The interplay of top-down focal attention and the cortical tracking of speech

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ABSTRACT

Many active neuroimaging paradigms rely on the assumption that the participant sustains attention to a task. However, in practice, there will be momentary distractions, potentially influencing the results. We investigated the effect of focal attention, objectively quantified using a measure of brain signal entropy, on cortical tracking of the speech envelope. The latter is a measure of neural processing of naturalistic speech. We let participants listen to 44 min of natural speech, while their electroencephalogram was recorded, and quantified both entropy and cortical envelope tracking. Focal attention affected the later brain responses to speech, between 100 and 300 ms latency. By only taking into account periods with higher attention, the measured cortical speech tracking improved by 47%. This illustrates the impact of the participant's active engagement in the modeling of the brain-speech response and the importance of accounting for it. Our results suggests a cortico-cortical loop that initiates during the early-stages of the auditory processing, then propagates through the parieto-occipital and frontal areas, and finally impacts the later-latency auditory processes in a top-down fashion. The proposed framework could be transposed to other active electrophysiological paradigms (visual, somatosensory, etc) and help to control the impact of participants' engagement on the results.

INTRODUCTION

Modelling neural processing of auditory stimuli is an important theme in audiology and neuroscience. While many studies rely on the use of simple, repetitive and non-realistic time-locked stimuli (e.g., clicks), there has been increased focus on the use of naturalistic speech (e.g., see [1]) as the ecological validity is greater [2]: the brain may process natural speech differently from artificial repeated stimuli. The interaction between a feature (e.g., the envelope or the phonetic representation) of the presented speech and the recorded brain signals can be modelled using approach like the temporal response function (TRF [3]) based on linear regression. This linear transformation can then be used to either reconstruct the speech feature from the brain signals (using a so-called backward model) or predict the brain response over the scalp to a specific speech segment (using a so-called forward model). The correlation between the reconstructed/predicted artificial time-course and the actual values is then a measure of cortical speech tracking. Measures of cortical speech tracking quantify speech processing within the brain opening doors to, for example, an objective measure of an individual speech understanding [4–7] or auditory attention decoding in a cocktail party scenario [8–10].

For the tracking of different speech features, the cortical activity in the delta (1 – 4 Hz) and theta (4 – 8 Hz) frequency bands has been found to be most important [4,5]. This could be partially explained by the matching of the time scale of such brain oscillations with the syllable (4 – 8 Hz), word and phrase (1 – 4 Hz) rates, suggesting a real-time transformation of the continuous acoustic information reaching the auditory cortex in those different linguistic representations [11–15]. On the contrary, the alpha and higher frequency bands show weak and noisy responses presumably reflecting the weaker phase locking of EEG neural data to the speech envelope at higher frequencies [6].

While their impact on speech decoding seems small or even absent, the alpha and beta EEG oscillations play a key role in the modulation of attention [16,17]. Although the term “attention” is widely used in several fields, delimiting and defining this board term was a tricky problem faced by scientists [18,19]. Attention is defined by the process of volitionally concentrating on a specific information while disregarding other information [20]. There are four main types of attention [21,22] that we use in our daily lives: selective attention (i.e., ability to focus on one out of several stimuli), divided attention (i.e., ability to maintain focus on more than one stimulus at a time), sustained attention (i.e., ability to actively focus on a specific stimulus over an elongated period of time), and alternating attention (i.e., the ability to switch back and forth between tasks).

Several studies have investigated the effect of attention on auditory brainstem responses (ABRs), auditory steady-state responses (ASSR [23]), or late auditory evoked potentials, mainly using an auditory attention protocol relying on the participant’s selective attention. While the results are inconclusive [24–28], the attention seems to have no impact on the ABR since they are present even during sleep. At the cortical level, Linden et al. (1987) did not find an effect of selective attention on the 40 Hz-ASSR [29]. The impact of attention on lower ASSR frequencies is controversial: Müller et al. (2009) found some differences on the 20 Hz-ASSR [30] while Skosnik et al. (2007) did not [31]. Studies using late auditory evoked potentials have shown that responses

in cortical regions are modulated by attention [32–36]. In particular, many researchers investigated the effect of selective attention in auditory attention decoding studies and showed attentional modulation of speech tracking. However, the latency of the attentional modulation effect has been controversial: Ding and Simon (2012a, 2012b) showed an early attentional gain effect at a time lag around 100 ms [11,37], while others reported a longer-latency attentional effect above 150-ms time lag [14,38,39]. Following this research, we could hypothesize that only later responses with a cortical origin are modulated by attention but, while these studies focused on selective attention, little is known about the impact of changes over time in the level of sustained attention in the modelling of the cortical speech tracking.

