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EEG Phase Synchrony Reflects SNR Levels During Continuous Speech-in-Noise Tasks

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Abstract— **Comprehension of speech in noise is a challenge for hearing-impaired (HI) individuals. Electroencephalography (EEG) provides a tool to investigate the effect of different levels of signal-to-noise ratio (SNR) of the speech. Most studies with EEG have focused on spectral power in well-defined frequency bands such as alpha band. In this study, we investigate how local functional connectivity, i.e. functional connectivity within a localized region of the brain, is affected by two levels of SNR. Twenty-two HI participants performed a continuous speech in noise task at two different SNRs (+3 dB and +8 dB). The local connectivity within eight regions of interest was computed by using a multivariate phase synchrony measure on EEG data. The results showed that phase synchrony increased in the parietal and frontal area as a response to increasing SNR. We contend that local connectivity measures can be used to discriminate between speech-evoked EEG responses at different SNRs.**

Index Terms— **Hearing impairment, speech in noise, multivariate phase synchrony, local connectivity, EEG**

I. INTRODUCTION

Background noise and competing talkers lead to increased listening effort for both normal-hearing (NH) and hearing-impaired (HI) individuals [1]. Previous studies have shown that the presence of background noise can negatively affect a subject's ability to perform a task. Houben et. al. [2] reported that the response time decreased significantly by increasing signal-to-noise ratio (SNR) of an audio signal. In addition, Sarampalis et. al. [3] reported that noise reduction (NR) algorithms in hearing aids (HAs) may reduce listening effort and free up cognitive resources for other tasks. Furthermore, NR algorithms in HAs can improve the performance of listeners during a selective attention task by enhancing the neural representation of speech and reducing the neural representation of background noise [4]. In this paper, we are interested in the change of the listening effort induced by the change SNR value.

A wide variety of methods have been used to assess the performances of subjects during different listening tasks (e.g., see [5]). This include behavioral [2], [3] and physiological measures such as pupillometry [6] and neuroimaging [7]. Neuroimaging measures tend to reflect changes in neural activity during the listening task [7]. Electroencephalography (EEG) has been widely used to measure the neural activity in response to audio stimuli due to its non-invasiveness and high temporal resolution [4], [6], [7].

Various advanced signal processing and information theory techniques have been applied to EEG signals in order to determine the effect of the different SNR values. For example, functional connectivity [8], time-frequency analysis [6], and neural speech tracking [4]. Functional connectivity describes statistical dependencies between neural data and can provide insights about how the brain functions. Transfer entropy [9] and phase synchrony [10], [11] have been proposed in the literature to assess functional connectivity.

Multivariate phase synchrony (MPS) is a standard approach to characterize the interaction within multichannel data and it has been used to assess functional connectivity in multichannel EEG data [10], [11]. Recently, a new MPS measure called circular omega complexity (COC) was proposed, which led to better performance than conventional MPS techniques in some specific cases [11].

Functional connectivity within a small region (for example a cortex) of the brain is called local connectivity. It has been shown that the local connectivity in the frontal cortex changes as the cognitive work load changes [12]. Similarly, The change of the local connectivity was used to classify left and right hand movement motor imagery in [10]. In the present study, we will use COC to assess local connectivity within 8 different regions of interest (ROIs).

Most studies (exceptions include [4], [6], [13]) investigate the effect of SNR when the stimuli is single words or short sentences. However, HI individuals in real-life encounter continuous speech and long sentences.

In this paper, we investigate changes in the local connectivity within EEG signals recorded on HI individuals in response to continuous speech at two different SNRs. Our results show that the phase synchrony reflects significant changes in the parietal and frontal areas as a response to changing SNRs.

II. MATERIALS AND METHODS

In this section we briefly describe the EEG data used in this study. This is followed by the review of the multivariate phase synchrony measure called COC. Finally, steps needed to calculate the local connectivity in the EEG signal to assess the effect of SNR will be explained.

