Electrode Reduction for EEG-based Imagined Speech BCI Applications

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Synopsis: EEG-based imagined speech BCIs try to decode imagined speech from EEG activity. While several studies have proven the feasibility of this innovative BCI concept, current implementations usually rely on high-resolution EEG devices with 64+ channels. These setups make EEG-based imagined speech BCIs inconvenient for everyday use. To overcome this problem and to evaluate the necessity of such complex setups, we applied electrode reduction on three different imagined speech EEG datasets, to find a best suitable subset of electrodes. Our results show that the commonly used 64+ channel setups are oversized, and a comparable performance could be achieved with half of the electrodes for all three datasets. A common subset shared between subjects could however not be found.

Background: Imagined speech BCIs try to decode unspoken speech from brain activity (Rekrut et al. 2022a) and offer a variety of useful applications whenever spoken speech is not an option. While the feasibility of such BCIs has been proven in several studies even for non-invasive brain measures as the Electroencephalography (Sereshkeh, 2017b) (Nguyen et al., 2018) current EEG-based setups are complex and rely on high resolution devices with 64+ channels (Lee et al., 2020) (Sereshkeh, 2017a). However, such high-resolution devices are expensive, cumbersome to wear, and inconvenient in everyday life. Although proven feasible, no study has so far questioned the necessity of such high-resolution setups, therefore within this work we aim at answering the following research questions:

RQ1: Is there a single best minimal subset of electrodes for EEG-based imagined speech BCIs?

RQ2: Are certain electrode positions related to good imagined speech classification accuracies?

Methods: We investigated 3 different imagined speech EEG datasets that were all recorded with the same 64 channel headset (Brain Products LiveAmp) during single word imagination, however, by different research groups and in the context of different studies. Dataset one (5 words, 70 repetitions/word) was taken from the 2020 international BCI competition[1], dataset two (9 words, 40 repetitions/word) was recorded in (Rekrut et al. 2022a), dataset three (5 words, 80 repetitions/word) in (Rekrut et al. 2022b). We applied the following signal processing pipeline:

Preprocessing: The data was bandpass filtered between 0.5 and 60Hz and notch filtered at 50 Hz. The parameters were chosen according to our previous work (Rekrut et al. 2021). After filtering the data was cut into epochs of two seconds starting from the onset of the fixation cross.

Three **feature extraction** methods were implemented, namely Common Spatial Patterns (CSP), Discrete Wavelet Transform (DWT) and a combination of the two referred to as CSPWav. The CSP was realized using multiclass implementation of the mne library (Gramfort et al., 2013) with default parameters. DWT was based on the PyWavelets library (Lee et al., 2013) with biorthorgonal 2.2 mother wavelet as suggested in (Feng et al., 2019) and decomposed until fourth level. Afterwards, a wavelet feature vector was created as presented in (Torres-García et al.,

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2016). The CSPwav feature extraction combined the previously explained methods by first applying CSP and creating the DWT of the resulting time signal.

For **classification** we used the Extreme Gradient Boosting algorithm (XGB) implemented based on (Chen & Guestrin, 2016) with a mean error as evaluation metric and instructed to stop if the value did not decrease for ten rounds. The objective function was chosen to be softmax for multiple classes.

Electrode Reduction was realized with Grey Wolf Optimization as described in (Ghosh et al., 2019). This evolutionary algorithm was implemented by evaluating classification accuracy as a fitness function, using a dataset in which a randomly selected electrode was excluded. This process was repeated for all electrodes consecutively and the electrode, without which the classification achieved the highest accuracy, was finally rejected. This process was repeated for each subset from 64 to 1 electrode.

Performance evaluation: The top performing subsets of electrodes per participant were calculated based on the classification accuracy using a Fuzzy Inference System implemented according to (Torres et al., 2016), to prevent excluding sets with only slightly lower classification accuracy but significantly lower number of electrodes.

Results

Figure 1 shows an overview of the reduced electrodes per feature extraction method (right) and classification accuracy (left), for all three datasets. The top sets of the wavelet transform for all participants in all datasets lie above 30 removed electrodes, which means that for this method we could have achieved the top set configurations with only 34 of the initial 64 electrodes. Although CSP based feature extraction methods seem to prefer more electrodes to achieve their top sets, we observed the first quartile for both implementations lying at 30 removed electrodes, meaning that for 75% of the participants we would have achieved the top results with 30 electrodes less. On average we can include 83% of the top sets for all three methods with roughly half the number of electrodes for these 3 datasets. A clear conclusion on the relevant positions of electrodes could not be drawn as shown in figure 2. Each electrode position is visualized at its position of the head, colored according to the percentage of occurrence in the top sets. The distribution appears homogeneous for all three feature extraction methods which does not allow for a clear conclusion on a certain brain region being dominantly involved in the classification process.

Discussion

Within this work we aimed at finding a best minimal subset of electrodes for EEG-based imagined speech BCIs by applying electrode reduction on 3 different imagined speech datasets. Although we could not find common relevant electrode positions, our results show, that 64+ channel setups are most likely oversized. We were able to significantly reduce electrodes by almost a half for all three datasets which suggests, that EEG-based imagined speech BCIs work perfectly fine with smaller setups of 32 electrodes. However, due to the strong variation among subjects we would not recommend a standard montage but rather reduce electrodes from an initial high-resolution setup to subject specific positions. This work therefore provides first steps towards less complex setups of EEG-based imagined speech BCIs applicable in everyday use.

