Data-driven spatial filtering for improved measurement of cortical tracking of multiple representations of speech

Lesenfants D[1], Vanthornhout J[1], Verschueren E[1], Francart T[1]

[1]*Experimental Oto-Rhino-Laryngology, Department of Neurosciences, KU Leuven, Belgium.*

Corresponding Author:
Damien Lesenfants, Ph.D.
KU Leuven Department of Neurosciences, ExpORL
Herestraat 49 bus 721
B-3000 Leuven, Belgium
damien.lesenfants@kuleuven.be

Keywords: cortical speech tracking, EEG, auditory processing, speech representations, generalized eigenvalue decomposition

Highlights:

- Automatic channel selection for evaluating the cortical tracking of continuous natural speech
- Data-driven spatial filtering for removing non-stimulus-related activity from the EEG signals
- Improved prediction of brain responses to speech by combining acoustical and phonetic speech information in Dutch

Disclosure: The authors report no disclosures relevant to the manuscript.

ABSTRACT

Objective - Measurement of the cortical tracking of continuous natural speech from electroencephalography (EEG) recordings using a forward model is becoming an important tool in auditory neuroscience. However, it requires a manual channel selection based on visual inspection or prior knowledge to obtain a summary measure of cortical tracking. In this study, we present a method to on the one hand remove non-stimulus-related activity from the EEG signals to be predicted, and on the other hand automatically select the channels of interest. We also aim to show that the EEG prediction from phonology-related speech features is possible in Dutch. **Approach** – Eighteen participants listened to a Flemish story, while their EEG was recorded. Subject-specific and grand-average temporal responses functions were determined between the EEG activity in different frequency bands and several stimulus features: the envelope, spectrogram, phonemes, phonetic features or a combination. The temporal response functions were then used to predict EEG from the stimulus, and the predicted was compared with the recorded EEG, yielding a measure of cortical tracking of stimulus features. A spatial filter was calculated based on the generalized eigenvalue decomposition (GEVD), and the effect on EEG prediction accuracy was determined. **Main results** – A model including both low- and high-level speech representations was able to better predict the brain responses to the speech than a model only including low-level features. The inclusion of a GEVD-based spatial filter in the model increased the prediction accuracy of cortical responses to each speech feature at both single-subject (270% improvement) and group-level (310 %). **Significance** – We showed that the inclusion of acoustical and phonetic speech information and the addition of a data-driven spatial filter allow improved modelling of the relationship between the speech and its brain response and offer an automatic channel selection.

INTRODUCTION

Understanding the brain processing of speech could impact our knowledge of hearing disorders, such as sensorineural hearing loss, and allows the improvement of current hearing aids and cochlear implants. In particular, brain-based decoding of speech features could open doors to objective evaluation of a patient's speech understanding. However, while time-locked event-related brain responses to an isolated acoustic event can be extracted by averaging over several presentations, the response of the brain to continuous natural speech is complex because of the overlapping responses of consecutive auditory tokens, the integration of multiple prosodic features dynamically changing over the continuous speech and, higher-order processes such as semantic analysis.

Low-frequency temporal fluctuations of the speech stimulus, i.e. the amplitude of the speech envelope, contain crucial information such as the speech rate [1], and contribute to the perception of speech [2–5]. Therefore, the envelope has been widely used as an input of a linear model (see [6] for more details) to predict the electroencephalographic (EEG) responses to speech. This linear model is called a forward model [7,8]. The inverse, a model (or decoder) to reconstruct the speech from the associated EEG recording, is called a backward model [9–12]. Increasingly complex attributes of speech are processed hierarchically in the brain, from simple acoustic deviants in the earlier areas, to low-level acoustic information and discrete features of speech (e.g., phonemes, syllables, words) in later areas [13–15]. Interestingly, Di Liberto et al. (2015, 2017) showed that the relationship between continuous English speech and its brain response could be best described using a model based on both the low-level acoustic (i.e., the spectrogram of the speech) and high-level discrete (i.e., phonetic tokens) representations [7,16].

Both the backward and the forward model have their limitations. A backward model is a data-driven approach for optimally combining time-shifted EEG channels: a range of delays (classically between 0 and 250 ms) is first applied to each channel, then all the delayed channels are weighted in order to linearly reconstruct the speech envelope. Inversely, a forward model combines the time-shifted speech envelope in order to predict the EEG responses to the speech stimulus. While the forward model can predict responses for individual EEG channels, allowing to study the topology of speech activation across the scalp, it requires a manual channel selection based on visual inspection or prior knowledge to obtain a summary measure of cortical tracking. On the other hand, the backward model will automatically weigh each channel's relevance using the input data with the loss of spatial information, but with higher resulting reconstruction accuracies than the forward model. Moreover, the backward model requires continuous speech features, excluding its applicability to discrete speech features such as words or phonemes.

In the current study we present a method to on the one hand remove non-stimulus-related activity from the EEG signals to be predicted, and on the other hand automatically select the channels of interest. Our method makes use of the Generalized Eigenvalue Decomposition GEVD [17], which has been used to remove artefacts from the EEG [18] or cancel EEG noise

[19,20]. Following this hypothesis, we here aim to (1) show that EEG prediction based on phonemes can be replicated in Dutch, (2) improve EEG prediction to several speech representations by removing non-stimulus-related components from the EEG signals, and (3) show that the channel selection problem of the forward model can be solved in a data-driven way using GEVD.

MATERIAL AND METHODS

2.1 Participants

Eighteen Flemish-speaking volunteers (7 men; age 24 ± 2 years; two were left-handed) participated in this study. Each participant had normal hearing, verified by pure tone audiometry (thresholds lower than 20 dB HL for 125 Hz to 8000 Hz using a MADSEN Orbiter 922–2 audiometer). The study was approved by the Medical Ethics Committee UZ KU Leuven/Research (KU Leuven, Belgium) with reference S59040 and all participants provided informed consent.

2.2 Experiment

Each participant sat in an electromagnetically shielded and soundproofed room and listened to the children's story “Milan”, written and narrated in Flemish by Stijn Vranken. The stimulus was 14 minutes long and was presented binaurally at 60 dBA. It was presented through Etymotic ER-3A insert phones (Etymotic Research, Inc., IL, USA) which were electromagnetically shielded using CFL2 boxes from Perancea Ltd. (London, UK). The acoustic system was calibrated using a 2-cm^3 coupler of the artificial ear (Brüel & Kjær, type 4192, Nærum, Denmark). The experimenter sat outside the room and presented the stimuli using the APEX 3 (version 3.1) software platform developed at ExpORL (Dept. Neurosciences, KU Leuven, Belgium) [21] and an RME Multiface II sound card (RME, Haimhausen, Germany) connected to a laptop running Windows.

