A Comparison of EEG Systems for Use in P300 Spellers by Users With Motor Impairments in Real-World Environments

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Abstract. Three EEG systems that vary considerably in price, portability and features are compared for use with P300 spellers. Data is recorded from seven subjects with severe motor impairments in their home environments and classified using a variant of LDA. These experiments suggest that a portable EEG system with a relatively moderate price may perform as well as an expensive system when used in P300 spellers. Furthermore, systems that are smaller and more comfortable are more practical and deliver a better user experience.

Keywords: Brain-Computer Interface, EEG System Comparison, P300 Speller, Motor Impairment, Home

1. Introduction

The P300 speller is rapidly gaining acceptance as a potential form of assistive technology and several research teams have begun testing this technology in real world environments with users that have severe motor impairments [Nijboer et al., 2008; Sellers et al., 2010]. However, there is little research comparing electroencephalography (EEG) systems and exploring the properties that future systems should have in order to construct practical P300 spellers.

In the present study, we seek to compare EEG systems for use with P300 spellers under real-world conditions. To this end, we have collected data from seven users with severe motor impairments in their home environments using three different EEG systems. This data was analyzed in an offline fashion using relatively well-established techniques for P300 classification. The results of our experiments illustrate that the use of a high-end EEG system does not necessarily yield an improvement in classification accuracy for the P300 speller. Instead, we suggest that portable mid-range EEG systems may provide a better user experience while still delivering acceptable performance.

2. Methods

The three EEG systems that we examine vary considerably with respect to price, portability and a number of features that may affect signal quality and comfort. Specifically, we compare the NeuroPulse Mindset-24R, the g.tec g.MOBILab+/g.GAMMAsys and the Biosemi ActiveTwo. The Mindset is relatively inexpensive and not very portable. The Mindset supports up to 24 passive electrodes with a sampling rate of 512 Hz. The g.MOBILab+ is highly portable with mid-range price and supports 8 active electrodes with a sampling rate of 256 Hz. The ActiveTwo is relatively expensive and moderately portable. The ActiveTwo supports a number of high-end features, such as high-density electrode arrays, 16 kHz sampling rates and a driven-right-leg circuit.

EEG was recorded from seven subjects in their home environments. Two subjects had quadriplegia as the result of high-level spinal cord injuries, including one subject that used a ventilator most of the time. One subject was largely locked-in as the result of a traumatic brain injury and had very limited communication using eye blink responses. The remaining three subjects had severe limitations in movement as a result of advanced multiple sclerosis.

Each subject was seated in front of a computer screen and asked to count the number of occurrences of a given letter within a sequence of flashing characters containing 20 target and 60 non-target characters. This process was repeated three times with the target letters *b*, *d* and *p*, which were selected to represent a difficult scenario. The entire session was repeated on three separate days using a different EEG system during each session. Upon completion of the final session, each user completed a questionnaire regarding their experience.

Since the focus of our work is on comparing EEG systems, we have elected to use a relatively well established algorithm for EEG classification; namely, Linear Discriminant Analysis (LDA) with shrinkage toward the average eigenvalue of the covariance matrix [Blankertz et al., 2011]. The shrinkage parameter and final classification results were obtained using a nested random-subsampling validation procedure. Class labels are assigned after encountering

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six EEG segments by estimating the joint probability of the segments belonging to each class. In order to achieve reasonable estimates of covariance, a subset of 8 channels was selected and decimated to a sampling rate of 32 Hz.

3. Results

In Table 1 we present the final classification accuracies obtained from our experiments. The highest mean classification accuracy was achieved with the g.MOBILab+ at 82.50 % correct. The ActiveTwo followed with a mean classification accuracy of 75.71 %. The lowest mean classification accuracy was obtained with the Mindset at 66.67 %. It is important to note, however, that we are unable to show statistically significant differences in mean classification performance between any of the systems with an ANOVA F-test ($p = 0.39$) or paired t-tests.

Table 1: *Six-Trial Classification Accuracies.*

Subject	ActiveTwo	g.MOBILab+	Mindset
01	**90.00%**	*NA*	37.50%
02	90.00%	**97.50%**	*NA*
03	75.00%	97.50%	**100.00%**
04	55.00%	*NA*	**60.00%**
05	**70.00%**	42.50%	62.50%
06	67.50%	**87.50%**	72.50%
07	82.50%	**87.50%**	67.50%
Mean	75.71%	**82.50%**	66.67%

In order to further investigate the ability of each EEG system to capture the P300 and related waveforms, we also examine averages of time-locked EEG segments. In Fig. 1 we see the difference in the grand averages between the target and non-target segments for each of the three systems at the site P4. We notice that the largest difference in responses is achieved for the g.MOBILab+, ActiveTwo and Mindset respectively, supporting our classification results. The variations in the peak timing across systems may be related to the different methods for synchronizing the stimulus.

4. Discussion

Although it may seem surprising that the ActiveTwo does not achieve the highest classification accuracy, this result may be explained in part by the fact that the P300 speller is a very specific application and that our implementation does not utilize a large number of electrode sites or high sampling rates. In fact, we would argue that the ActiveTwo system may be advantageous in general research settings and, potentially, other types of Brain-Computer Interfaces. Nevertheless, it appears that the g.MOBILab+ may be more appropriate for use in practical P300 spellers.

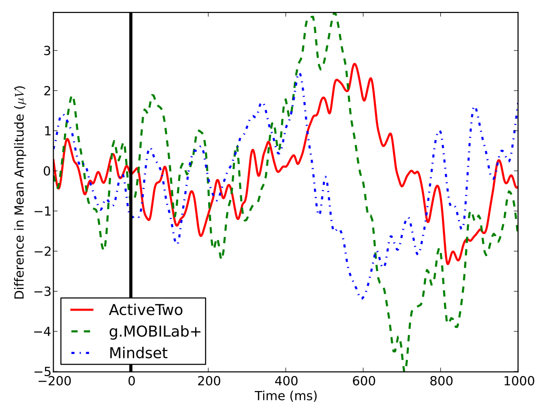

Figure 1: *Difference between the grand averages of the target and non-target responses for each system.*

Perhaps equally as important as classification results is the insight gained by interviewing and working with subjects with motor impairments in their homes. These potential users of P300 spellers overwhelmingly mention the comfort and application time of the EEG cap as concerns. This alone may preclude the use of low impedance systems such as the Mindset because of the lengthy and somewhat uncomfortable cap application process. These users also require systems that are highly mobile and that can continue to function through daily activities and movement. This suggests that an ideal EEG system for use in P300 spellers should be portable, lightweight and have active electrodes that are comfortable but not easily dislodged.

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References

Blankertz, B., Lemm, S., Treder, M., Haufe, S., and Müller, K.-R. (2011). Single-trial analysis and classification of ERP components – a tutorial. *Neuroimage*, 56(2):814–825.

Nijboer, F., Sellers, E., Mellinger, J., Jordan, M., Matuz, T., Furdea, A., Halder, S., Mochty, U., Krusienski, D., and Vaughan, T. (2008). A P300-based brain-computer interface for people with amyotrophic lateral sclerosis. *Clin Neurophysiol*, 119(8):1909–1916.

Sellers, E., Vaughan, T., and Wolpaw, J. (2010). A brain-computer interface for long-term independent home use. *Amyotroph Lateral Sc*, 11(5):449–455.