A. EEG data

EEG data used in this study is explained in detail in [4], which focused on neural tracking of the speech signals. In the sequel we briefly describe the data and refer to [4] for further details

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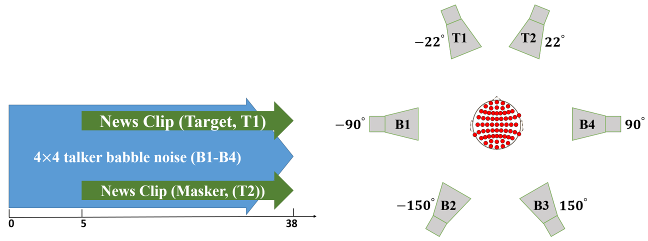

(a) Trial design (b) Experimental setup

Fig. 1: Schematic demonstration of the a) trial design and b) experimental setup.

1) Participants: Twenty-two native HI Danish speakers (11 males, audiometric threshold = 45 dB HL) aged between 40 and 80 (mean = 67, SD = 11.2) years were recruited from the Eriksholm Research Centre database. The experimental procedures were approved by the ethics committee for the capital region of Denmark [4].

2) Experiment Design: All target streams consisted of Danish news clips of neutral content read by the same male and female talker and were presented from two different loudspeakers in the front of the participant (±22° azimuth). The background noise was delivered from the four loudspeakers in the back ($\pm 90°$ and $\pm 150°$ azimuth), each playing a different four-talker babble, leading to an overall effect of 16-talker surrounding babble (see Fig 1b). Participants were asked to attend to one of the two target talkers (target) while ignoring the contralateral talker (masker) and the background noise.

The SNR was defined as the ratio between signal power of the attended talker and the total signal power of the background noise [4]. The sound pressure level (SPL) of the target talker and background noise was set in a way to generate two different SNR values, +3 dB and +8 dB.

In total 20 trials for each SNR (+3 dB and +8 dB) were used for the analysis per subject. Each trial comprised a short period of silence, 5 s of background noise followed by 33 s of simultaneous target, masker and babble stimuli from all speakers (see Fig 1a).

3) EEG data acquisition and preprocessing: The BioSemi ActiveTwo amplifier system (Biosemi, Amsterdam, Netherlands) were utilized to record the EEG data . The international 10–20 system was used to apply the location of 64 scalp electrodes. The EEG signals were sampled at 1,024 Hz.

The preprocessed EEG data used in this study is the same as data used in [4], where all preprocessing procedures are described in detail

Due to technical issues, only data from 19 subjects are included in this study.

B. Circular Omega Complexity

In this study, we use the COC phase synchrony measure [11] to assess the local connectivity. The COC measure determines the level of MPS within signals by quantifying the dimensionality of the state-space which is formed based on the instantaneous phase (IP) of the signals [11]. The first step to calculate the COC is to estimate the IP of the signal by using the Hilbert transform [11]. The IP of a mono-component real valued discrete signal $X[n]$ is estimated as:

$$\phi_X = \tan^{-1}\left(\frac{\hat{X}[n]}{X[n]}\right) \tag{1}$$

where $\hat{X}[n]$ is the Hilbert transform of $X[n]$. Considering a K-dimensional signal $\mathbf{X}[n]$ and its corresponding K-dimensional IP signal $\phi_{\mathbf{X}}$, the circular correlation matrix $C^{\mathbf{X}}$ is defined as [11]:

$$C^{\mathbf{X}} = [C^{A,B}]_{K*K}, \tag{2}$$

where $C^{A,B}$ is the circular correlation between N time points signal ϕ_A and ϕ_B which is given by [11]:

$$C^{A,B} = \frac{\sum_{n=0}^{N-1}\sin\left(\phi_A[n]-\bar{\phi}_A\right)\sin\left(\phi_B[n]-\bar{\phi}_B\right)}{\sqrt{\sum_{n=0}^{N-1}\sin^2\left(\phi_A[n]-\bar{\phi}_A\right)\left(\phi_B[n]-\bar{\phi}_B\right)}}, \tag{3}$$

where $\bar{\phi}_A$ is the circular mean of ϕ_A given by:

$$\bar{\phi}_A = \arg\left(\sum_{n=0}^{N-1}\exp^{i\phi_A[n]}\right). \tag{4}$$

The COC is then defined as [11]:

$$COC = 1 + \frac{\sum_{m=0}^{K-1}\bar{\lambda}_m \log\bar{\lambda}_m}{\log K}, \tag{5}$$

where $\bar{\lambda}_m = \frac{\lambda_m}{\sum_{i=0}^{K-1}\lambda_i}$ and $\lambda_m; m = 0,\ldots,K-1$ are the eigenvalues of $C^{\mathbf{X}}$. The COC value varies between 0 and 1 where higher values show that more channels are pair-wise phase correlated, which means that only fewer eigenvalues of the $C^{\mathbf{X}}$ are significant [11].