2.3 Recordings

EEG signals were recorded from 64 Ag/AgCl ring electrodes at a sampling frequency of 8192 Hz using a Biosemi ActiveTwo system (Amsterdam, Netherlands). The electrodes were placed over the scalp according to international 10-20 standards.

2.4 Data analysis

All analyses were done with custom-made Matlab scripts and the mTRF Toolbox [6,22].

S*peech features* – We extracted five different representations of the speech stimulus, selected according to [7]:

1. The broadband amplitude envelope (Env) was extracted as the absolute value of the (complex) Hilbert transform of the speech signal.
2. The spectrogram representation (Sgram) was obtained by first filtering the speech stimulus into 16 logarithmically-spaced speech frequency bands using zero phase Butterworth filters with 80 dB attenuation at 10 % outside the passband between 250 Hz and 8 kHz, according to Greenwood's equation [23], assuming linear spacing in the

cochlea. We then calculated the energy in each frequency band using a Hilbert transform (see Env).

3. The time-aligned sequence of phonemes (Ph) was extracted using the speech alignment component of the reading tutor [24], which allows for reading miscues (skipped, repeated, misread words), automatically segmenting each word into phonemes from the Dutch International Phonetic Alphabet (IPA) and performing forced alignment. We then converted this into a binary matrix mask representing the starting and ending time-points (i.e., a '1' from the start until the end of each presentation) for each 37 phonemes present in both the story and the matrix sentences.
4. The time-aligned binary sequence of phonetic features (Fea) was assembled using the following groups of phonemes: short vowels, long vowels, fricative consonants, nasal consonants and plosive consonants.
5. The combination of time-aligned sequence of phonetic features and the spectrogram as proposed by Di Liberto et al. (2015) [7], hereinafter named FS.

EEG signal processing – EEG artifacts were removed using a multi-channel Wiener filter algorithm [18]. We then re-referenced each EEG signal to a common-average reference before downsampling from 8192 to 1024 Hz to decrease processing time. EEG signals were bandpass filtered between 0.5-4 Hz (delta), 4-8 Hz (theta), 8-15 Hz (alpha), 15-30 Hz (beta), or 30-45 Hz (low gamma; for this frequency, we then computed the envelope of the filtered signals) using zero phase Butterworth filters with 80 dB attenuation at 10 % outside the passband. Stimulus representations and EEG signals were then downsampled to 128 Hz.

Models' performance - Stimulus representation and EEG signals were then downsampled to 128 Hz. Each 14-min dataset was split into 7 consecutive non-overlapping 2-min segments (segment 1: from second 0 to second 120; segment 2: from second 120 to second 240; etc). A 7-fold leave-one-out cross-validation was used to separate the segments in a training set and a testing set. A quantitative mapping (i.e., a model) between each speech representation and the recorded EEG (training set) was computed based on a least-squares linear regression with ridge regression and a temporal integration window of 0-400 ms. This mapping was used to predict EEG signals using each stimulus representation from the test set. The cortical speech tracking was computed as the correlation (Spearman's rank-order correlation) between the recorded and predicted EEG signals at the different electrode locations. We calculated the averaged correlation over an area by first computing each electrode's correlation and then averaging these correlations over the area.

Temporal response function (TRF) estimation – A model was trained using either single-subject specific training data (ss or ssGEVDss; see panel A and C, Fig. 1) or a group-level training dataset (gen, genGEVDss or genGEVDgen; see panel B, D and E, Fig. 1). In the second case, the grand-average model is computed by averaging the covariance matrix across subjects. Averaging data across subjects ("grand-average") has the benefit that more data is available, and subject-specific quirks are avoided, resulting in a more stable model. However, it has the downside that individual differences in brain anatomy and physiology are not taken into account. The different

models specified below, are designed to leverage the strengths of both grand average and subject-specific models.

In the xGEVDy models (x = dataset used for training the initial TRF, y = GEVD-corrected dataset used for updating the TRF; x and y can either be a subject-specific, ss, or grand-averaged, gen, dataset), we applied a spatial filter **U** on the training and testing data allowing to remove non-stimulus-related activity from the EEG signals to be predicted by optimizing the mapping between the recorded and the predicted EEG signals from the training dataset. In other word, we here make the assumption that an EEG recording $e(t) = e_s(t) + e_r(t)$ can be decomposed in EEG activity in response to the speech $\mathbf{e_s}$(t) and EEG activity unrelated to the speech $\mathbf{e_r}$(t), such that $U[e(t)] = U[e_s(t) + e_r(t)] = e_s(t)$. The optimization process in this method relies on the GEVD, which find linear combinations that maximise the SNR (based on predicted clean EEG and actual EEG). Considering an N-channel EEG recording $e(t) \in R^N$ and a N-channel EEG prediction $p(t) \in R^N$ based on a speech feature. The underlying assumption of this method is that a group of eigenvectors **V** can be extracted such that $R_E * V = R_P * V * D$, with $\mathbf{R_E}$, the covariance matrix of the EEG recording = $E\{ee^T\}$; $\mathbf{R_P}$, the covariance matrix of the EEG prediction $E\{pp^T\}$ and **D** the eigen-values . Computing this joint diagonalization of the covariance matrices allows to extract M components (with M ≤ N) associated with the M highest eigen-values such that the N-M speech-unrelated components can be filtered out the EEG recordings. The mapping **U** is then equal to the M first components of **D**, the remaining ones being set to zero.

A scheme of each model estimation is shown in Fig. 1. In ss model, TRFs were estimated using subject specific training data, then used to predict the EEG responses to the test speech data (see Fig. 1, panel A). In the gen model, the training datasets of all the participants were concatenated and used to extract the grand-average TRF of this group. Each averaged model is then convolved with data from the corresponding individual test set to predict the cortical responses to speech (see Fig. 1, panel B). In the ssGEVDss model, we first computed the subject-specific TRF as explained in the ss model. We then computed the mapping between the recorded training EEG and the predicted training EEG based on the speech stimuli of the training dataset. We then recomputed new TRFs based the newly mapped EEG training data (i.e., by applying the M-filtered-out-component eigenvectors of the GEVD on the recorded EEG training dataset related to the M-highest eigenvalues) and applied this corrected TRF to the mapped test set (see Fig. 1, panel C). The genGEVDgen relied on the same principle of the ssGEVDss except that we used the concatenated group training dataset rather than the subject-specific dataset in order to extract both the TRF and the spatial GEVD-mapping (see Fig. 1, panel D). Note that in the GEVD-based models, we can either back-project the M-selected components in the electrode space or compute correlations between components extracted from the recorded and predicted test set. In the following, to facilitate the visualization of areas related to speech activation, we will back-project the selected components in the electrode space.

 # Insert figure 1 here

Statistical analysis - A permutation test [25,26] was used to evaluate the significance level for each model (1000 repetitions, $p < .01$). The significance of change between conditions was assessed with a non-parametric Wilcoxon signed-rank test (alpha = 0.01), with Bonferroni correction for multiple comparisons.

