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Abstract

Incremental improvements are continuously being made to P300-Speller BCI paradigms. Accurate classification depends on a high signal-to-noise ratio (SNR) between the target and nontarget items. Fixed presentation rates produce a large flash-evoked response that persists throughout the recording epoch, which can potentially undermine the classification of P300-responses. By introducing a random interstimulus interval (ISI) to a previously improved P300-Speller paradigm (i.e., Checkerboard Paradigm; CBP) we expect to reduce the deleterious flash-evoked responses and increase the P300 classification SNR. Data were recorded from 32 EEG locations (right mastoid referenced) from 13 subjects using the CBP with two conditions. In the Random ISI (RI) condition, ISI varied between 0 ms and 187.5 ms and averaged 93.75 ms. In the Fixed ISI (SI) condition, ISI remained static at 93.75 ms. In both conditions, participants were instructed to spell out 72 characters using an 8x9 matrix of alphanumeric characters by silently counting each target flash. The first 36 characters served as 'calibration' data for a stepwise linear discriminant analysis (SWLDA; 0 - 800 ms poststimulus epochs). This SWLDA classifier was then used to provide online feedback for an additional 36 character selections. Absolute amplitude of target and nontarget responses were summed across the recording epoch for each subject and averaged between Pz and Cz (maximum). Target averages were then divided by nontarget averages to create a SNR measure and compared between RI and FI conditions. The RI manipulation produced a significantly ($p = .04$) larger SNR ($M = 5.85$) than the FI condition ($M =4.07$).Further analysis of the averaged waveforms revealed a significantly ($p = .05$) greater positive peak at Cz (253 ms peak latency) for the RI condition. Classification performance measures for RI and FI conditions were high for accuracy (84 and 85%, respectively; NS) and bitrate (21 and 23 bits/min, respectively; NS). Together these results suggest that while randomizing ISI can yield higher SNR, response classification is not affected. It is possible that SWLDA is a useful classification method, in general; however, these data suggest that it does not capitalize on the additional information gained from the increase in SNR. Alternative classification techniques that can take advantage of specific subcomponents of the response may be able to utilize this additional information to improve BCI speed and accuracy.

Keywords: *brain-computer interface, inter stimulus interval, EEG*

Introduction

P300 and Brain-Computer Interface (BCI). P300-based brain-computer interface utilizes scalp-recorded electroencephalogram (EEG), specifically the P300 response, to facilitate communication. The P300 is an event-related potential (ERP) characterized by a positive deflection in the time-locked at approximately 300ms post stimulus presentation. This signal is indicative of attentional expenditure in response to an event, or stimulus, of low probability (see Duncan-Johnson, C., Donchin, E., 1977). Elicitation of the P300 relies on discriminative cognitive processing, but it occurs within 300 ms of stimulus onset, providing superior temporal resolution to fMRI and PET. Farwell and Donchin (1988) introduced the system as a potential communication technology for individuals with neuromuscular degeneration or injury. Individuals that are unable to communicate by standard means (e.g. speaking) must use alternate forms of communication, and BCI is an appropriate device to assist people with severe motor disabilities in forming and delivery of messages relaying deliberate content (Sellers, Vaughan, & Wolpaw, 2010). High information transfer rates and accuracy are paramount to system efficiency, and research is geared toward increasing these qualities with aims of producing a BCI of greater utility and more extensive application.

BCI Advancements. For the last two decades, improvements in electrode montage (Krusenski et al., 2008), paradigm design (Sellers et al., 2006), and data processing techniques (Kaper et al., 2004; Kaper and Ritter, 2004; and Serby, Inbar, & Yom-Toy, 2005) have yielded higher online accuracy and bitrate, measurements which establish standards of efficiency for BCI use (Serby et al., 2005, Wolpaw et al., 2000, and Wolpaw et al., 2002). A more pronounced P300 facilitates more accurate classification, and expanding matrix dimensions achieves this by making the target stimuli occur less frequently (Duncan-Johnson and Donchin, 1977; Allison and Pineda, 2003). Components of stimulus presentation rate (e.g. characteristics and frequency of flashing characters) influence classification and accuracy, including inter stimulus interval (ISI), time between stimulus onsets. Previous research indicates that ISI affects accuracy (Farwell and Donchin, 1988; Meinicke et al., 2002; Sellers et al., 2006), but strategies for selecting an optimal ISI have not reached consensus. Meinicke et al. (2002) found that a shorter ISI increases selections per minute and classification accuracy, while Farwell and Donchin (1988) discovered higher classification with a longer ISI. Findings of Sellers et al. (2006) coincided with Meinicke, and reasons for their discrepancy with Farwell and Donchin's results are unclear.