Attention is a conscious, active process and has a robust top-down effect on processes along most of the cortical auditory pathway [33,40]. A network of frontal and parietal cortical areas is involved in the selection required for top-down attention [41–45]. In the following, the level of sustained attention during a task will be referred to as "focal attention" or "attention". Understanding and accounting for the user's attention is important in active paradigms and could help understanding discrepancies observed in the cortical tracking, such as the fluctuation of cortical tracking over time. However, it is difficult to behaviorally measure the level of focal attention for each participant since it would extend experiment time and require an efficient behavioral scale. Objective measures of focal attention using evoked brain responses under different attentional levels, computed as the correlation between the brain response at a specific frequency and behaviorally measured task error rate [46], or energy changes of beta [47] or alpha [17] EEG rhythms have been proposed. Lesenfants et al. (2018) showed that focal attention could be tracked using spectral entropy measures [48,49]. This measure could help distinguish active from passive periods during an active task in both healthy volunteers and participants with locked-in syndrome (i.e., fully conscious but suffering from brain injuries leading to full or partial tetraplegia).

We here aim to study the impact of sustained attention, objectively evaluated using brain entropy measures, on the modelling of cortical speech tracking and evaluate the potential of correcting for attention in a standard speech paradigm.

METHODS

Participants

In this study, we included nineteen normal hearing volunteers (1 male; age 22 ± 4 years; two were left-handed). All the participants were Flemish-speakers and their hearing were evaluated by pure tone audiometry (thresholds lower than 20 dB HL for 125 Hz to 8000 Hz using a MADSEN Orbiter 922–2 audiometer). The experiment was approved by the Medical Ethics Committee UZ KU Leuven/Research (KU Leuven, Belgium) with reference S59040 and all participants provided informed consent. All methods were carried out in accordance with relevant guidelines and regulations.

Experiment

Each participant was comfortably sat and wore Etymotic ER-3A insert phones (Etymotic Research, Inc., IL, USA), protected from electromagnetic fields with CFL2 boxes from Perancea Ltd. (London, UK). The room, in which the experiment took place, was electromagnetically shielded and soundproofed. Prior the experiment, we calibrated the acoustic system using a 2-cm^3 coupler of the artificial ear (Brüel & Kjær, type 4192, Nærum, Denmark). They were instructed to listen attentively to the children's story "The Little Mermaid", written and narrated in Flemish by Katrien Devos, and regular questions were asked about the contents of the story, to ensure compliance. The stimulus was 44 minutes long and was presented binaurally at 60 dBA using the APEX 3 (version 3.1) software platform (ExpORL, Dept. Neurosciences, KU Leuven, Belgium; see [50]) and an RME Multiface II sound card (RME, Haimhausen, Germany). During the presentation of the speech stimulus, the experimenter sat outside the room and visually inspected the EEG signals in real-time.

Recordings

64-channel EEG was recorded at a sampling rate of 8192 Hz using Ag/AgCl ring electrodes and a Biosemi ActiveTwo system (Amsterdam, Netherlands). The electrodes fixed to the cap were positioned to the International 10-20 method of electrode placement.

Data analysis

All analyses were done with custom-made Matlab scripts and the mTRF Toolbox [3,51].

Data preprocessing - EEG artifacts were removed using a multi-channel Wiener filter algorithm [52]. We then re-referenced each EEG signal to a common average reference before downsampling from 8192 to 1024 Hz to decrease processing time. The speech envelope was extracted using a gammatone filterbank (24 channels spaced by 1 equivalent rectangular bandwidth, with center-frequencies from 50 Hz until 5000 Hz) followed by a power law [53], and then downsampled to 1024 Hz and band-pass filtered (see below).

Attentional level – Entropy measures [49] were extracted from pre-processed EEG signals using power spectral estimation based on Multitapers Spectral Analysis (7 tapers). This measure reflects signal regularity or predictability; usually, a high value corresponds to low regularity or predictability (e.g., uniform distribution of the power spectrum), while a low value corresponds to high regularity (e.g., concentration of the activity in a single band). Importantly, while this measure is classically computed in the frequency band from 0.5 to 32 Hz, we here decided to reduce this band to 8.5-32 Hz, with a 0.5 Hz step, so the influence of the speech processing, investigated in the delta and theta EEG bands, on this measure of attention is limited.