RESULTS

In Fig 2, grand-average TRFs are shown for the different stimulus features, for a selection of fronto-temporal electrodes (F, Fc, Ft, C and T electrodes), using signal processing scheme A from Fig 1. The grand-average TRF of the model based on the envelope showed a positive activation at around 50 ms, 150 ms and 250 ms, and a negative activation at around 100ms (see Fig. 2, upper left panel). For the model based on the spectrogram (see Fig. 2, lower left panel), we observed a positive activation at early latencies and between 100 ms and 200 ms, as well as a negative activation at around 100 ms for frequencies below 600Hz. Frequencies above 600 Hz showed a positive activation at around 100 ms and a negative activation at around 50 ms. The phoneme-based model showed a positive activation for all the phonemes at 175ms (see Fig. 2, upper right panel) and a negative activation at around 125 ms. A majority of the phonemes (i.e., mainly the consonants) also showed an earlier positive activation at around 75 ms. All the different phonetic features showed a positive activation at 175 ms. Interestingly, while plosive (resp. the nasal and fricative) consonants showed a strong (resp. weak) activation at around 75 ms, the long vowels showed no earlier activation. Short vowels presented an activation at around 50 ms (see Fig. 2, lower right panel).

 # Insert figure 2 here

Fig.3 is a replication of Di Liberto et al (2015) showing the impact of the frequency bands on the tracking of the speech features. Note that we decided to include more electrodes (see Fig. 3, lower right panel) in order to take into account topographical differences observed between the different frequency bands (see below; Fig. 4). The averaged EEG prediction in the frontotemporal regions decreased with the EEG frequency band frequency using a generic model. Using the delta or theta EEG band, the models based on FS showed higher EEG predictions than the others (Wilcoxon Signed-Rank Test, WSRT, $p = 0.025$ for Ph; $p < 0.01$ for Sgram and Env), except the Fea model. The Fea-based model showed higher EEG predictions than the models based on either Env or Sgram (WSRT, using the delta band: $p = 0.02$ for Sgram, $p < 0.01$ for Env; using the theta band, $p < 0.01$ for both). The Ph-based model outperformed the Env-based model using the delta EEG band (WSRT, $p = 0.04$) and both the Env- and Sgram-models using the theta EEG band (WSRT, $p < 0.01$). The spectrogram-based model outperformed the envelope-based model using the theta EEG band (WSRT, $p = 0.01$) but not the delta EEG band. Using the alpha band, the FS model outperformed both the Env model (WSRT, $p = 0.01$) and the Sgram model (WSRT, $p < 0.01$). No difference could be observed between the different speech representations using the beta or the low-gamma EEG frequency bands, with correlations below the level of significance (at $p = 0.01$, significance is at around 0.007).

 # Insert figure 3 here

A visualization of the EEG prediction over the scalp using the different approaches is shown in Fig. 4 (with the use of the five first components for the GEVD-based methods). Note the increase of the EEG prediction accuracy with the use of GEVD-based methods, and the highlight of the areas of interest (i.e., the spots in the fronto-temporal areas as well as parieto-occipital areas). Interestingly, for the delta EEG band, we observed a temporal and occipital dominance while for the theta EEG band, we observed higher EEG prediction in the centralized frontal area. Focusing on the different ss and gen models, we observed a left delta dominance in the temporo-frontal area for the Env and Sgram model, while the other models presented a wider area of higher correlation connecting the left and right temporal areas. The ss-theta and gen-theta models showed a shared area of activation between the different speech representations; the correlation value of this area increased from Env to FS representations. Looking at the GEVD-based delta models, the left/right balance seems less pronounced and both sides show higher correlations than ss and gen models. The theta GEVD models also showed a centralized dominance better highlighted by the genGEVDgen models.

 # Insert figure 4 here

For both the genGEVDgen and the ssGEVDss models, the highest EEG prediction could be reached using only one GEVD component for either a model based on the delta or theta EEG activity (see Fig. 5, first and second rows). This suggests that stimulus-related activity could be captured by picking the EEG responses associated with the first GEVD component. Predictability decreases with the number of components until reaching a plateau at around five components. The hybrid genGEVDss model showed a maximum correlation using two (resp. four) components using EEG delta (resp. theta) activity (see Fig. 5, third row).

 # Insert figure 5 here

We investigated the addition of a GEVD approach in the different models using one (ssGEVDss and genGEVDgen), two (genGEVDss with the delta band) or four (genGEVDss with the delta band) components (see Fig. 6). In the following, we will mention the difference in the EEG prediction (i.e., the difference in the averaged Spearman correlations over the brain area shown in Fig. 3) between either the ss model and the ssGEVDss model, the ss model and the hybrid genGEVDss model, and finally the gen model and the genGEVDgen model.

Using the EEG delta band, the addition of GEVD results in an increase in correlation (WSRT, $p < 0.01$ for all comparisons) for the individual dataset (i.e., ss vs. ssGEVDss) of 0.045 (Env/FS models), 0.050 (Ph), 0.040 (Sgram) and 0.065 (Fea). The maximum Spearman correlation (0.100 ± 0.050) is reached using the ssGEVDss-Fea model. Using the EEG theta band, the addition of a GEVD approach allows increasing the correlation for the Env model by 0.025 (WSRT, $p = 0.03$). No differences could be observed using higher EEG frequencies in single-subject models (increases in correlation were below 0.005; WSRT, $p > 0.05$). Interestingly, the hybrid genGEVDss model improved the prediction of EEG responses to none of the speech features (WSRT, $p > 0.05$).

Using a genGEVDgen model provides significant increases for each model using either the delta, theta or alpha EEG bands (delta : an increase of 0.040 for Env/Sgram, 0.060 for FS, 0.065 for Ph and 0.070 for Fea; theta : an increase of 0.025 for Env/Sgram, 0.055 for FS, 0.050 for Ph and

0.040 for Fea; alpha: an increase of 0.010 for Env/Sgram, 0.020 for FS/Ph and 0.015 for Fea). No differences were observed using beta and low-gamma frequency bands (WSRT, $p > 0.05$).

 # Insert figure 6 here

DISCUSSION

The present study illustrates the potential of improving the modeling (TRF) of the brain responses to a speech stimulus by optimally combining EEG channels using a GEVD approach for predicting the brain responses to different speech representations. We showed that the addition of this linear spatial filter allows improving both EEG prediction using subject-specific and generic approaches. In addition, using GEVD avoids manual selection of channels, a limitation of standard forward models.