Classification and Signal-to-Noise Ratio (SNR). Accurate classification of target and nontarget responses depends on sufficient SNR, which can be increased through various methods: preprocessing, spatial filters, and paradigm design. Signal-to-noise ratio refers to the proportion of desirable signals (i.e. targets) to electrical activity disassociated with a target response. As "noise" increases, SNR decreases, potentially diminishing classification accuracy. Noise consists of attention paid to nontargets, impulses from electronic devices exclusive to the system, and physiological factors (e.g. fatigue, lack of attention).

Stepwise Linear Discriminant Analysis (SWLDA). Stepwise Linear Discriminant Analysis (SWLDA), an algorithm used in offline analysis, selects features, essentially characteristic peaks in EEG that account for variance in the data. Since it does not rely on explicit markers to discriminate targets from nontargets, this model is data-driven. The model selects spatio-temporal data qualities to derive classification coefficients. To derive the classifier, SWLDA uses target and nontarget ERPs (800 ms post-stimulus epochs). These resulting coefficient weights provide a user specific discriminative linear model that is subsequently used to classify averaged responses to each of the items in the character matrix. The matrix item receiving the highest discriminant score is presented to the user as feedback to the correctness of the computer's decision.

Inter Stimulus Interval. ISI affects classification accuracy, but its implications for improving SNR have not been thoroughly explored. An unchanging ISI elicits electrical responses in a rhythmic pattern. In comparison, responses to stimuli with a random ISI have more temporal variation, due to the fluctuating intervals between stimulus onsets. Since waveforms are averaged together, random ISI nontarget responses produce a smoother decimated waveform than those of a fixed ISI. I hypothesized that a random ISI would produce greater temporal variation in amplitudes of nontarget responses, reducing nontarget amplitude, and increasing signal-to-noise ratio. Moreover, it is well documented that probability affects the P300 response (e.g., Duncan-Johnson and Donchin, 1977; Allison and Pineda, 2003) ; thus, random ISI may decrease perceived probability of target occurrence, which has also shown to affect P300 amplitude on a trial by trial basis (Duncan-Johnson and Donchin, 1977). may be altered with a random ISI, potentially increasing the P300 amplitude.

Methods

Participants. Thirteen able-bodied individuals recruited through the SONA psychology undergraduate research pool at East Tennessee University (ETSU) participated in this study, and all had corrected-to-normal vision. The ETSU Institutional Review Board approved this research, and participants provided informed consent prior of admission to this study.

Data Acquisition. EEG was collected via 32-channel tin electrode caps (Electro-Cap International Inc.), with channels referenced to the right mastoid and grounded to the left mastoid. Data was digitized at 256 Hz, down-sampled at 20 Hz, and bandpass filtered from .5 to 30 Hz. BCI2000 was used for stimulus presentation and data collection.

