Auditory Attention Decoding with Ear-EEG - Revisited

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Previous research has shown that we can identify the attended among several speakers from the listener's brain activity using high-density scalp electroencephalography (EEG). In future, this information could be used for neuro-steered hearing aids to selectively enhance the attended speaker. In such a scenario, instead of high-density scalp EEG, a concealed, and unobtrusive ear-EEG setup such as the cEEGrid (Figure 1A, Debener et al. 2015) would be preferred. However, initial investigations have shown that performing auditory attention decoding (AAD) with cEEGrids results in significantly decreased decoding accuracies compared to high-density scalp EEG (Mirkovic et al. 2016). Therefore, we explored different factors that may improve the decoding accuracy when using cEEGrids. For that we analyzed cEEGrid data of 36 normal hearing participants which were instructed to attend to one of two simultaneously presented speakers. To identify the attended speaker, we used a backward model in which the speech envelope is reconstructed from a linear combination of EEG channels (Crosse et al. 2016). First, we tested the effect of artefact correction on the decoding accuracy when using cEEGrids. Artefact correction was implemented with artefact subspace reconstruction (ASR). Second, we compared the decoding accuracies when choosing model parameters individually for each participant with those of mutually chosen ones. As model parameters, we examined the time lag between the speech envelope and the EEG data as well as the regularization parameter of the backward model. Our results show that artefact correction did not significantly change the decoding accuracies whereas selecting individual parameters significantly increased them (Figure 1B). Therefore, we argue that AAD models should be trained individually to account for individual differences in the neural processing of speech. We further conclude that the cEEGrid appears to be a promising candidate to decode the attended speaker in a concealed and unobtrusive manner.

A B

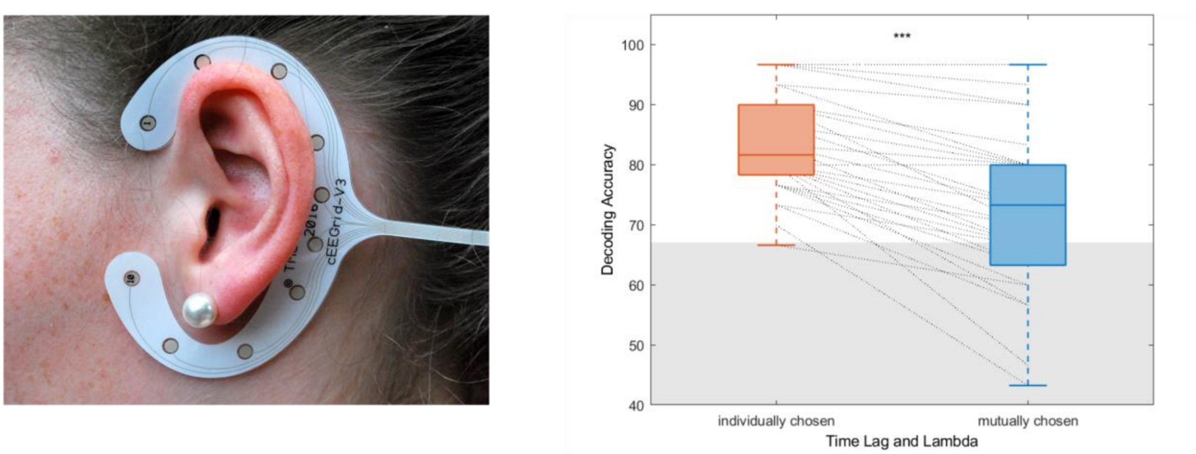

Figure 1 A. The cEEGrid. A flex-printed grid of 10 electrodes arranged in a c-shape placed around the ear. B. Individual decoding accuracies using speech envelope reconstruction. On the left (red) the optimal time lag window and regularization parameter lambda are individually chosen. On the right (blue) these parameters are the same for all participants based on the grand average decoding accuracy as a function of time lag window and lambda. Gray-shaded area marks chance level decoding accuracy (*** $p < 0.001$).

References:

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