Consistent with Di Liberto et al (2015), we showed an improvement of the grand-average EEG prediction (gen) using a FS model as compared to the Env, Sgram and Ph speech representations. This highlights the benefit of using both low- and high-level speech representations to improve the modelling of brain responses to speech as well as the increased information captured in higher representations, as suggested by the increases of the cortical tracking to either Ph and Fea, as compared to Env and Sgram. However, we did not find any difference between Fea and FS-based models. Also, while Di Liberto et al (2015) showed an increase of the Pearson's correlation from the delta to the theta EEG band [7], we here observed a decrease of the EEG prediction with increasing EEG frequencies. This could be explained by a difference in the size of the dataset used for training and testing the decoder, or a difference in prosodic features between English and Dutch languages [27]. Indeed, while Di Liberto recorded EEG in response to an English speech during a story lasting more than one hour, our Dutch-narrated story lasted only around 14 min. They later showed that an averaged difference between the Pearson's correlations for the FS and S models (in their paper, referred to as FS-S neural index) of around 0.020 could be observed using only 10-min and a grand-average model [16] while we here observed a difference of 0.010 between the two models using 12-min of data and a grand-average model. Interestingly, this FS-S neural index increases to 0.04 using the genGEVDgen approach. Note that our electrode selection differs from Di Liberto et al (2015), who only used the six electrodes with the highest averaged correlation over the group in each temporal area. Based on the topographical differences observed between the different frequency bands, we here decided to include central, frontal, as well as temporal electrodes.

Interestingly, the temporal responses of high-level speech showed delayed activations (P1 at around 75 ms, N1 at around 125 ms and P2 at 175ms) as compared to low-level speech representations (P1 at around 50 ms, N1 at around 90 ms and P2 at 140ms). This is in agreement with literature suggesting higher-order brain areas processing phonemes, compared to the acoustic envelope. Note that the long vowels showed a decreased P1 and absent N1 with a strong P2, while other phonetic features showed both a P1 and N1 activations. This could be explained by the difficulty in precisely detecting the onset to a long vowel, resulting in smeared TRFs as compared to other phonetic groups.

The comparison of the topographic distribution of the cortical tracking of the speech over the scalp showed a temporo-occipital dominance in the delta EEG band. We also observed a central-frontal dominance of the EEG prediction to each speech representation in the theta band. Ding & Simon (2014) [28] suggested that the theta band encodes syllabic information [29–31] present in the envelope while the delta EEG band is sensitive to the envelope prosody, in particular the sentence and word rhythms [32]. We here hypothesized that the frontal area, associated with top-down control, is more involved in the encoding of syllabic features critical for speech recognition, explaining this frontal-theta dominance, while early brain areas processed the encoding of prosodic information of speech, linked with the delta cortical tracking of the speech.

We demonstrated that the brain responses to naturalistic speech could be better predicted by extracting speech-related information from the recorded EEG signals using a GEVD approach combined with standard multivariate TRF [6]. This method allows substantially increasing the EEG prediction, with a correlation of around 0.1 reached using the delta EEG band and a high-level speech representation. Moreover, we here showed that the inclusion of this linear spatial mapping allows removing the impact of manual channel selection on the performance by automatically weighting channels in a data-driven way.

ACKNOWLEDGEMENTS

The authors would like to thank Giovanni Di Liberto for his helpful advice on the analysis, as well as Hugo Van hamme and Lien Decruy for helping with the phoneme segmentation. Financial support was provided by the KU Leuven Special Research Fund under grant OT/14/119 to Tom Francart. This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program (grant agreement No 637424, ERC starting Grant to Tom Francart). Research funded by a PhD grant of the Research Foundation Flanders (FWO) for Jonas Vanthornhout (1S10416N) and Eline Verschueren (1S86118N). The authors declare that they have no conflict of interest.

References

1. Ríos-López, P., Molnar, M. T., Lizarazu, M. & Lallier, M. The role of slow speech amplitude envelope for speech processing and reading development. *Front. Psychol.* **8,** (2017).

2. Rosen, S. Temporal Information in Speech: Acoustic, Auditory and Linguistic Aspects. *Philos. Trans. R. Soc. B Biol. Sci.* **336,** 367–373 (1992).

3. Shannon, R. V., Zeng, F. G., Kamath, V., Wygonski, J. & Ekelid, M. Speech recognition with primarily temporal cues. *Science (80-.).* **270,** 303–304 (1995).

4. Giraud, A. L. & Poeppel, D. Cortical oscillations and speech processing: Emerging computational principles and operations. *Nature Neuroscience* **15,** 511–517 (2012).

5. Abrams, D. A., Nicol, T., Zecker, S. & Kraus, N. Right-Hemisphere Auditory Cortex Is Dominant for Coding Syllable Patterns in Speech. *J. Neurosci.* **28,** 3958–3965 (2008).

6. Crosse, M. J., Di Liberto, G. M., Bednar, A. & Lalor, E. C. The Multivariate Temporal Response Function (mTRF) Toolbox: A MATLAB Toolbox for Relating Neural Signals to Continuous Stimuli. *Front. Hum. Neurosci.* **10,** (2016).

7. Di Liberto, G. M., O'Sullivan, J. A. & Lalor, E. C. Low-frequency cortical entrainment to speech reflects phoneme-level processing. *Curr. Biol.* **25,** 2457–2465 (2015).

8. Di Liberto, G. M. & Lalor, E. C. Isolating neural indices of continuous speech processing at the phonetic level. *Adv. Exp. Med. Biol.* **894,** 337–345 (2016).

9. Ding, N. & Simon, J. Z. Neural coding of continuous speech in auditory cortex during monaural and dichotic listening. *J. Neurophysiol.* **107,** 78–89 (2012).

10. Ding, N. & Simon, J. Z. Adaptive Temporal Encoding Leads to a Background-Insensitive Cortical Representation of Speech. *J. Neurosci.* **33,** 5728–5735 (2013).

11. O'Sullivan, J. A. *et al.* Attentional Selection in a Cocktail Party Environment Can Be Decoded from Single-Trial EEG. *Cereb. Cortex* **25,** 1697–1706 (2015).

12. Vanthornhout, J., Decruy, L., Wouters, J., Simon, J. Z. & Francart, T. Speech Intelligibility Predicted from Neural Entrainment of the Speech Envelope. *JARO - Journal of the Association for Research in Otolaryngology* 1–11 (2018). doi:10.1007/s10162-018-0654-z

13. Okada, K. *et al.* Hierarchical organization of human auditory cortex: Evidence from acoustic invariance in the response to intelligible speech. *Cereb. Cortex* **20,** 2486–2495 (2010).

14. Peelle, J. E., Johnsrude, I. S. & Davis, M. H. Hierarchical processing for speech in human auditory cortex and beyond. *Front. Hum. Neurosci.* **20,** 2486–2495 (2010).

15. Chang, E. F. *et al.* Categorical speech representation in human superior temporal gyrus. *Nat. Neurosci.* **13,** 1428–1432 (2010).

16. Di Liberto, G. M. & Lalor, E. C. Indexing cortical entrainment to natural speech at the phonemic level: Methodological considerations for applied research. *Hear. Res.* **348,** 70–77

(2017).

