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A Performance Study of the Wavelet–Phase Stability in the Quantification of Neural Correlates of Auditory Selective Attention

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Abstract—**Large–scale neural correlates of auditory selective attention reflected in the electroencephalogram (EEG) have been identified by using the complex wavelet–phase stability measure (WPS). In this paper, we study the feasibility of using the WPS in extracting the correlates of selective attention by comparing its performance to the widely used linear interdependency measures, i.e., the wavelet coherence and the correlation coefficient. The outcome reveals that the phase measure outperforms the others in discriminating the attended and unattended single sweep auditory late responses (ALRs). Particularly, the number of response sweeps that are needed to perform the differentiation is largely reduced by using the proposed measure. It is concluded that a faster (in terms of using fewer sweeps) and more robust objective quantification of selective attention can be achieved by using the phase stability measure.**

I. Introduction

Synchronization of EEG provides crucial information to understand the higher cognitive and neuronal processes [1], [2], [3]. In [4] it is argued that EEG phase synchronization reflects the exact timing of the communication between distant but functionally connected neural populations, the exchange of information between global and local neuronal networks, and the sequential temporal activity of neural processes in response to external stimuli (refer [4] for a detailed review).

Event–related potentials (ERPs) are widely used in the studies of neuronal synchronization associated with several higher cognitive processes. However, the amplitude information of single sweep event–related potentials turned out to be fragile in some cases [5], [6]. Large amplitude fluctuations can easily be introduced by slight accidental changes in the measurement setup over time. Since the signals exhibit a high degree of variance from one sweep to another, even robust amplitude independent synchronization measures such as the time–scale entropy [7] can hardly be applied to assess their synchronization stability.

In order to address this issue, we have proposed a novel approach to identify the neural correlates of auditory selective attention which employs wavelet–based measure that highlights the phase information of the EEG exclusively. In particular, the wavelet–phase stability (WPS) of single sweeps auditory late response (ALR) sequences is confirmed to be linked to attention [8].

In signal processing, Oppenheim and Lim emphasized the importance of the phase in signals by using the Fourier representation [9], [10]. They applied numerical experiments to illustrate the similarity between a signal and its only phase–reserved reconstruction. More recently, the significance of phases in the continuous wavelet representation of analytic signals has also been shown [11]. