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by the higher order model further causes the character probabilities to converge faster.

The accuracy and average character selection time were used to calculate bit rate, including the time pauses between character selections [8]. Figure 3B shows participant bit rates with both algorithms. Due to similar accuracy levels and a significant reduction in character selection time, most participants observed significant improvement in their performance ($p < 0.007$), with on average 26% increase in bit rate. Performance improvements with the $n$-gram model are consistent with off-line analysis performed on EEG data from [5].

## 4 Discussion

The relatively slow communication rates of ERP-based BCI speller systems can be improved by exploiting the predictability of language. However, sometimes the manner of integration of language information in the ERP speller can lead to a decrease in performance due to increased task difficulty e.g. selecting from a drop-down menu in a predictive speller as in [2]. Our online results indicate there is potential to improve performance with a higher order language model in dynamic data collection, with additional consideration to minimize erroneous character revisions when used in combination with a dictionary. Further development includes adapting the algorithm for sentence spelling tasks, where word-space boundaries are important. There is the potential to further enhance performance using natural language processing tools such as word prediction and/or dictionary-based spelling correction. For example, the algorithm can be adapted to include likely word alternatives generated from the prefixes which can be displayed directly in the speller matrix [3], as this has been shown to not negatively affect performance.

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