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# Improving Dynamic Data Collection in P300 Spellers With a Language Model

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***Abstract.*** P300 spellers provide a means of communication that doesn't rely on neuromuscular control. The P300 speller operates by processing the user's EEG data after character subsets are flashed on a screen and these responses are averaged after multiple flashes to improve SNR. Adaptive selection of the number of flashes per character improves spelling speed and accuracy. The goal of this study was to optimize a previously developed dynamic stopping algorithm, a probabilistic method that has the advantage of both assessing the quality of the data currently under consideration and incorporating *a priori* knowledge of the language of the user to increase spelling speed. Participants (n=17) completed spelling tasks using the dynamic stopping algorithm with and without a language model. The addition of a language model significantly improved spelling speed and communication rate.

*Keywords:* EEG, BCI, P300 Speller, Amyotrophic Lateral Sclerosis (ALS), Dynamic Stopping, Language Model

## 1. Introduction

P300 spellers provide a means of communication for patients with severe physical limitations who lack the neuromuscular ability to control other forms of assistive devices, such as patients with amyotrophic lateral sclerosis (ALS) [Sellers and Donchin, 2006]. The P300 speller operates by evaluating the user's EEG responses as character subsets are flashed on a screen; when a flashed subset contains the desired character, an event related potential occurs [Farwell and Donchin, 1988]. These responses are averaged after multiple flashes to improve signal-to-noise ratio. Adaptively varying the number of flashes per character improves spelling speed and accuracy. Throckmorton et al. demonstrated improved accuracy and communication speed using a dynamic stopping algorithm which accomplished adaptive selection by maintaining a probability distribution over characters, integrating each classified flash response into the model via a Bayesian update. Data collection was stopped when a character probability reached a threshold and that character was selected as the intended target [Throckmorton et al., 2012]. We hypothesize that incorporating *a priori* knowledge of the user's language will also improve spelling performance. In this study, we optimize the dynamic stopping algorithm to include a language model.

## 2. Material and Methods

Seventeen non-disabled participants were recruited from Duke University for this study. BCI2000 software was used for stimulus presentation and data collection, with additional functionality added to implement dynamic stopping (DS) and dynamic stopping with language model (DSLM) algorithms. The row/column speller paradigm was used, with letters, numbers and keyboard commands presented in a 9 x 8 grid. EEG responses were measured using a 32-channel electrode cap, with the left and right mastoids used for ground and reference electrodes, respectively. Data from electrodes Fz, Cz, P3, Pz, P4, PO7, PO8 and Oz were used for classification.

EEG data obtained during the training phase was grouped into target and non-target responses and used to train a stepwise linear discriminant (SWLDA) classifier. SWLDA weights were used to calculate classifier responses of the training data and kernel density estimation was used to smooth the histogram of these responses to generate likelihood probability density functions (pdfs). In the testing phase, prior to data collection each possible character is assigned an initial probability of being the target. With each new flash, the classifier response is calculated and used to estimate the character non-target and target likelihoods from the likelihood pdfs. The character probabilities are updated with these likelihood values using Bayesian inference. If a character probability exceeds the threshold, it is selected as the target character. If not, a new flash is presented and the process of updating the character probabilities is repeated. In DS, the initialization probabilities assumed no prior knowledge; hence a uniform distribution was used. In DSLM, the initialization probabilities of alphabet characters were dependent on the previously spelled character, while non-alphabet characters assumed a uniform distribution. A character pair probability matrix was generated from the Carnegie Mellon Online dictionary ("The CMU Pronouncing Dictionary").

## 3. Results

Fig. 1 shows the theoretical bit rate obtained under DS and DSLM. Theoretical bit rate takes into account accuracy, the number of possible target characters and the time required to complete the task (excluding the 3.5 s pauses between character selections). A significant improvement in theoretical bit rate was observed in DSLM (M=54.42 bits/min, SD=23.78 bits/min), compared to DS (M=46.12 bits/min, SD=20.63 bits/min), $p < 0.0065$ (Wilcoxon signed-rank test). No significant difference in accuracy was observed across participants (DS: M=88.89%, SD=9.32%; DSLM: M=90.36%, SD=8.95%), $p < 0.2426$. Participants completed the task in less time under DSLM (M=6.27 min, SD=2.11 min), compared to DS (M=6.80 min, SD=2.21 min), $p < 0.00025$.

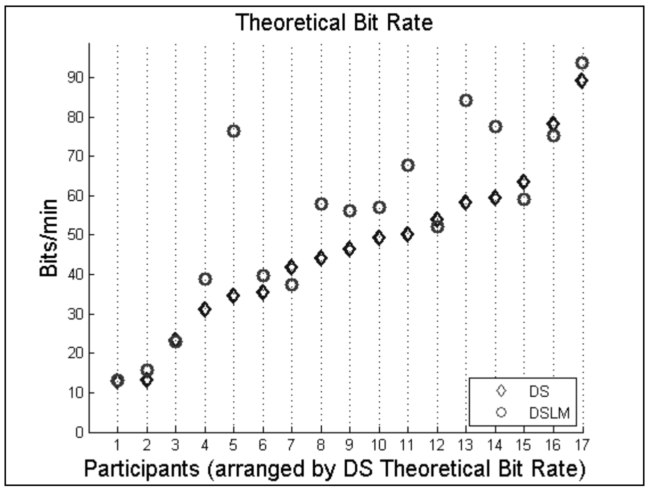


***Figure 1.*** *Comparison of theoretical bit rate between DS and DSLM.*

## 4. Discussion

Improving spelling speed and communication rate in P300 spellers results in more practical and efficient day-to-day use in patients with severe disabilities, thereby restoring some level of independent communication. The amount of data collection prior to character selection has competing effects on speller speed and accuracy: decreasing it improves speed while increasing it improves spelling accuracy. The DS algorithm has been shown to improve spelling speed and accuracy. Prior knowledge via a language model based on character pairs adds more predictability to the algorithm and can reduce the time required to reach the decision threshold. Although each participant’s distribution of flashes for character selection varied widely, character selection occurred on average with fewer flashes under DSLM compared to DS. Some participants observed an increase in accuracy under DSLM; coupled with a reduction in task completion time, this resulted in a significant increase in their theoretical bit rates. These results demonstrate the potential that spelling speed and communication rate in dynamic data collection can be improved with the addition of a language model.

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