17. Hassani, A., Bertrand, A. & Moonen, M. GEVD-Based Low-Rank Approximation for Distributed Adaptive Node-Specific Signal Estimation in Wireless Sensor Networks. *IEEE Trans. Signal Process.* **64,** 2557–2572 (2016).

18. Somers, B., Francart, T. & Bertrand, A. A generic EEG artifact removal algorithm based on the multi-channel Wiener filter. *J. Neural Eng.* **15,** 36007 (2018).

19. Serizel, R., Moonen, M., Van Dijk, B. & Wouters, J. Low-rank Approximation Based Multichannel Wiener Filter Algorithms for Noise Reduction with Application in Cochlear Implants. *IEEE/ACM Trans. Audio, Speech, Lang. Process.* **22,** 785–799 (2014).

20. Hajipour Sardouie, S., Shamsollahi, M. B., Albera, L. & Merlet, I. Interictal EEG noise cancellation: GEVD and DSS based approaches versus ICA and DCCA based methods. *IRBM* **36,** 20–32 (2015).

21. Francart, T., van Wieringen, A. & Wouters, J. APEX 3: a multi-purpose test platform for auditory psychophysical experiments. *J. Neurosci. Methods* **172,** 283–293 (2008).

22. Gonçalves, N. R., Whelan, R., Foxe, J. J. & Lalor, E. C. Towards obtaining spatiotemporally precise responses to continuous sensory stimuli in humans: A general linear modeling approach to EEG. *Neuroimage* **97,** 196–205 (2014).

23. Greenwood, D. D. Auditory Masking and the Critical Band. *J. Acoust. Soc. Am.* **33,** 484–502 (1961).

24. Duchateau, J. *et al.* Developing a reading tutor: Design and evaluation of dedicated speech recognition and synthesis modules. *Speech Commun.* **51,** 985–994 (2009).

25. Noirhomme, Q. *et al.* Biased binomial assessment of cross-validated estimation of classification accuracies illustrated in diagnosis predictions. *NeuroImage Clin.* **4,** (2014).

26. Nichols, T. E. & Holmes, A. P. Nonparametric permutation tests for functional neuroimaging: A primer with examples. *Hum. Brain Mapp.* **15,** 1–25 (2002).

27. Moskvina, A. in 86–91 (Springer, Cham, 2013). doi:10.1007/978-3-319-01931-4_12

28. Ding, N. & Simon, J. Z. Cortical entrainment to continuous speech: functional roles and interpretations. *Front. Hum. Neurosci.* **8,** 311 (2014).

29. Drullman, R., Festen, J. M. & Plomp, R. Effect of temporal envelope smearing on speech reception. *J. Acoust. Soc. Am.* **95,** 1053–64 (1994).

30. Drullman, R., Festen, J. M. & Plomp, R. Effect of reducing slow temporal modulations on speech reception. *J. Acoust. Soc. Am.* **95,** 2670–80 (1994).

31. Elliott, T. M. & Theunissen, F. E. The Modulation Transfer Function for Speech Intelligibility. *PLoS Comput. Biol.* **5,** e1000302 (2009).

32. Goswami, U. & Leong, V. Speech rhythm and temporal structure: Converging perspectives? *Lab. Phonol.* **4,** 67–92 (2013).

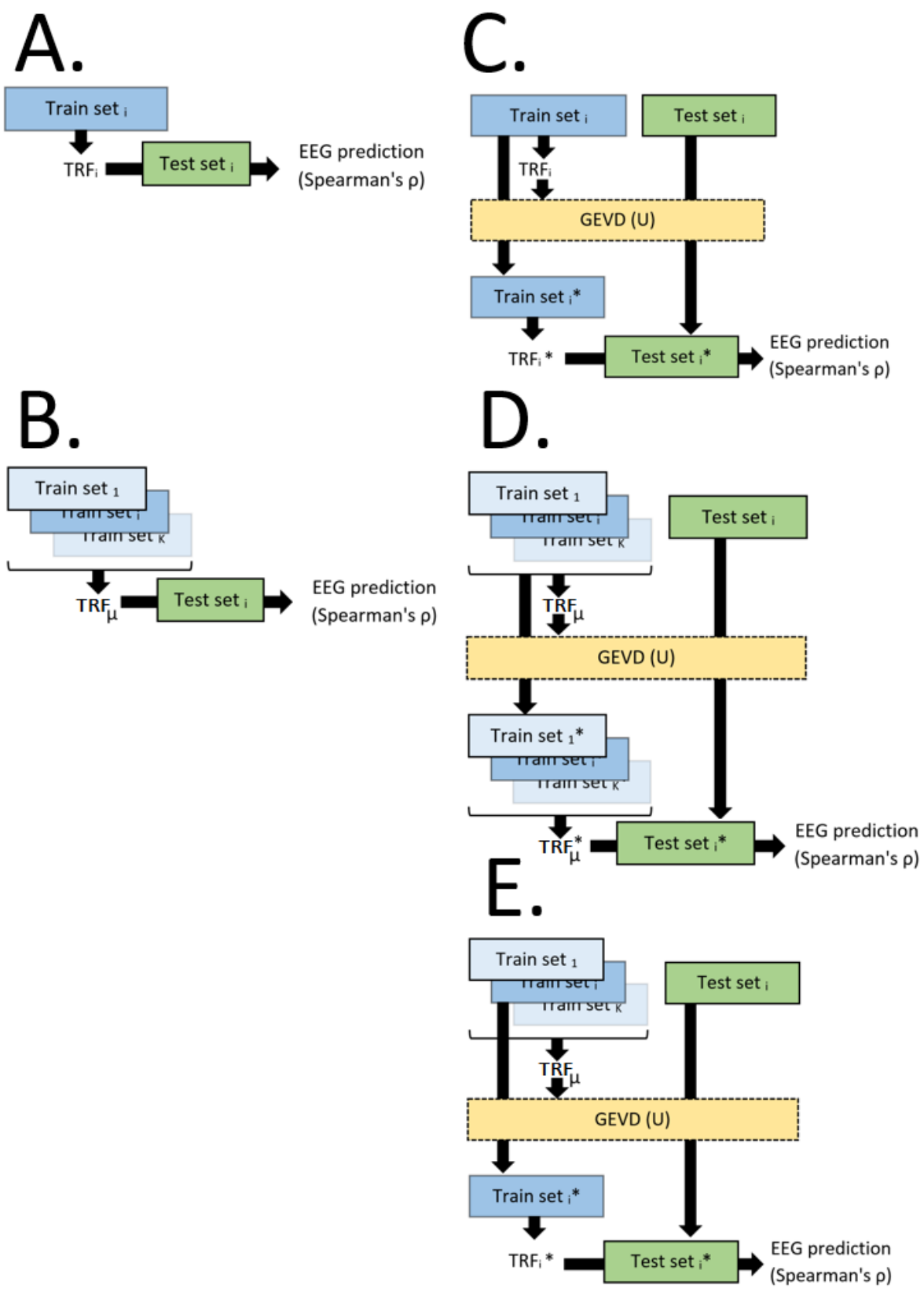

Fig. 1 - Illustration of the different algorithms evaluated in the current manuscript. A quantitative mapping (TRF) computed between the training speech and recorded EEG was used

