Towards Clinically Acceptable BCI Spellers: Preliminary Results for Different Stimulus Selection Patterns and Pattern Recognition Techniques

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We type with our brains, not our hands

Introduction

Our research focuses on improving P300 spellers in two areas: channel selection techniques for detecting P300 event-related potentials (ERPs) in the measured multi-channel EEG data, and optimal stimulus selection for improved efficiency and performance.

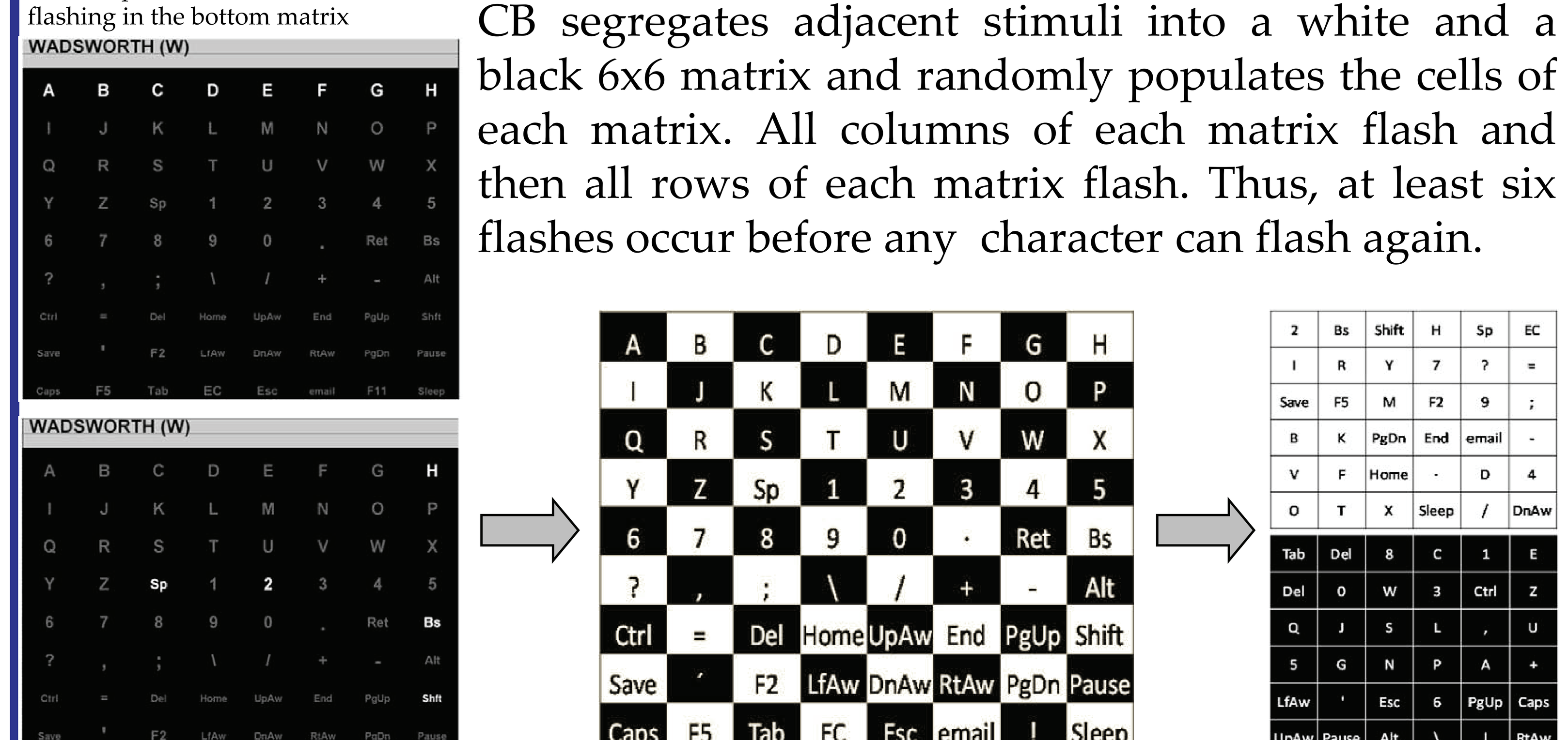
The standard row/column (RC) P300 BCI paradigm has been shown to be an effective means of controlling a speller (e.g. [1]); however, it has limitations: 1) misclassifications tend to occur within the rows/columns that contain the target characters (e.g. [2]); and 2) the RC presentation cannot control the amount of time between target flashes which allows target characters to flash in succession or in close temporal proximity, presumably reducing the P300 response. To investigate possible mitigation of these issues, two new speller paradigms are introduced: the Random (Ra) and Checkerboard (CB) flash paradigms. Ra removes the row/column structure but does not control timing while CB [3] removes the row/column structure and controls timing. Comparing the RC, Ra, and CB will help determine whether target flash timing or presentation paradigm provides optimal stimulus selection.