C. Local Connectivity Assessment in EEG

The effect of SNR in continuous speech on local connectivity will be investigated in this study. Accordingly, the COC of 8 different ROIs will be calculated and compared during two SNR values. The ROIs include left frontal, frontal, right frontal, left temporal, central, right temporal, parietal and occipital. Table I shows EEG electrodes corresponding to ROIs.

The EEG channels were common average re-referenced to minimize the effect of volume conduction. Additionally, due to the multi-component nature of EEG signals, the analysis

TABLE I: Mapping EEG electrodes to ROIs

ROI	Electrodes	ROI	Electrodes
Left Frontal	**AF7, AF3, F3 F5, F7, Fp1**	**Frontal**	**Fp1, Fp2, AF4 AF3, F1, F2**
Right Frontal	**AF4, AF8, F8 F6, F4, Fp2**	**Central**	**FC1, FC2, C1 CP1, C2, CP2**
Left Temporal	**FT7, T7, TP7 CP5, FC5, C5**	**Parietal**	**CP1, CP2, P1 P2, PO4, PO3**
Right Temporal	**FT8, T8, TP8 CP6, FC6, C6**	**Occipital**	**O1, O2, PO3 PO4**

was performed on conventional EEG bands; Delta (0.5-4 Hz), Theta (4-8 Hz), Alpha (8-12.5 Hz) and Beta (12.5-25 Hz). Window-based FIR band-pass filters were utilized to filter the EEG channels. Following the analysis done in [11], [14], we also calculate the mean of all band-specific MPS values, which will be referred to average-band MPS value. It can describe the MPS within a ROI over all bands with a single index.

The analysis was performed at the time interval of 32 second duration from 1 to 33 second relative to the onset of the target speaker. The 32 second time interval was divided into 16 non-overlapping 2 second windows and the COC value was extracted for each time window. The local connectivity for each trial and band was then computed by averaging all 16 time windows COC values. In summary, the following steps were performed to assess local connectivity:

- Filter the data to four different bands.
- Estimate the IP of each channel at each band using Eq. (1).
- Extract the COC value at 16 time windows for each band using Eq. (5).
- Compute the local connectivity by averaging all 16 time window COC values for each band.

The aforementioned four steps were repeated for 19 subjects and 40 trials, 20 trials for each SNR value.

Two sample t-test was applied on the obtained values (380 values for each SNR value) to check the significant different local connectivity. The null hypothesis is that the mean value of the local connectivity at two SNR values are equal. Since a series (8 ROIs and 5 bands leading to 40 tests) of t-tests were performed, we applied the Bonferroni correction to compensate the multiple comparisons effect. The significance level was therefore chosen as $\alpha = \frac{0.05}{40} = 0.0013$.

III. RESULTS

Table II summarizes the p-values obtained from a two sample t-test applied on the results from all trials. The p-values that are less than the significance level are shown in boldface. As shown in Table II, the parietal ROI shows a significant difference over all the bands, except the theta band. The local connectivity in the left and the right frontal ROIs in the delta band are also statistically different for the two SNR levels.

The mean values over all trials of the statistically different local connectivities are shown in Fig. 2. As illustrated in Fig. 2, all significant local connectivities increase as the SNR level increases. The increase in local connectivity is consistent over subjects; i.e. the mean over all trials for each subject tend to increase when the SNR level increases. As an example, Fig. 3 shows the parietal (averaged over all frequency bands) results averaged over trials for each subject. The blue lines show the increase in local connectivity by increasing the SNR level for each subject while the red line shows otherwise. As shown in Fig. 3, the parietal average-band connectivity attains generally a higher value at 8 dB, except for three subjects (red line).