to predict EEG signals using each stimulus representation from the test set (i. The cortical speech tracking was computed as the Spearman's correlation between the recorded and predicted EEG signals at the different electrode locations. A model was trained using either single-subject specific training dataset (TRF_i; see ss and ssGEVDss models in panels A and C respectively) or group-level training dataset (μTRF; see gen, genGEVDss and genGEVDgen models in panels B, D and E respectively). In ssGEVDss, genGEVDss and genGEVDgen models (see panels C, D and E), a spatial filter U was extracted from the training dataset to remove non-stimulus-related activity from the EEG signals by optimally mapping the recorded and predicted EEG signals. This spatial filter was finally applied to both training and testing dataset prior to rebuilding the TRF and computing the model's performance. A set (or dataset) refers to the EEG data plus the corresponding stimulus features.

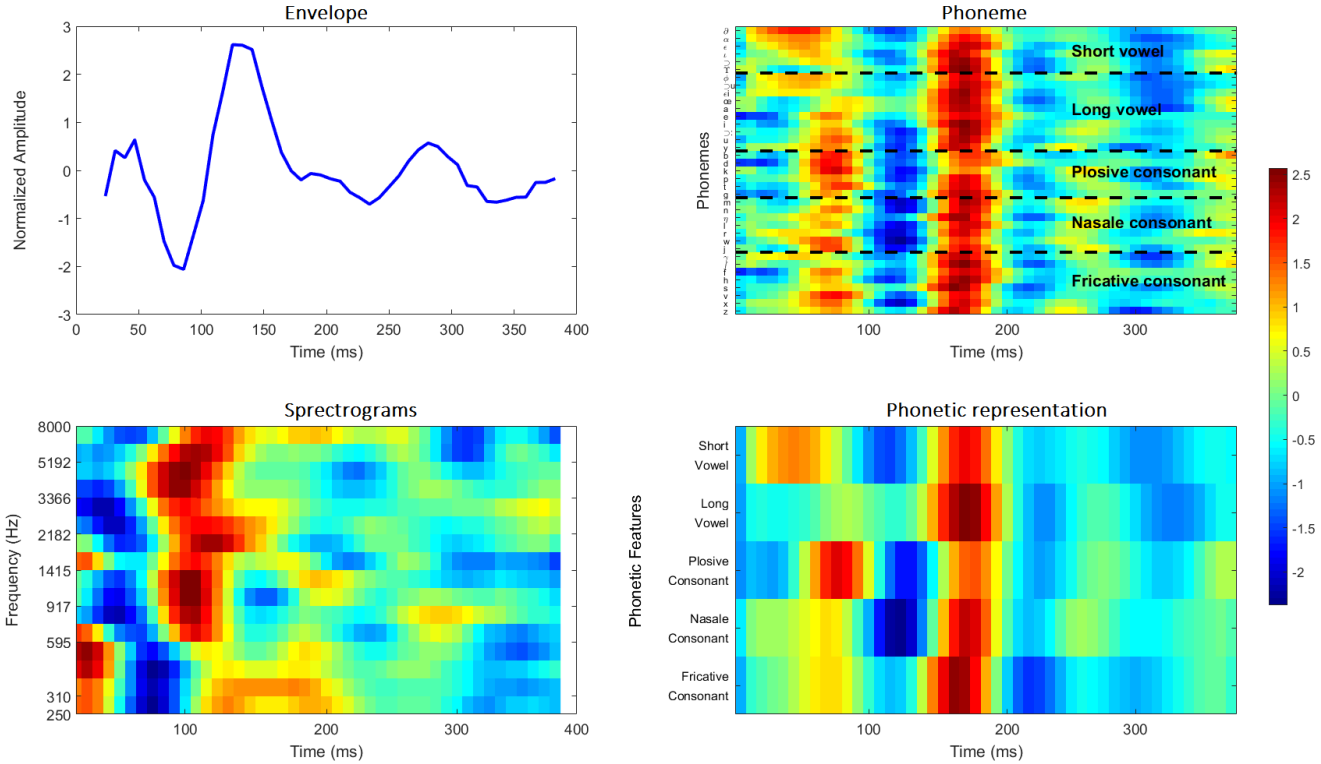

Fig. 2 – Grand-average Temporal Response Function for a model based on the envelope, the spectrogram, phoneme and phonetic representation averaged over cross-validation folds and fronto-temporal electrodes.