Pattern recognition performance is often improved by reducing high dimensional data (i.e., EEG data from many sensors) to lower dimensional data. Down-selecting the number of channels used to train the classifier has been shown to increase performance (e.g. [4]), and through investigation, a set of eight channels that maximizes performance across subjects has been proposed [5]. However, channel selection across subjects may not be robust to inter-subject variation. To investigate the potential impact of subject-dependent channel selection, training data is used to select the channels used to train a SWLDA classifier for testing subsequently measured data. Performance is compared to a standard eight-electrode configuration.

Speller Paradigms

Example Illumination of the RC Paradigm (above) and CB Paradigm (below)

Note: Top row of white matrix is flashing in the bottom matrix



From Townsend et al. (2010)

Checkerboard: The CB controls timing and selects stimuli by creating virtual rows and columns. The CB segregates adjacent stimuli into a white and a black 6x6 matrix and randomly populates the cells of each matrix. All columns of each matrix flash and then all rows of each matrix flash. Thus, at least six flashes occur before any character can flash again.

Methods

SPELLER PARADIGM:

- 6 participants
- 32 channels recorded 8, used for SWLDA training and online spelling
- Three illumination paradigms: Row/Column, Random, Checkerboard
- Three sessions, random order across subjects
- Phase 1: 36 item selections no-feedback (used to train classifier)
- Phase 2: 36 online item selections with SWLDA feedback

CHANNEL SELECTION:

- 18 participants: data from Townsend et al. (2010)
- Row/Column Paradigm
- Sequential forward and backward channel selection and leave-one-out cross-validation with five training tokens, resulting in 8 channels
- Channel selection performed for each participant
- Selected channels were used to train a SWLDA classifier which was tested on an additional five copy-spelled tokens

Results

Illumination Paradigm Comparison

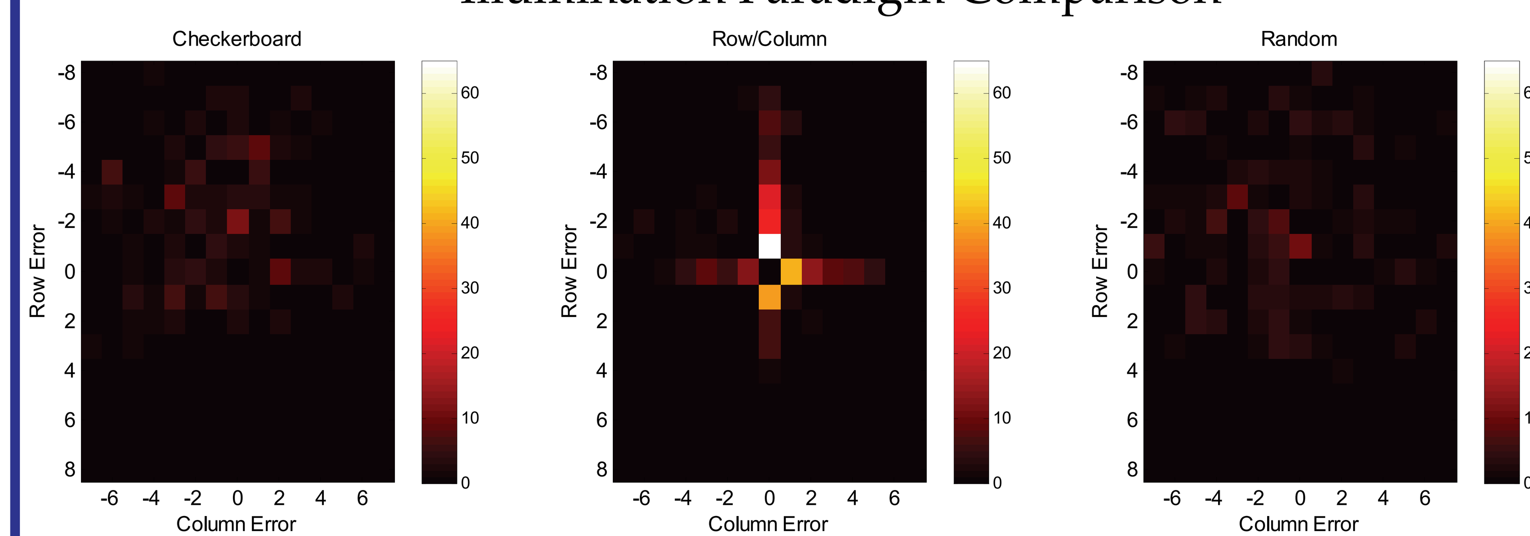


FIGURE 1: *Error locations for the three paradigms.* As expected, the CB and Ra paradigms decoupled the errors from the location of the target character.

