M. De Vos, M. Kroesen, R. Emkes, and S. Debener, “P300 speller BCI with a mobile EEG system: comparison to a traditional amplifier,” J. Neural Eng., vol. 11, no. 3, pp. 8–15, 2014.

[60] P. Gavin, “EmotivEEG headset toolbox,” Matlab Central File Exchange, http://www.mathworks.com/matlabcentral/fileexchange/36111-emotiveegheadset-toolbox [Online; accessed May 23, 2013].

[61] M. Coltheart, “The MRC psycholinguistic database,” Q. J. Exp. Psychol., vol. 33, no. 4, pp. 497–505, 1981.

[62] K. J. Gilhooly and R. H. Logie, “Age-of-acquisition, imagery, concreteness, familiarity, and ambiguity measures for 1,944 words,” Behav. Res. Meth. Instr., vol. 12, no. 4, pp. 395–427, 1980.

[63] P. Anderer, S. Roberts, A. Schlögl, G. Gruber, G. Klösch, W. Herrmann, P. Rappelsberger, O. Filz, M. J. Barbanoj, G. Dorffner et al., “Artifact processing in computerized analysis of sleep EEG–a review,” Neuropsychobiology, vol. 40, no. 3, pp. 150–157, 1999.

[64] E. S. Kappenman and S. J. Luck, “The effects of electrode impedance on data quality and statistical significance in ERP recordings,” Psychophysiology, vol. 47, no. 5, pp. 888–904, 2010.

[65] N. E. Crone, A. Sinai, and A. Korzeniewska, “High-frequency gamma oscillations and human brain mapping with electrocorticography,” Prog. Brain Res., vol. 159, pp. 275–295, 2006.

[66] N. Brunet, M. Vinck, C. A. Bosman, W. Singer, and P. Fries, “Gamma or no gamma, that is the question,” Trends Cogn. Sci., vol. 18, no. 10, pp. 507–509, 2014.

[67] S. Monto, S. Palva, J. Voipio, and J. M. Palva, “Very slow EEG fluctuations predict the dynamics of stimulus detection and oscillation amplitudes in humans,” J. Neurosci., vol. 28, no. 33, pp. 8268–8272, 2008.

[68] B. J. Fisch and R. Spehlmann, Fisch and Spehlmann's EEG primer: basic principles of digital and analog EEG. Elsevier Health Sciences, 1999.

[69] J. R. Wolpaw et al., "Brain-computer interface technology: a review of the first international meeting," IEEE Trans. Rehab. Eng., vol. 8, no. 2, pp. 164–173, 2000.

[70] S.-M. Kamp, A. R. Murphy, and E. Donchin, "The component structure of event-related potentials in the P300 speller paradigm," IEEE Trans. Rehabil. Eng., vol. 21, no. 6, pp. 897–907, 2013.

[71] S. Halder, E. M. Hammer, S. C. Kleih, M. Bogdan, W. Rosenstiel, N. Birbaumer, and A. Kübler, "Prediction of auditory and visual P300 brain-computer interface aptitude," PLoS ONE, vol. 8, no. 2, pp. 1–11, e53 513, 2013.

[72] S. J. Luck, "Ten simple rules for designing ERP experiments," in Proceedings of the 5th International BCI Conference, 2011, pp. 160–163, MIT Press Cambridge, MA.

[73] M. Marchetti and K. Priftis, "Effectiveness of the P3-speller in brain– computer interfaces for amyotrophic lateral sclerosis patients: a systematic review and meta-analysis," Front. Neuroeng., vol. 7:12, pp. 1–6, 2014.

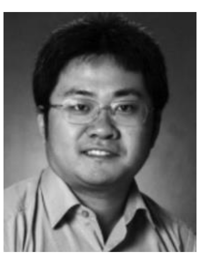
[74] S. Pannasch, J. R. Helmert, S. Malischke, A. Storch, and B. M. Velichkovsky, "Eye typing in application: a comparison of two systems with als patients," J. Eye Mov. Res, vol. 2, pp. 1–8, 2008.

Qasem T. Obeidat received the B.Sc. degree in computer science from Yarmouk University, Irbid, Jordan, and the M.Sc. degree in computer information systems from the University of Banking and Financial Sciences, Amman, Jordan, in 2002 and2005, respectively, and the Ph.D. degree in software engineering from the North Dakota State University, Fargo, USA, in 2014. Currently, he is an Assistant Professor in software engineering at Al-Zaytoonah University of Jordan, Amman, Jordan, since 2014.

His research interests include brain-computer interfaces, EEG signal processing, and software engineering.

Tom A. Campbell Tom A. Campbell has obtained a B.Sc. (University of York, UK, 1996), an M.Sc. (University of Manchester, UK, 1997), and a Ph.D. (University of Reading, UK, 2000). Since 2007, he has held a Docentship (equivalent to Associate Professor) in cognitive neuroscience at the University of Helsinki, Finland, where he is now at the Neuroscience Center.

Current research interests include auditory neurocognition, visual distraction, self-organized criticality and magnetoencephalography; international collaborations concern neural prostheses including BCI spellers and bilateral cochlear implants.



Jun Kong received the B.S. degree from the Huazhong University of Science and Technology, Wuhan, China, in 1998, the M.S. degree from Shanghai Jiao Tong University, Shanghai, China, in 2001, and the Ph.D. degree from the University of Texas at Dallas, Richardson, USA, in 2005, all in computer science.

He has been an Associate Professor of computer science with North Dakota State University, Fargo, USA, since 2012. His research and teaching interests include human–computer interaction, visual languages, software modeling and design, brain-computer interface, and pervasive computing.