Cortical speech tracking - Pre-processed EEG signals and speech envelope were bandpass filtered between 0.5-8 Hz using zero phase Butterworth filters with 80 dB attenuation at 10 % outside the passband. Stimulus representations and EEG signals were then downsampled to 256 Hz. Each 44-min dataset was split into consecutive non-overlapping 1-minute periods and the averaged entropy values were computed for each segment in the frontal and parieto-

occipital areas. Cross-validation was used to separate the segments in a training set and a testing set (see Figure 1). Forty minutes were used for training and the remaining 4 min for testing. Both the training and the testing sets were then separated in two: the first part, hereinafter named "high SpE" contains the epochs with the 50% highest entropy values while the second, hereinafter named "low SpE" contains the epochs with the 50% lowest entropy values. This results in a "high SpE training" (20 1-min epochs), "low SpE training" (20 1-min epochs), "high SpE testing" (two 1-min epochs) and "low SpE testing" (two 1-min epochs) dataset. For each subject, we first normalized both the speech envelope and each EEG signal. A subject-specific backward model between the speech envelope and the EEG was computed using ridge regression with a time-lag window of 0-400 ms using either the low SpE training or the high SpE training dataset. This model was used to reconstruct the speech envelope using the EEG signals from the test set. The cortical speech tracking was computed as the correlation (Spearman's rank-order correlation) between the actual and reconstructed speech envelope.

#Insert Figure 1 here

Impact of attention on the cortical tracking – Prior to evaluating the impact of attention on the cortical speech tracking, we need to pick electrodes involved in the attentional process for calculation of spectral entropy. We use a data-driven method to select electrodes by applying a linear model using ridge regression with a time-lag window of -150 to 650 ms between the cortical speech tracking and the spectral entropy values extracted at each channel location. Suppose a cortical speech tracking over time c(t) and the spectral entropy measure at each channel location SpE(t,n). We then find a linear mapping "g" allowing to understand how the changes in SpE at the different electrodes induce changes in c(t). This could be expressed by:

$$c(t) = \sum_{n} \sum_{\tau} SpE(t+\tau).\, g(\tau, n)$$

with an integration of spectral entropy values over a range of time lags τ (here, from -150 to 650 ms).

Since attention regroups a fronto-parieto-occipital network [41–45], we can hypothesize that mainly electrodes over the frontal (F), parieto-occipital (PO) and occipital (O) areas will be involved in this mapping.

Statistics - A permutation test [54,55] was used to evaluate the significance level for each model (1000 repetitions, $p < 0.01$). The significance of change between conditions was assessed with a non-parametric Wilcoxon signed-rank test (WSRT; $\alpha = 0.01$), with Bonferroni correction for multiple comparisons.

RESULTS

When investigating the relation between spectral entropy and cortical speech tracking, a parieto-occipital activation (see Figure 2, red circles) could be observed at around 150 ms, followed by a frontal activation at around 300 ms (see Figure 2, green circles). This suggests that the fluctuation of the spectral entropy over these areas induces changes in the cortical tracking of the speech envelope over time. This is in accordance with the literature suggesting a network of frontal and parietal cortical areas is involved in the selection required for top-down attention. In the following, the averaged spectral entropy over the frontal and the parieto-occipital electrodes will be used as a marker of the level of attention in each period.

#Insert Figure 2 here

When considering stimulus reconstruction accuracy, both the data used for training the decoder and for testing the decoder can play a role. We first investigated the effect of training data. Using only periods of higher attention to train the decoder, the median cortical tracking across subjects reached a correlation of 0.22 ± 0.07 (median ± iqr) at group-level (see Figure 3, left panel, in red). Using only periods of lower attention to train the decoder, the median cortical tracking was 0.15 ± 0.08. At the individual level, 14/19 individuals presented a higher cortical tracking using periods with high attentional level (WSRT, for each of these 14 individuals $p<0.05$) than periods with low attentional level. Two out of the 19 subjects showed no difference. Interestingly, comparing between training the decoder on the whole training set versus only the high-attention segments, 12/19 participants achieved higher cortical tracking using only periods of higher attention (WSRT, for each of these 12 individuals p were below 0.05), even though there is only half as much data in the high-attention part. Two out of the 19 subjects showed no difference. This suggests we could decrease the session time by tracking the participant's attention during the recording (e.g., by comparing in real-time the level of attention in every new minute of recording, while the first minute is set as a baseline under the assumption that the participant is attentive on the task straight at the beginning of the experiment).