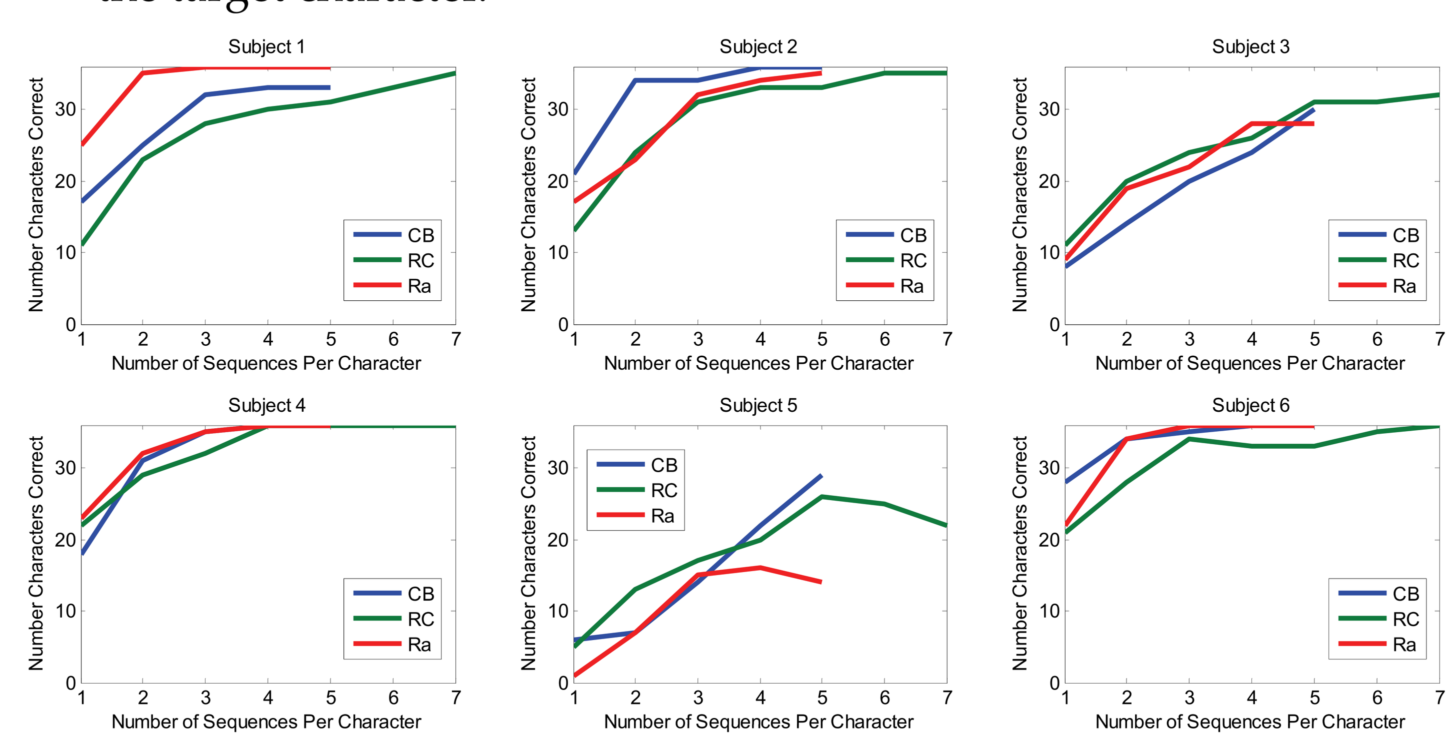


FIGURE 2: *Spelling accuracy for the three paradigms.* For three subjects (S3, S4, and S5), all three paradigms seem to work equally well. For the other three, the Checkerboard provides a performance improvement, and for two of those subjects, the Random paradigm also provides improved performance over Row/Column.

Table I: *Spelling accuracy for the three paradigms.* The checkerboard paradigm results in greater accuracy, particularly when compared to the random paradigm.