Experimental Task, Procedure and Design. Two counterbalanced sessions with specific manipulations of inter stimulus interval were completed within one week, and each session had duration of 1.25 h. Sessions included five runs, or blocks, for calibration (described below) and an additional five runs for online testing, equaling 72 total selections. For the task, participants fixated on a monitor approximately 1 m away, displaying an 8 X 9 matrix of flashing alphanumeric characters. The experimental tasks consisted of "copy-spelling," where assigned target words (e.g. DRIVING) or numeric sequence were presented with instructions to spell them by selecting letters in the appropriate syntax from the matrix below. Letters in each target were selected consecutively, with a 2 second pause between selections. By mentally identifying or counting chosen characters when they flashed, thereby eliciting the P300 response, participants attempted to select appropriate characters. The Checkerboard Paradigm (CBP), a recent improvement to paradigm design (Townsend et al. 2010), was utilized for stimulus presentation, with ISI differing between two conditions: fixed ISI (FI) and random ISI (RI). The FI session (max ISI = 3,375 ms; min = 1,125 ms) had a constant ISI of 93.75 ms, and the ISI varied from 0 – 6 (1.0 = 31.25 ms) in the RI condition (max ISI = 5,462.5 ms; min = 562.5 ms). Randomization of ISI (RI) yielded smallest of 0 ms and highest of 187.5 ms, and it averaged at 93.75 ms.

Classification. Initially 36 character selections served as calibration data for SWLDA. After calibration, online feedback was provided for another 36 selections. SWLDA sampled 60 features averaged across 800 ms post-stimulus epochs. Channel locations Cz, Pz, Fz, Oz, P3, P4, P07, and P08 were used to derive the classifier. Written symbol rate (WSR; Townsend et. al., 2010) was used to optimize the number of stimulus presentations for each subject and condition.

Analysis

SNR. Absolute amplitudes of targets across channels Cz and Pz were summed and divided by summed absolute amplitudes of nontarget waveforms (205 samples, 800 ms epochs) to generate SNR values. These channels were selected because of their chief involvement in propagation of the P300 response. Dependent t-test analyses were run within groups to determine significant differences in SNR.

Waveforms and Bitrate. Peaks (RI pos. window: 150-350 ms; FI pos. window: 150-350 ms) and latencies (RI neg. window: 300-500 ms; FI neg. window: 400-600 ms) for channels Cz, Pz, Fz, P07, and P08 were compared between conditions, and values were analyzed with dependent t-tests.

Results

Accuracy and Bitrate. Accuracy and bitrate were statistically similar across RI (84%; 21 bits per minute, respectively) and FI (85%; 23 bits per minute) conditions.

SNR and Waveform Morphology. Significantly higher SNR for the RI condition (p=.04) confirmed our hypothesis that a variable, random ISI would produce a less pronounced average nontarget waveform. Although SNR increased in the RI condition, average target amplitudes were similar across conditions. Further analysis revealed significantly smaller nontarget amplitudes for channels Cz ($p = .03$), Pz ($p = .001$), P07 ($p = 6.8$ E -05, and P08 ($p = .001$) in the RI condition.

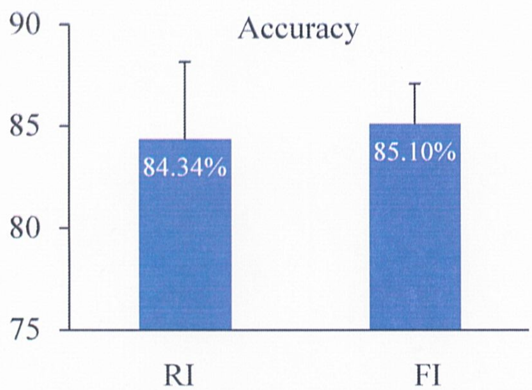


Figure 1. Performance accuracy for FI and RI conditions.

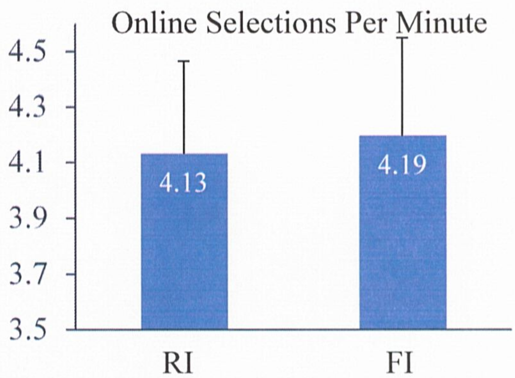


Figure 2. Online information transfer rate

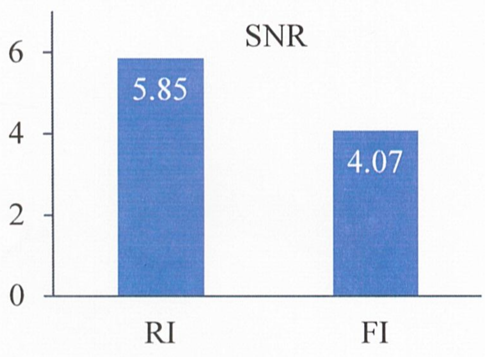


Figure 3. SNR across conditions.