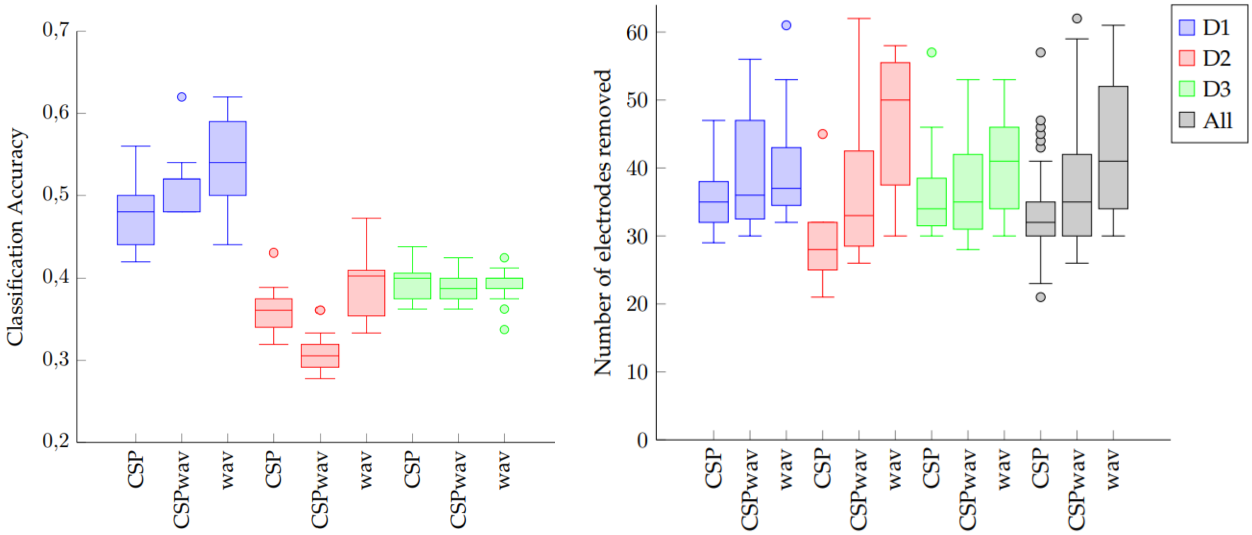

Figure 1 Boxplots of the classification accuracies (left) and the number of electrodes removed (right) for each of the three datasets (D1, D2, D3) and feature extraction methods. The black boxes for the removed electrodes on the right show the average results for all datasets combined (All).

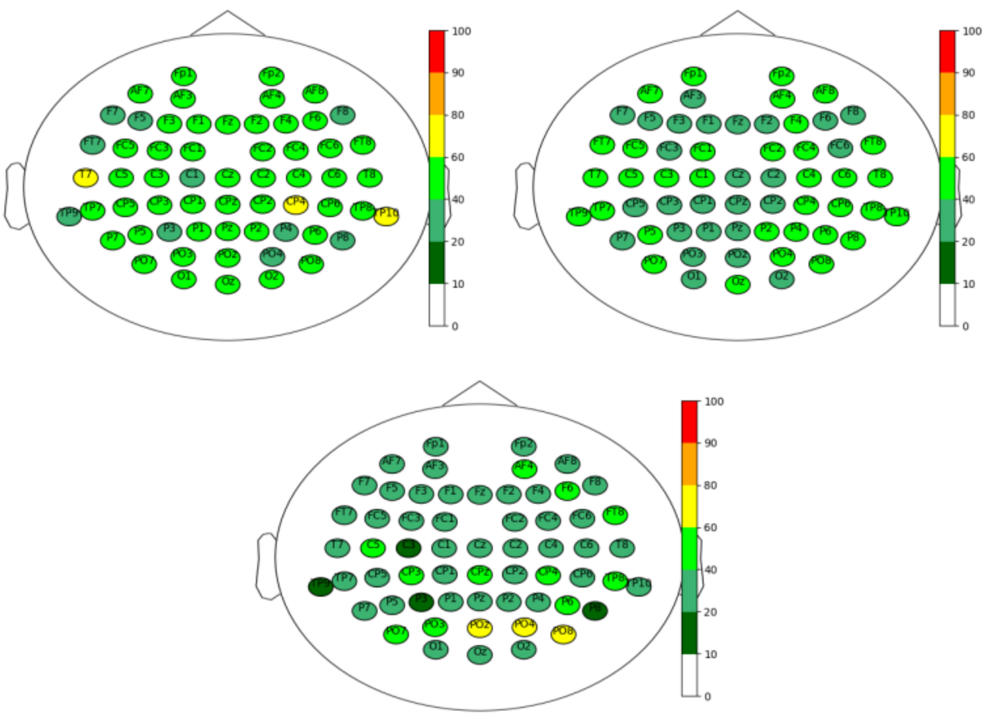

Figure 2 Electrode positions for the top sets of all three datasets and the three different feature extraction methods in percent. Top left: CSP, top right: CSPwav and bottom: wav.

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