#Insert Figure 3 here

Next, we investigated the effect of testing data. Using the same decoder, we did not observe any difference in the cortical tracking computed using the reconstructed envelope in either testing periods of higher vs lower attention (see Figure 4; the left and right panel show individual performance using a decoder trained on periods with, respectively, higher and lower attention only).

#Insert Figure 4 here

We then compared models built using periods of either low or high level of attention. For the early latencies (below 100 ms), no delay could be observed between the temporal response function built using either high or low attention periods. For latencies between 100 and 300

ms, a delay could be observed in the left and right frontal and fronto-central channel locations (see Figure 5, electrodes F and FC). This delay is around 8 ms (mainly at FC1, FC3 and FC5 channels) at 100-ms latencies and increased to 16 ms for latencies between 200 and 300 ms. For later latencies (i.e., above 300 ms), no delay could be observed.

#Insert Figure 5 here

DISCUSSION

In this study, we showed that we could improve the modelling of cortical speech tracking using only data from periods with high attention, measured using spectral entropy. Three quarters of the participants showed an improved cortical speech tracking using only the 20 minutes of data with more attention. Interestingly, they also presented improved performance compared to the use of the complete 40 minutes training dataset. This illustrates the impact of attention in an active EEG paradigm in which the participant's attention could be decreased or shifted to distractors.

We first evaluated the impact of the spectral entropy on cortical speech tracking and showed that the modulation of the attention in the frontal and parieto-occipital areas impacts the cortical tracking of the speech envelope. This is consistent with many studies that evaluated the interaction of brain networks in the processing of attention and showed increased activity in the frontal and parieto-occipital cortex, as well as in the thalamus, cingulate cortex and temporal parietal junction [56–58].

While focusing on periods with higher attention allows improving the modelling of the brain-speech interaction, no clear impact of the testing dataset could be observed in our study, i.e., applying the same decoder on periods of higher or lower attention of the testing dataset did not produce significant differences. This could be explained by an insufficient amount of testing data to find significant effects. We could also hypothesize that, once the model is corrected for attention by accounting for this top-down process, it could then decrease the impact of attention by focusing on the neural sources related to speech only. Note that, while the differences are not significant, there was a trend of improvement of lower correlations (see Fig. 4, left panel, the three leftmost points) using only testing periods of higher attention. This suggests that, while the selection of training periods improves all the cortical speech tracking, the selection of testing periods corrects for lower performance only.

The evaluation of the temporal response functions resulting from the modelling of the brain-speech interaction using periods with either low or high attentional level highlights the importance of later-latencies brain responses, appearing between 100 and 350 ms. We found slightly delayed brain responses to speech in this latency range over the frontal and fronto-central areas. This suggests a top-down frontal attention mechanism during task processing similar to the P3a event-related brain potential [59]. It is important to note that the attention mechanism results from a top-down process [33], thus we expect this to mainly affect brain responses with a cortical origin (i.e., the later auditory evoked potentials). In figure 6, we

schematically illustrated how information could be transferred between the different brain areas. The presentation of the speech to the participant's ear induces cortical tracking in the early auditory areas (see P50 and N100 peaks). As soon as the speech reaches the first auditory layers, we hypothesize that a signal is sent to the visual and associative areas (see Figure 2), which allows them to reinforce the speech tracking in the later auditory areas (see brain response after 100 ms) using a top-down connection. The delay between the emission of this signal and the effect on the speech processing could potentially be linked to the time to close the auditory-associative-auditory loop. We do not have a clear explanation why an increase in attention induced a delay in the brain responses (see peaks in Figure 5). It has been shown that peaks from the temporal response function could be delayed when decreasing the level of speech understanding [11,60]. Moreover, a delayed brain response to auditory stimuli has been observed in patients with decreased level of consciousness as compared to healthy volunteers [61,62]. This would suggest that a decrease in the attentional level would produce a positive delay in the brain responses to speech, which was not the case (i.e., the peaks in the model of the "high attention" condition are delayed as compared to the peaks in the "low attention" condition). Ones could argue that attention, speech understanding and consciousness are parallel processes.

#Insert Figure 6 here

Our method of measuring spectral entropy and using the results to control for attention has a number of important applications. Implementing the method in real-time could allow the experimenter to act directly on the participant with the benefit of shorter experimental time with an equivalent data quality. Indeed, we here show that 20-minutes of data with high attentional level provides better performance than the standard "use-it-all" 40-minutes training dataset. This spectral entropy-based index of the participant's attention could be used in many active attentionally-driven paradigms and correct the recorded data so the modulation of attention does not directly impact the extracted cortical measures. This is particularly relevant in neuroscience experiments in which data collection is getting longer and longer with the cost of participant's tiredness and fluctuation of attention over time. Our results highlight the importance of controlling for attention: a large effect was found, even though the task (listening to a story) was engaging and pleasant, the participants received clear instructions to sustain attention, and compliance was monitored by asking questions.