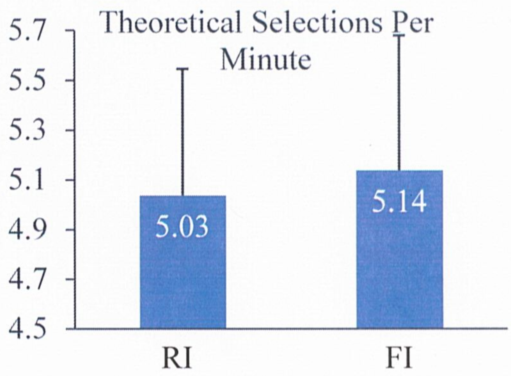


Figure 4. Theoretical bits/minute

Figure 5, (right). 16-channel electrode montage utilized for study. Electrodes in green are especially important for examining P300 response.

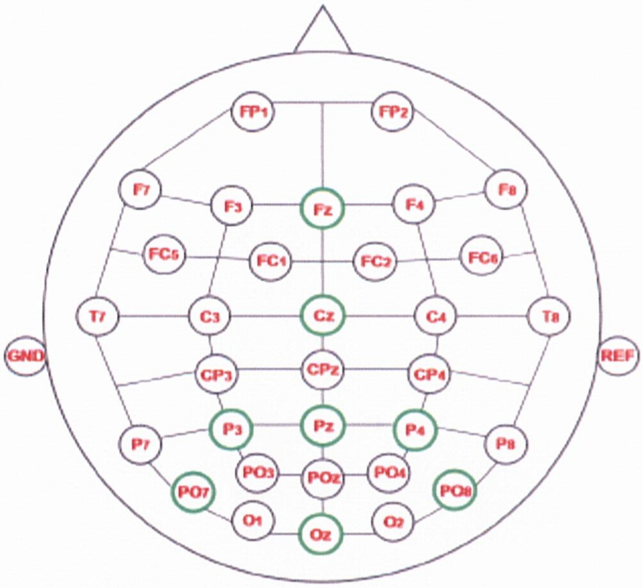
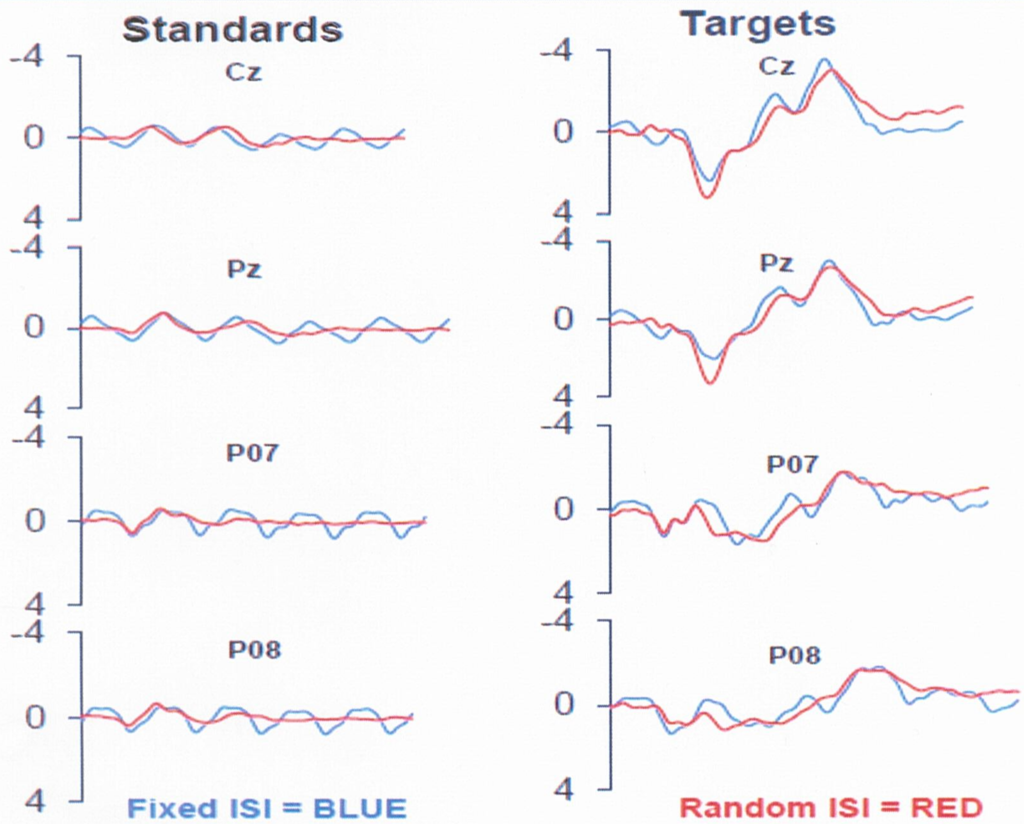