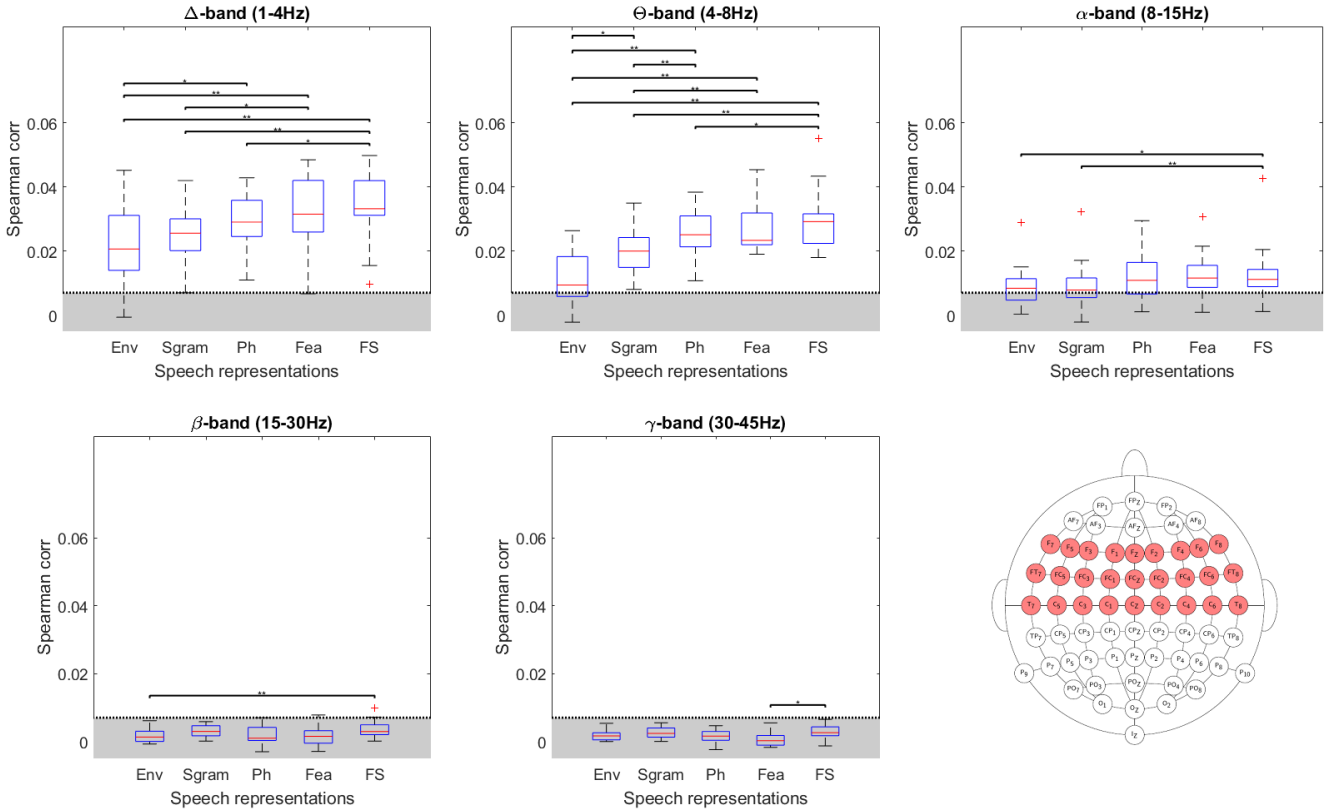

Fig. 3 - Grand-average EEG prediction correlation (Spearman's ρ) for each speech model using delta, theta, alpha, beta, and low-gamma EEG frequencies (signal processing scheme B). In grey, the level of significance at p = 0.01. Note the improved EEG prediction using lower frequency bands.

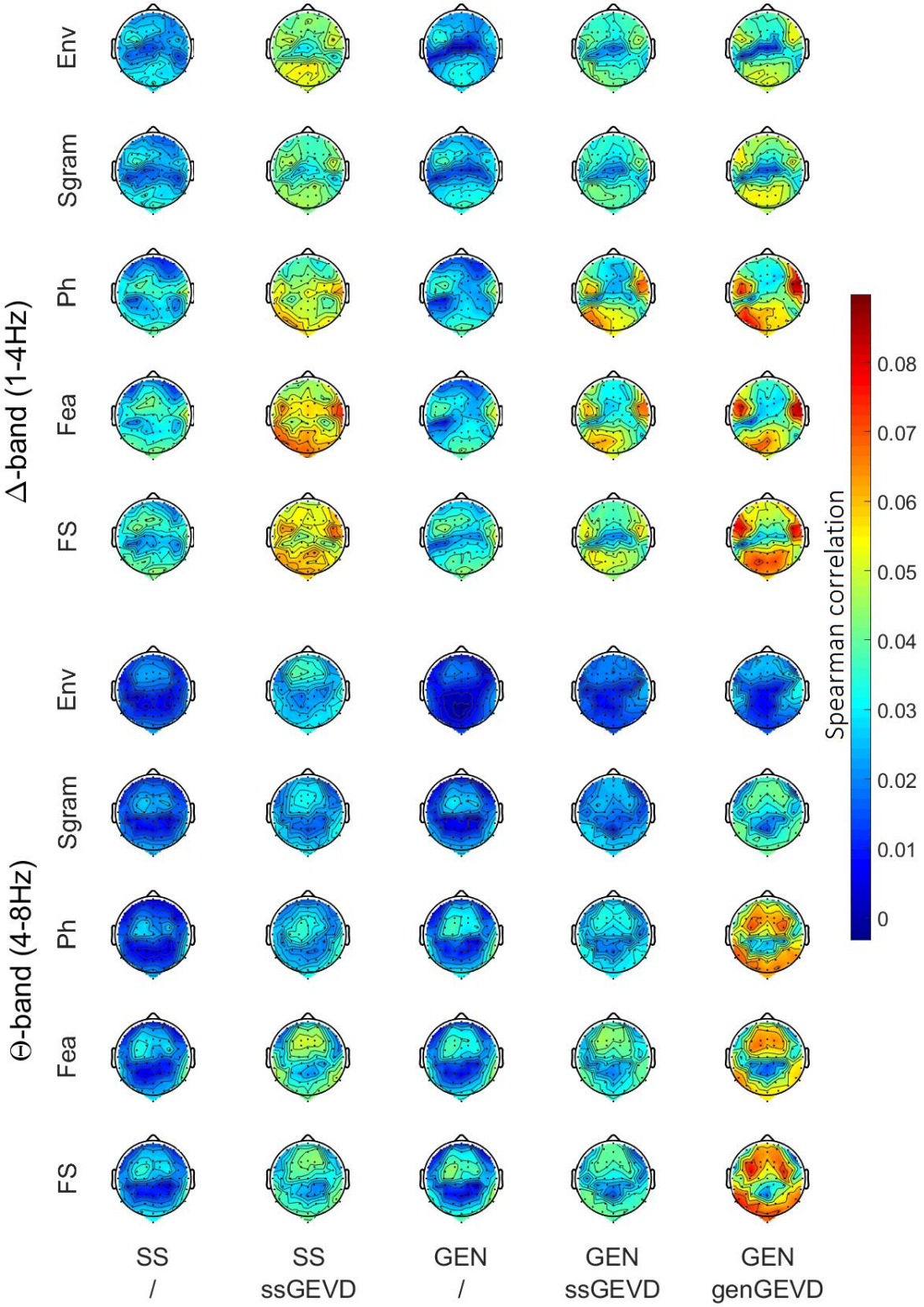

Fig. 4 - Spatial distribution of the cortical tracking of each speech representation over the scalp (64 electrodes) using subject-specific (ss) or group (gen) data, as well as a GEVD approach (using the five first components). Note the temporal-occipital dominance of the cortical tracking using

delta EEG frequency band, while the theta dominance seems more centralized in the frontal-temporal areas.