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AUTHOR CONTRIBUTIONS

DL analyzed and interpreted the data, wrote the manuscript. TF designed the protocol, contributed to the writing and revised the manuscript.

COMPETING INTERESTS

The author(s) declare no competing interests.

AVAILABILITY OF MATERIALS AND DATA

Due to ethical concerns, supporting data cannot be made openly available. Further information about the data and conditions for access are available via Professor Tom Francart (see corresponding author).

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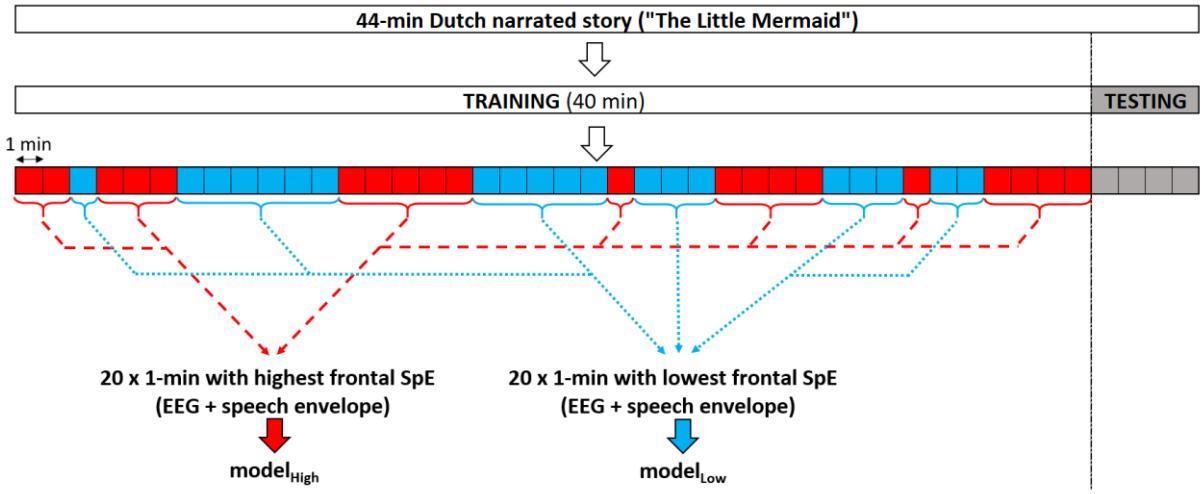

Figure 1 – Segmentation of the dataset. In red/blue, example 1-min epochs with a high/low averaged attentional level, computed using spectral entropy values in the frontal and parieto-occipital areas are shown.