	Checkerboard	Row/Column	Random
Accuracy	92.5%	90.7%	85.6%
Information Transfer Rate	22.5	22.2	20.2

Channel Selection

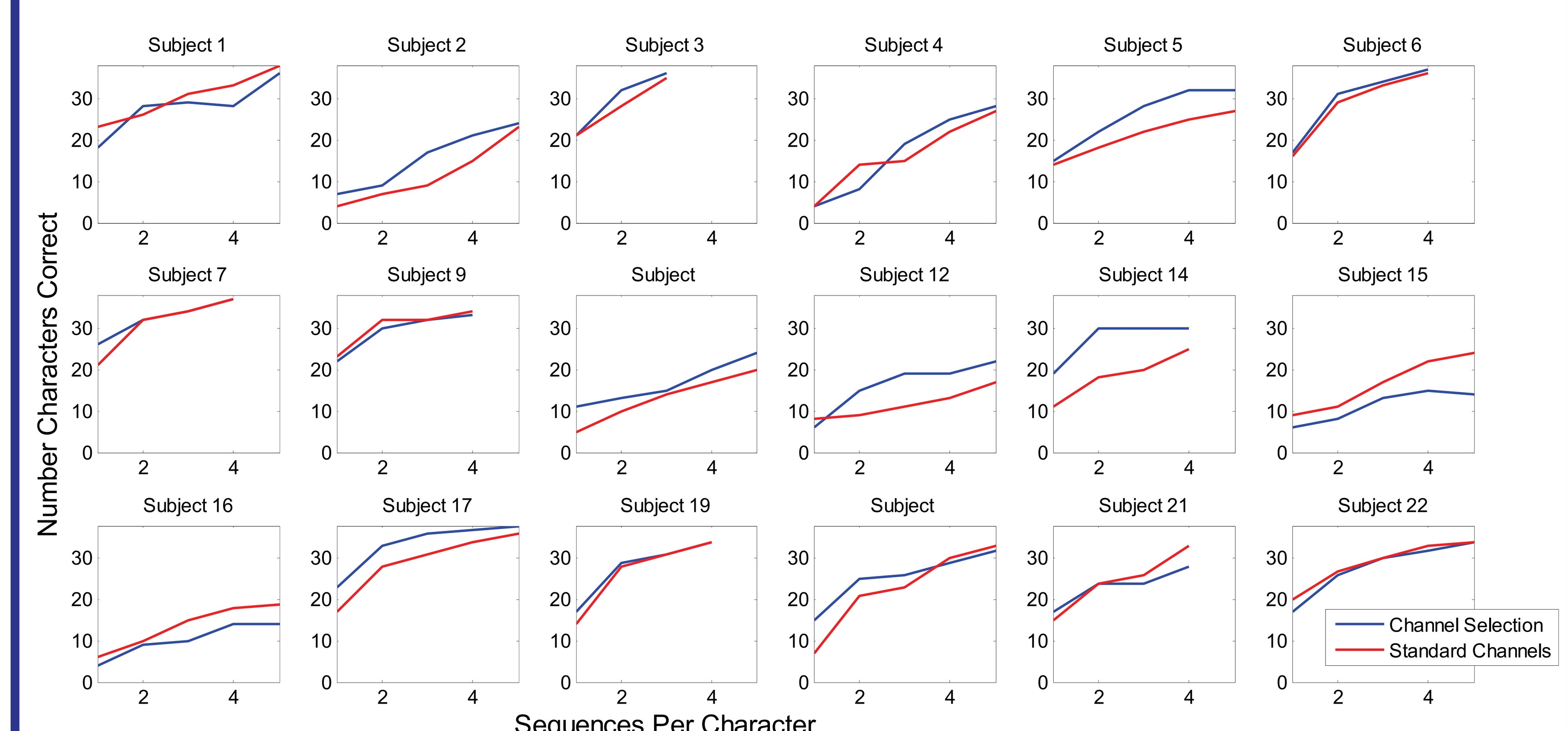


FIGURE 3: *Spelling accuracy with and without channel selection*. In the majority of cases, channel selection results in similar or improved accuracy. In only three cases (S15, S16, and 21) does channel selection result in poorer performance.

Discussion

Although Ra and CB paradigms decouple errors from characters adjacent to the target, it did not result in greater accuracy for the Ra. Thus, the heuristic control for the timing of inter-item flashes in CB may be more important in reducing error rate, as evidenced by the increase in accuracy, indicating the potential for increasing accuracy via controlled selection of stimuli.

Channel selection greatly improved accuracy for some subjects, had no affect on most, and rarely decreased accuracy. However, two of the three subjects that decreased were the two poorest performers overall. Thus, channel selection may be a useful factor for improving accuracy under conditions less controlled than a lab environment.

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[4] Rakotomamonjy, A., and Guigue, V. BCI Competition III: Dataset II Ensemble of SVMs for BCI P300 Speller. *IEEE Trans Biomedical Engineering* 55, 1147 1154 (2008).
[5] D. J. Krusienski, E. W. Sellers, D. J. McFarland, T. M. Vaughan, and J. R. Wolpaw, "Toward enhanced P300 speller performance," *Journal of Neuroscience Methods*, vol. 167, pp. 15-21, 2008.

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