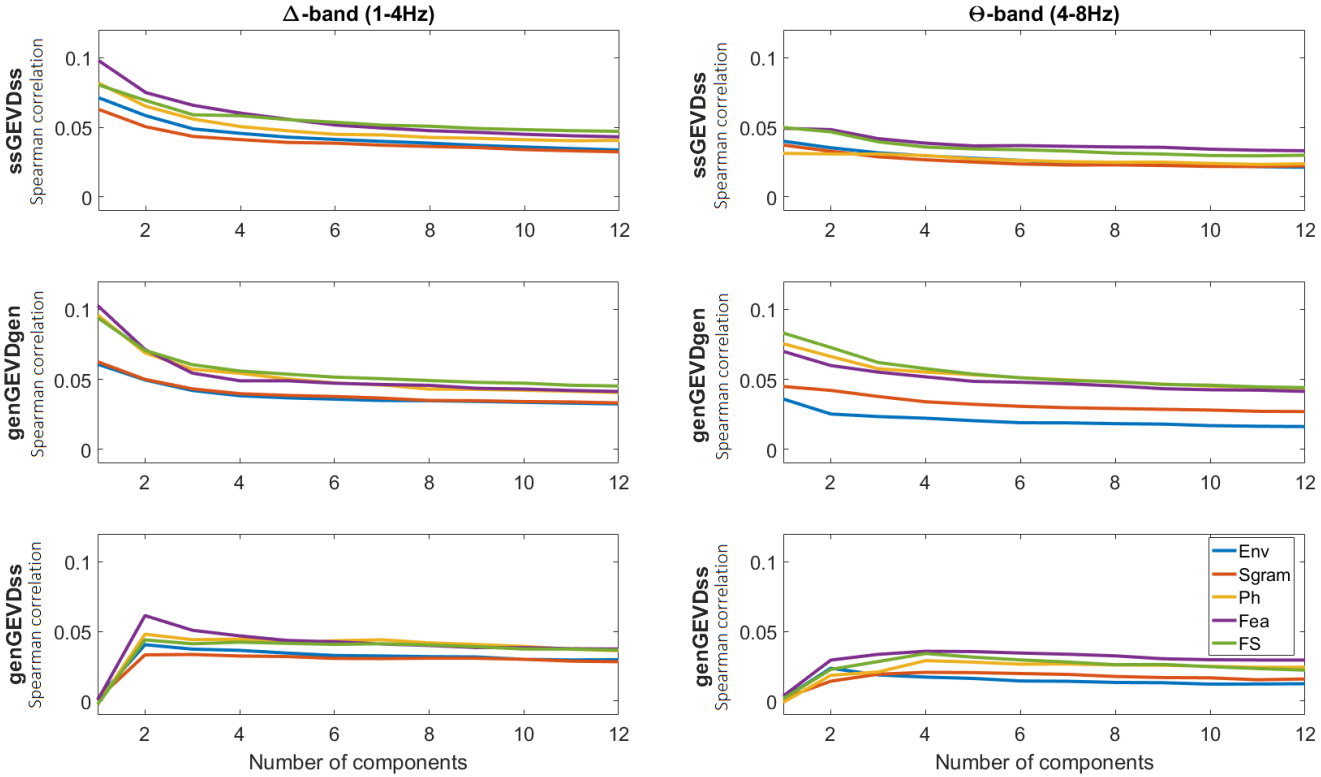

Fig. 5 - Effect of number of components included in the GEVD-based modeling of the brain responses to the speech. Note the decrease of the averaged Spearman correlation with increasing number of components, except for the hybrid genGEVDss approach.

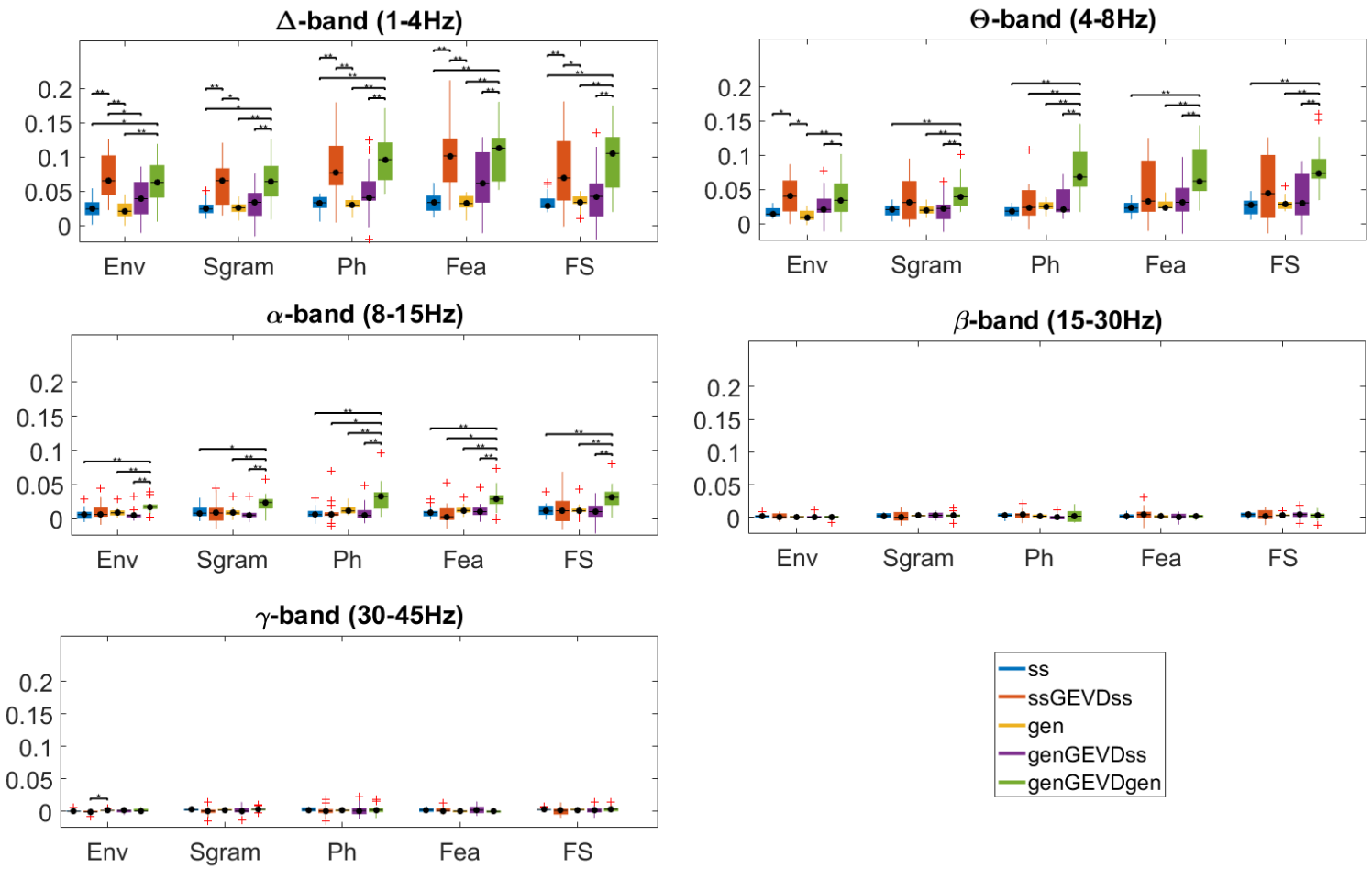

Fig. 6 - Impact of the inclusion of a GEVD mapping approach on the averaged performance using different EEG frequency bands (delta, theta, alpha, beta, and low gamma) and speech representations (Env, Sgram, Ph, Fea, and FS) as an input to the linear model. Note the improved model using a GEVD approach for both single-subject and group-level decoder.