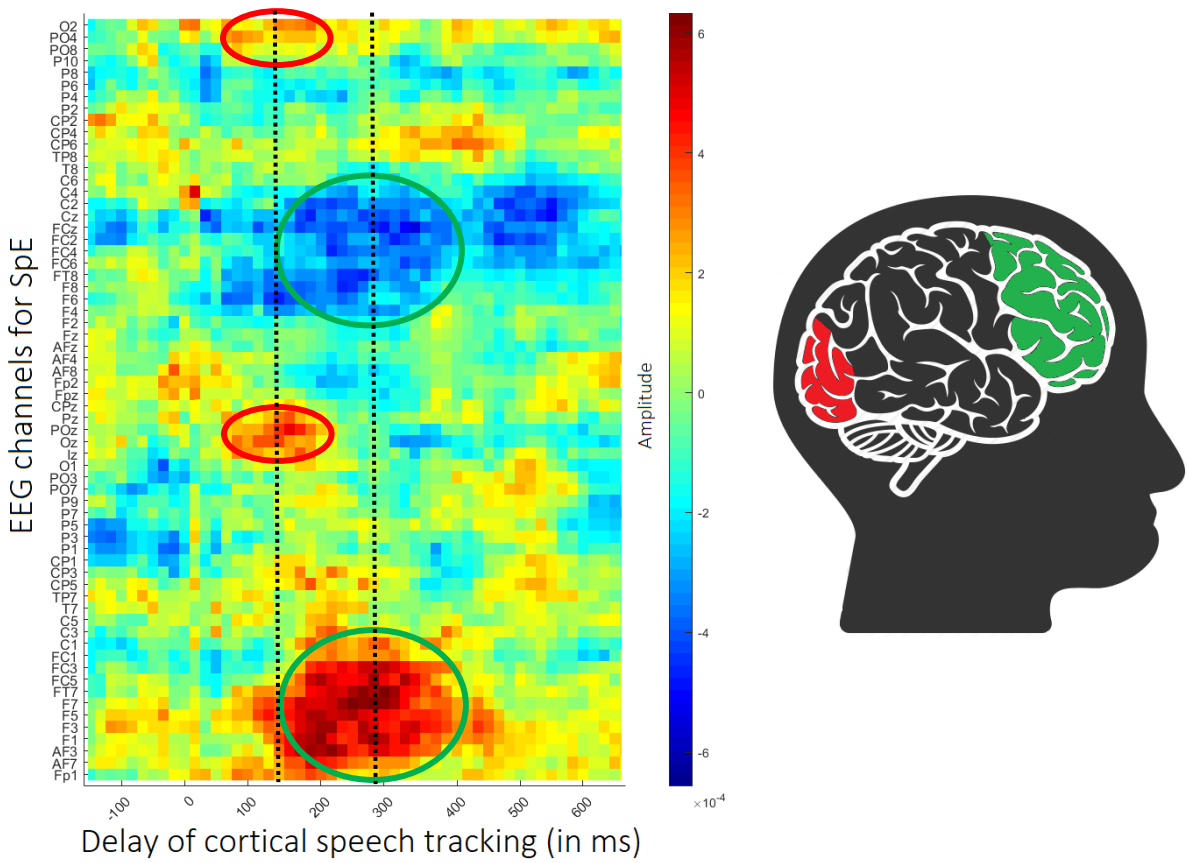

Figure 2 – Impact of the spectral entropy (8.5-32Hz) on the cortical tracking to the speech (0.5-8Hz). Note the activation of the occipital area at around 150 ms followed by an activation in the frontal area at around 300ms.

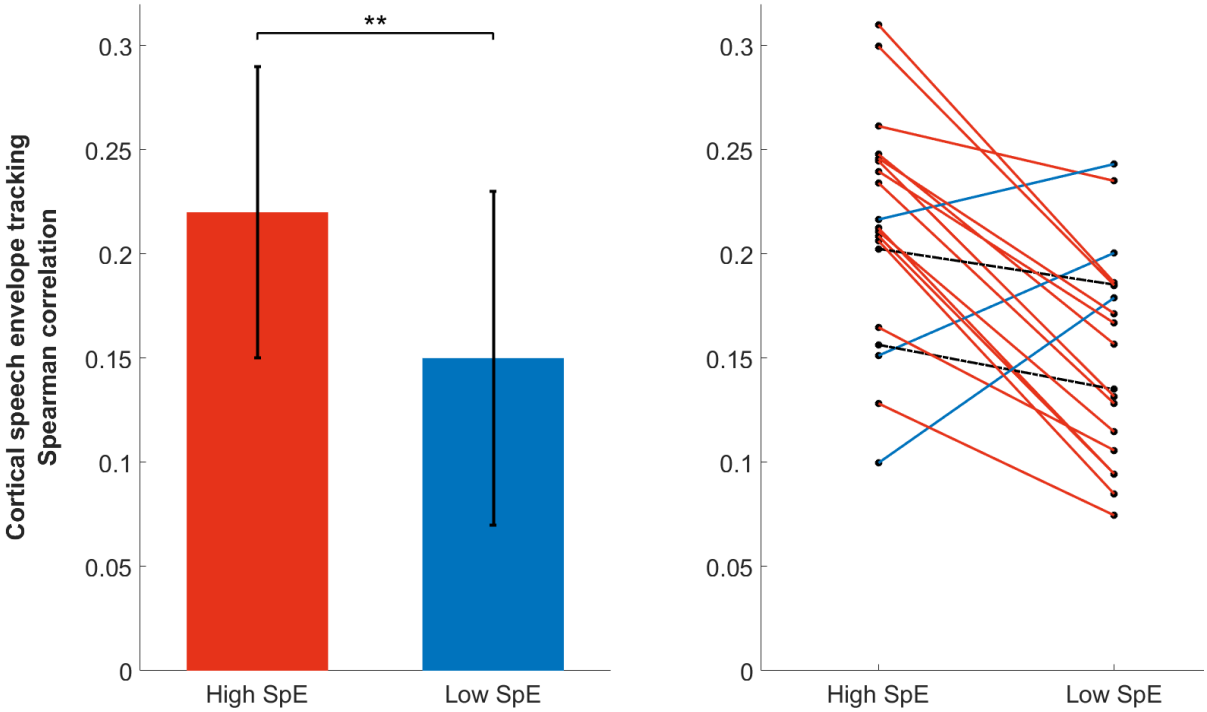

Figure 3 – Group (left) and individual (right) Spearman correlation using only periods of high (high SpE) or low (low SpE) attention on the computation of the decoder (median ± iqr). Note that more than 80% of the group showed higher correlation using a decoder based on periods of high attention than low attention.