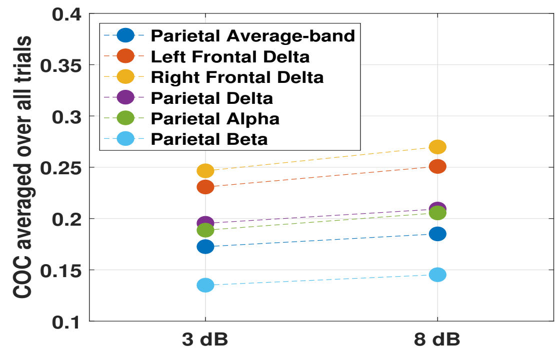

Fig. 2: The mean values of statistically different local connectivity at two different SNR values, 3dB and 8dB.

IV. DISCUSSION

In this study, we investigated whether a change of SNR level would result in a significant change of the local connectivity in the EEG signal. The target group was hearing impaired subjects and the stimuli was continuous speech in noise. The local connectivity at five frequency bands and 8 ROIs were estimated at two SNR levels of the speech stimuli. The two sample t-test was used to check if the changes were statistically different.

Table II and Fig. 2 show that local connectivity values in parietal, left frontal and right frontal ROIs were significantly higher at +8 dB in comparison to that at +3 dB (harder condition). The increase of connectivity observed in the alpha band in the parietal region when decreasing the difficulty of the task is in line with the results of [6]. In [6], the influence on the EEG power distribution of the SNR level was investigated, and it was concluded that the power in the alpha band in the parietal region was inversely related to the background noise level. It was argued that the reason might be that sustained attention is required over long speech presentation [6] and optimal sustained attention performance is linked to greater alpha oscillation [15]. [16].

The decrease in the local connectivity in the frontal ROIs

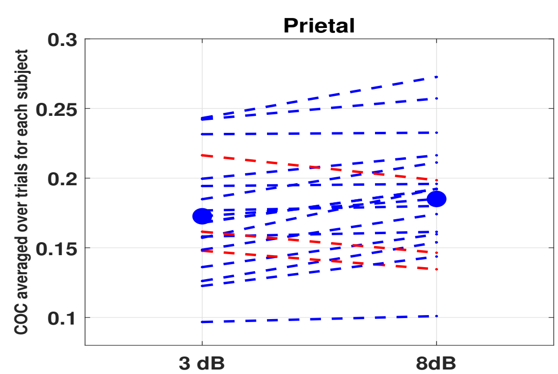

Fig. 3: The mean over all trials for each subject in the parietal average-band. Blue lines show the increase and red lines a decrease of local connectivity by increasing SNR level.

TABLE II: The p-value of the two sample t-test. The bold face numbers shows the rejection of the null hypothesis. The significance level was $\alpha = \frac{0.05}{40} = 0.0013$.

	Left Frontal	Frontal	Right Frontal	Central	Left Temporal	Parietal	Right Temporal	Occipital
Delta	**3.31e-6**	0.34	**7.66e-7**	0.13	0.002	**2.01e-5**	0.07	0.65
Theta	0.36	0.16	0.12	0.57	0.06	0.007	0.73	0.52
Alpha	0.37	0.68	0.11	0.02	0.04	**7.88e-4**	0.09	0.03
Beta	0.40	0.02	0.65	0.28	0.35	**2.36e-5**	0.55	0.37
Average-Band	0.23	0.20	0.06	0.09	0.02	**4.68e-5**	0.31	0.23

within the delta band, when the listening situation is more difficult, might be due to the increase in working memory load induced by the SNR level. The decrease in frontal local connectivity within the delta band is consistent with the results reported in [17] in which they also found lower energy near the frontal lobe, when the difficulty of the working memory task increases.

V. Future Work

The feasibility to discriminate two SNR levels based on local connectivity measures provides future perspectives for hearing care rehabilitation. First, the methodology may be used to gain further understanding of brain processes in realistic listening scenarious for hearing impaired individuals using HAs. Such new understanding may be used to support the development of new signal processing algorithms in HAs. Secondly, further research may be focused on classification of single-sweep EEG segments to assess the possibility to use local connectivity to control future HAs.

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