## Speech mode classification from electrocorticography signals

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*Introduction*: Speech processing involves distributed networks across the brain with similarities observed across speech modes. However, the interplay among these modes remains elusive. In this study, we classified 5 different speech modes: speaking, listening, imagining speaking, reading and miming.

Materials, Methods and Results: Electrocorticography signals were recorded from 27 participants using one of two paradigms. In the sentence paradigm, 19 participants were asked to speak, listen and imagine speaking 20 Dutch sentences. In the navigation paradigm, 8 participants first either read or listened to a word (up, down, left, right, stop in Dutch) and then spoke, imagined speaking or mimed the word. Hilbert envelopes were computed for 7 different frequency bands from delta to high gamma. Linear discriminant analysis (LDA) classifiers were trained to classify trials (1 second epochs) of different speech modes. Statistically significant accuracies were observed at both electrode- and subject-level when concatenating the features from all channels of each subject. Figure 1a shows the distribution of the electrode-level normalized accuracy. The highest performance was achieved in the sensorimotor cortex and superior temporal gyrus. We did not observe an increased performance in the left hemisphere compared to the right hemisphere. This might be attributed to a stronger engagement of all speech modes in the language-dominant hemisphere (left hemisphere for most participants) not helping the classification due to shared patterns across modes. Figure 1b displays the confusion matrix of the speech mode classification at subject-level, averaging predictions from subject-specific models. The overall accuracy was 69.54% (chance level: 20%).

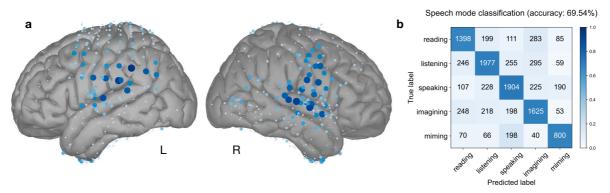


Figure 1- **Speech mode classification a** Electrode-level: The size and color of the electrodes are proportional to the normalized accuracy (see color bar in b). **b** Subject-level: The confusion matrix shows the labels predicted by subject-specific models against the true labels for all trials.

## Conclusion

High performance could be achieved using a simple linear model. The results confirm the importance of the sensorimotor cortex and superior temporal gyrus in speech processing and highlight their role in differentiating between speech modes. In a self-paced speech brain-computer interface, a speech mode classifier would prevent spurious output while the patient is engaging speech-related brain areas through activities such as reading or listening to speech.