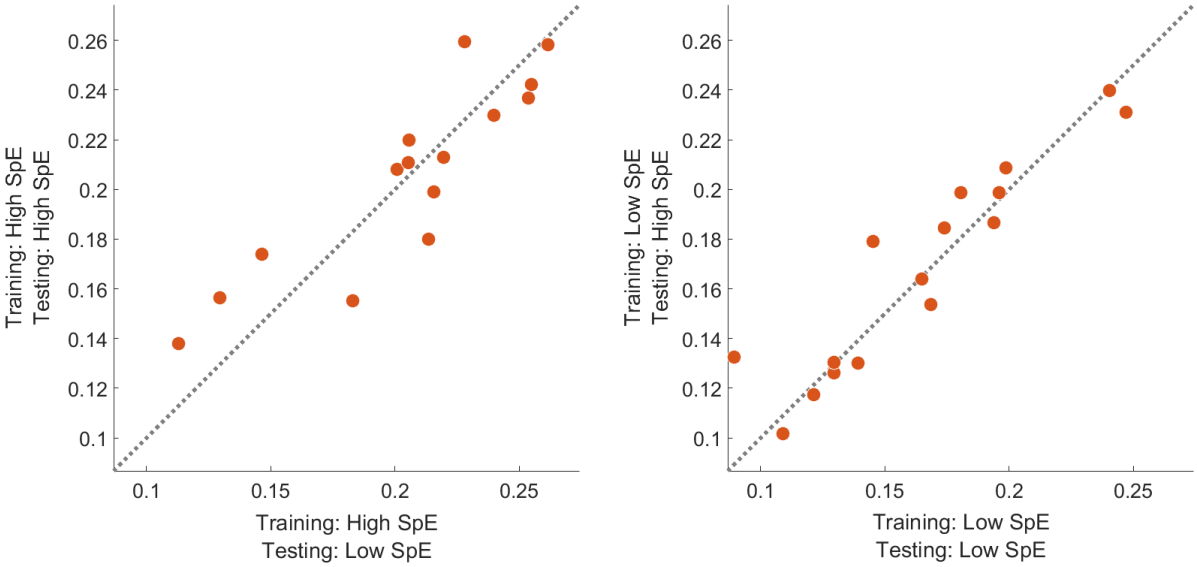

Figure 4 – Individual performance using either a training set based on periods of high (left panel) or low (right panel) entropy and a testing set based on periods of high (y-axis) or low (x-axis). Note that while an improvement could be observed when the decoder is trained using periods of high entropy as compared to low entropy, the selection of periods in the testing set did not affect the performance.