Figure 6, (below). Target amplitudes for conditions were very similar, but amplitudes of nontargets differed significantly. Nontarget waveforms for RI are noticeably less oscillatory than for FI.



Conclusions

Increasing accuracy in P300-based BCI performance is a multi-component process, and paradigm design, algorithms, and data analysis must be examined in isolation and in combination to maximize the system's utility for individuals. Manipulating elements of paradigm design is an inexpensive and effective method to increase accuracy. EEG does not have characteristically high SNR, and mitigating deleterious nontarget waveforms in SNR processing can be achieved through a random ISI. Extensive technical expertise of researchers is not necessary to apply these methods in subsequent data collection sessions, unlike spatial filtering and variations of data-processing. ISI is just one element of paradigm design that can be advantageously altered to increase performance accuracy.

Interactions among components are expected, but this study yields unexpected results. SNR increases significantly in the experimental RI condition, but performance accuracy remains nearly equivalent to scores in the FI condition. Theoretically, enhancing SNR should afford a classifier more representative of target responses, increasing online accuracy. However, SWLDA did not take advantage of this increase.

Robust target responses allow SWLDA to discriminate characteristics of EEG data more successfully, and reducing non-target response, or noise, also enhances this capability for higher classification accuracy. With a random ISI, more variance in nontarget ERPs could undermine SWLDA's function. A fixed ISI produces a nontarget waveform with more uniformly, temporally arranged oscillations. SWLDA selects feature weights that account for the most unique variance between target and nontarget epochs. It is possible that the consistency of the nontarget ERPs play a role in providing consistent features used for classification. This could explain the unexpected similarity in performance accuracy between the two conditions, despite the increase in SNR in the RI condition.

Although participants were not aware of paradigm manipulations, random ISI could affect perception of probability, potentially influencing amplitude of the P300 (Duncan-Johnson and Donchin, 1977; Allison and Pineda, 2003). Average waveforms across conditions were similar, but individual P300 responses in the RI condition may have been diminished, accounting for absence of improvement in classification that should have resulted from SNR results. The smaller ISI's in the RI condition may not have been enough time between target stimuli presentation, eliciting a P300 of smaller amplitude. Although a longer ISI in the RI may have enhanced amplitudes, a comparable number of diminished amplitudes and enhanced amplitudes would average together, yielding similar averages for both conditions. More research manipulating ISI is necessary to determine whether or not a random ISI can improve speed and accuracy. Although the current results are inconclusive, the higher SNR in the random ISI condition suggests that the classification method being used may not benefit from this additional information. In theory, increased SNR should enhance classification; future research will focus on testing various classification procedures that may benefit from the increases in SNR observed in the present study.

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