

# Brain Computer Interface Speller based on Visual Imagery

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*Background.* Disruption in the neural transmission due to motor neuron disorders (such as ALS and brainstem injuries) results in the reduction of muscle control, impairing a patient's ability to communicate [1]. One potential application of Brain-Computer Interfaces (BCIs) is to provide an alternative means of communication for such individuals [2].

To communicate text, one such common BCI system is the P300 Speller [3] which allows users to spell out messages by just using their brain. P300 BCIs, especially in the last decade, have emerged as one of the main BCI categories [4]. Researchers over the years have experimented with various variations of the P300 Speller—the row/column paradigm [5], single character paradigm [6], checkerboard paradigm [7], region-based paradigm [8], etc. However, unfortunately the typing speed achieved by users is relatively slow [9]. Speier et al., in two different studies [3, 10], were able to achieve an average typing speed of 11.97 characters/minute from 10 healthy participants and 10.38 characters/minute from 5 ALS patients and 1 brainstem necrosis patient.

Similar to using a computer mouse or a finger on a mobile computing device, another alternative to P300 Spellers is the use of neurally driven cursor on a virtual keyboard [2]. Nuyujukian et al. [2], in their study demonstrated a communication prosthesis by simulating a typing task with two rhesus macaques implanted with electrode arrays. Using highest known performing BCI decoders, the monkeys J and L were able to achieve typing rates of 12 and 7.8 words/minute respectively. These typing rates, according to the authors, represent the highest of any BCI under any control modality.

Sousa et al. [11], in their study presented three types of stimuli to their participants—static dot, a dot moving in two opposing directions (along y axis) and a dot moving in four opposing directions (along x and y axes). Later, the participants were asked to imagine the three previously presented stimulus conditions. The authors, based on the electroencephalogram (EEG) data of the participants, achieved an average classification accuracy of 87.64% for the three visual motion imagery tasks with an average sensitivity and specificity of 83.52% and 91.76% respectively. A similar study was conducted by Bobrov [12] where the authors classified between three states—imagining a face, imagining a house and relaxation. However, the highest average classification accuracy achieved was just 54%.

*Proposed Work.* Based on the results achieved by Sousa et al. [11], we hypothesize that the prospects of visual imagery speller from EEG data can be very high. To test the validity of this hypothesis, we plan to setup an experiment similar to that of [11] and [12]. The experiment will be divided into two segments, visual stimulation and visual imagery. In the visual stimulation segment, participants will be presented with three different visual stimuli (three images of three alphabets) which they will be asked to imagine in the visual imagery segment. The reason for the visual stimulation segment is mainly because the neural response during imagery is similar to the neural response during perception [13] and therefore the EEG signals during stimulation can be considered as ground truth data.

We hope to experiment with several state-of-the-art algorithms for each of the submodules (i.e. Pre-processing, Feature Extraction, Feature Selection, and Classification) of the Signal Processing module of a BCI system [14] on the visual imagery EEG data to convert brain signals into specific alphabets. Even if the accuracies achieved are low, this system can be blended with the knowledge of natural language to incorporate error corrections [1] and several others.

Significance. Based on our pre-experiment results, human beings can spell out about 140 characters/minute, i.e. approximately equal to 27 words/minute (as per [15]) which is about 1 character every 429 msec. Considering signal transmission lags and computational time needed for classification of a single character, this rate may decrease up to 1 character/second which is about 12 words/minute. 1 second epochs are not unusual in BCIs and therefore, online classification of 1 second EEG data is quite feasible provided that the classifier is pre-trained.

This proposed visual imagery based BCI Speller has the potential to overcome the major drawbacks of typing rate for P300 Spellers and invasiveness for the neurally driven cursor on a virtual keyboard. To the best of our knowledge, there are no studies regarding visual imagery spellers and thus, this can become a pioneering work. Not only will this improve the lifestyle of the physically disabled people but will also increase the quality of life for all people across the world.

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