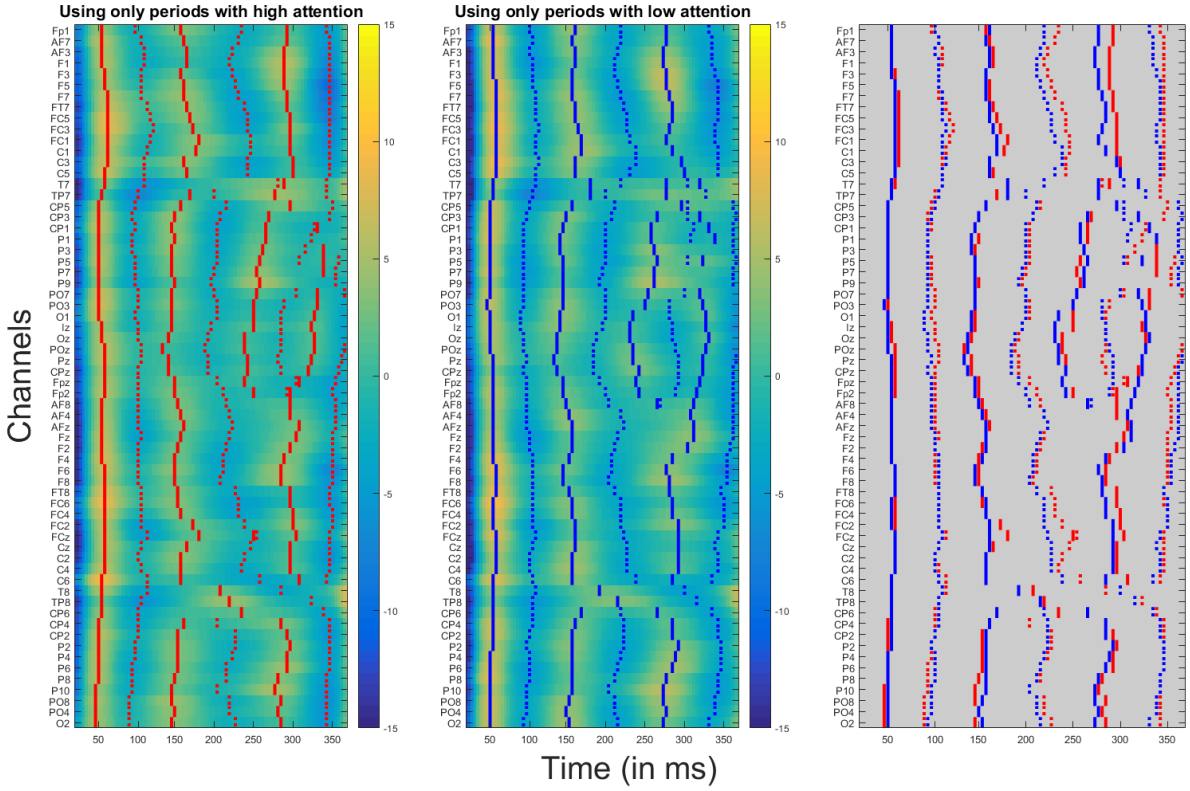

Figure 5 – Temporal response function using periods of high (left panel) or low (center panel) attention for training the model. In red/blue, the peaks are indicated. In the right panel, peaks from the two different conditions are overlaid. Note the delay in later latencies (between 100 and 350 ms) observed in the frontal and fronto-central electrodes, while earlier and later latencies did not show any delay in the activations.

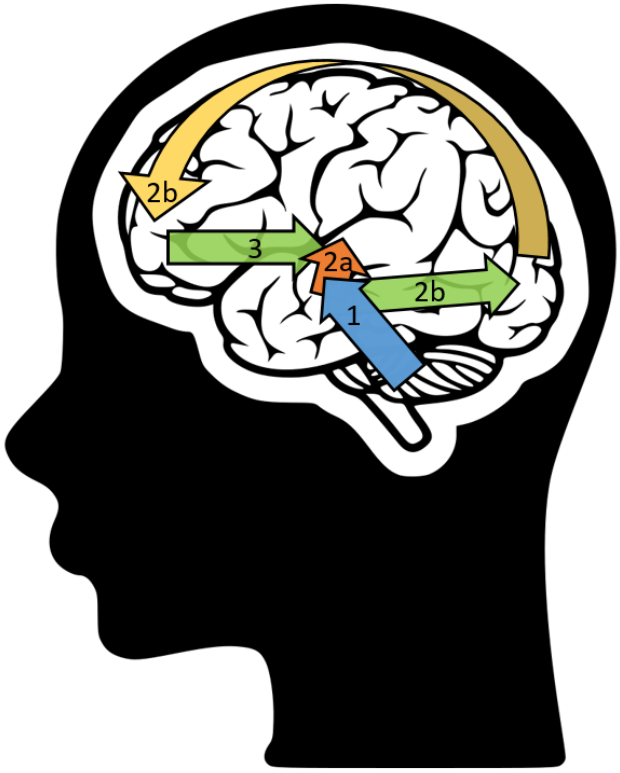

Figure 6 – Bottom-up and top-down processes involved in the cortical tracking of the speech envelope. First, the speech stimulus enters the ears and its information is processed all the way through the first stage of the auditory cortex (see arrow 1). Once this information reaches the cortical layers, the cortical speech tracking starts. Then two streams are initiated: 2a. a bottom-up auditory stream (see the 0-100ms of the temporal model at Figure 4); 2b. a bottom-up attentional stream, which first propagates through the occipital areas, then through the frontal areas (see Figure 1). Then, the associative frontal areas impact the later-latencies auditory process through top-down processing (see latencies between 150 and 300 ms in Figure 4), represented by the arrow 3.