

The N100 of Averaged ERPs Predicts LDA Classifier Success on an Individual Basis

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Abstract. We examine the success of a common LDA classification algorithm for P300 Speller BCI systems on an individual basis. Experiments performed on 16 subjects (7 with severe motor impairment, 9 with no motor impairment) indicate that the P300 Speller should, on average, work in both client and neurotypical populations. Here, we find that the N100 of an averaged ERP, a measure associated with selective attention, has a significant relationship with LDA classifier results, and may account for a large portion of variability we see in individual success in operating P300 Spellers.

Keywords: Brain-Computer Interfaces, P300 Speller, N100, Linear Discriminant Analysis, Individual Differences

1. Introduction

Brain-computer interfaces (BCI) show great promise for individuals with motor impairments in regaining the ability to communicate. One form of BCI widely studied in hopes of achieving this goal is the P300 Speller. The P300 speller operates by flashing a series of letters to the user. When the target letter is flashed, we expect to see a P300 response, a large positive voltage deflection in the user's brain activity approximately 300 ms after a stimulus presentation as recorded by electroencephalography (EEG). In order for this system to work, however, a computer must be able to classify each letter as a target or a non-target presentation based only on the user's brain activity during each response segment. Classification of EEG segments is commonly achieved using linear discriminant analysis (LDA). Past literature shows a great deal of variability in the success of LDA classification from person-to-person with clients often performing lower than unimpaired. To date, the cause for this variability is unknown.

Here we investigate potential predictors of LDA success on an individual basis by exploring another component of EEG responses, the N100, a negative voltage deflection approximately 100 ms after a stimulus presentation obtained from an averaged ERP. The N100 has been implicated in selective attention, and is known to be affected by individual factors such as fatigue [Hillyard et al., 1973]. This is important in P300 Spellers as the user must selectively focus on a single letter and with extended use, the user may become fatigued. Fatigue may affect his or her ability to attend, thus implicating the usefulness of the LDA algorithm. Many individuals in need of BCI technology cannot communicate verbally and may not be able to voice their fatigue levels or ability to maintain their attention to stimulus presentation. Because of the N100's relationship to selective attention, we hypothesize that the N100 will have some predictive power in determining the success of LDA classification in individuals. We also posit that the N100 may be an effective measurement of fatigue, thus eliminating the difficulty of communication lapses between users and caregivers or researchers.

2. Material and Methods

First, using traditional ERP methodology and repeated measures ANOVA we show that both client and neurotypical participants having no motor impairments produce P300 amplitudes that are, on average, significantly different for a target letter compared to non-target letters ($F = 13.9$, $p = .002$) with no significant differences between the groups ($F = .009$, $p = .93$; see Fig. 1 and Table 1). Thus, we conclude that the P300 Speller should be successful on average for both groups.

Next, we show that LDA is an effective classification tool (see Table 1). Following the suggestions of [Blankertz et al., 2011], we regularize LDA using shrinkage toward the average eigenvalue of the

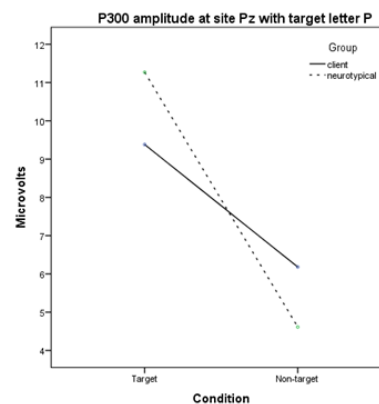


Figure 1. A comparison of mean P300 amplitudes for clients and neurotypicals in target and non-target letter conditions.

covariance matrix. The shrinkage parameter is selected using 10 repetitions of random sub-sampling validation with a 60%-20%-20% split between the training, validation, and test partitions respectively. Class labels are assigned after encountering six EEG segments by estimating the joint probability of the segments belonging to each class, i.e., by summing the evaluation of the LDA discriminant functions.

Finally, using linear regression we examine if the relationship of N100 and P300 amplitudes from averaged ERPs of both target and non-target stimuli can be predictive of the success of LDA classification in individuals. Our analyses indicate that a model with only the N100 target and P300 target amplitudes significantly predicts LDA success, $R^2=.48$, $F_{(2, 13)} = 5.97$, $p = .015$. Examination of beta weights reveal that that only the N100 amplitude is the significant predictor, $\beta = -.71$, $t = -3.44$, $p = .004$ and P300 is not a significant contributor ($\beta = .25$, $t = 1.21$, $p = .25$). A separate analysis revealed that if the model is expanded to include N100 and P300 amplitudes for non-target letters, neither of these variables contributes to prediction of LDA success; F Change $_{(2,11)} = .089$, $p = .92$.

Table 1. Individual LDA classification results and N100 and P300 amplitudes.

Client Results				Neurotypical Results			
Subject	LDA Classification	N100 Amplitude	P300 Amplitude	Subject	LDA Classification	N100 Amplitude	P300 Amplitude
B001	100	-1.72	4.45	B011	87.50	-4.24	12.13
B002	65.00	-3.75	10.11	B012	80.00	-2.9	12.54
B003	67.50	-4.95	25.44	B013	82.50	-4.46	9.72
B004	47.50	-3.41	5.09	B014	82.50	-7.83	15.03
B005	45.00	-2.95	2.79	B015	95.00	-4.49	13.91
B006	85.00	-1.98	10.21	B016	62.50	-1.52	9.18
B007	95.00	-4.34	7.57	B017	95.00	-4.52	6.52
				B018	55.00	-2.11	14.00
				B019	52.50	-1.81	8.41

3. Discussion

Our data indicate that while the P300 speller should, on average, work successfully, the N100 does have a significant relationship with LDA classification abilities. Individual factors such as fatigue and decline in selective attention may be interfering with users' ability to successfully operate P300 spellers. However, LDA techniques force the limitation of data and may exclude this important N100 information. Future classification algorithms may benefit from including more contextual information in the analysis of neural responses rather than just the P300. In an online BCI, the N100 could be used to provide cues to remind users to attend, thus improving their success rates. Researchers and caregivers may also use the N100 as a means to preselect individuals who will and will not be successful in using the P300 speller; according to our data, an individual with a larger N100 response to visual stimuli should be more successful in operating a P300 speller than an individual with a smaller N100 response.

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