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Inner Speech Decoding from EEG and MEG

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Introduction: Despite the prevalence of inner speech in everyday life, research on this has been limited, particularly when it comes to non-invasive methods [1]. Our study aims to fill this gap by using EEG and MEG to collect data from three different inner speech paradigms, and by conducting an initial decoding analysis. Such research has the potential to pave the way for word-level communication through brain-computer interfaces [2].

Material, Methods and Results: We conducted a study to examine the differences between silent reading, repetitive inner speech, and generative inner speech using five patient-relevant words (*help*, *hungry*, *tired*, *pain*, *thirsty*) in healthy participants. Our experiment consisted of two versions. Before and after each session, 5 minutes of resting state data were collected. For all sessions, we also collected ECG, EOG, EMG (on the jaw), and eye-tracking data.

In version one of the experiment, participants silently read words on a screen (one at a time), followed by a visual fixation-cross cue to repeat the word in their minds. In some trials, they were next prompted to imagine speaking a different word from the set of five (the generative inner speech task). All visual stimuli appeared for 0.8-1.0 seconds and are followed by a blank screen lasting 0.8-1.0 seconds. We collected combined MEG (Elekta Neuromag 306-channel) and EEG (Easycap 64-channel) data from 3 male participants, with 6, 2, and 2 sessions per participant, respectively. The resulting sessions consist of around 325 reading, 325 repetitive inner speech, and 250 generative inner speech trials, divided nearly equally between the 5 words (word selection was randomised). In version two of the experiment, instead of having a single cue, four consecutive crosses were shown, spaced at 1-second intervals so that participants repeated the word 4 times. We collected 1 session of combined MEG and EEG data from a male participant, 1 MEG and 1 separate EEG session from another male participant, and 1 MEG and 10 separate EEG sessions for a third male participant. Each of these sessions contains around 173 reading, 692 repetitive inner speech, and 640 generative inner speech trials.

For preprocessing, maxfiltered MEG data was bandpass filtered between 0.1-40Hz. It was further preprocessed using bad channel and segment detection, and artefact rejection with a 64-component ICA. Although several methods were tried, no significant decoding was obtained on the MEG inner speech data. On the reading trials of version one of the experiment, we trained a 2-layer linear neural network using the entire 1-second epoch with 20-fold cross-validation. For the participant with six sessions, 30% validation accuracy was obtained, with 44% for the other participants. The chance level is 20%. Using a sliding-window LDA model the peak accuracy was observed between 300 and 400ms post-stimulus.

Having analysed the MEG data, we next investigated the generative inner speech data from the 10 EEG sessions. EEG preprocessing consisted of a 1-40Hz bandpass filter, bad channel and bad segment detection. LDA models were trained on each session using the covariance over the 1-second epoch with 5-fold cross-validation. We found above-chance validation accuracy in only 3 sessions, with an average of 25%. Next, we trained a single LDA model across these 3 sessions, achieving 33% validation accuracy, with the following modifications; 4-second epochs of the four consecutive cues were used, mean session-level evoked response was subtracted from each trial, and mean session-level covariance was also subtracted from each trial.

Discussion: We explored the potential of decoding inner speech from a new MEG and EEG dataset through three paradigms across a few participants, but with a large number of trials. Our initial findings suggest that decoding word-level inner speech is challenging, and more effective methods are needed for non-invasive data.

Significance: Our study has the potential to provide a useful and more direct platform for building decoding models for BCI applications, due to the high number of trials. Having multiple sessions also allows for testing across-session performance. The use of three different paradigms can lead to a deeper understanding of the neuroscience of inner speech. However, we highlight the difficulty of decoding inner speech.

References

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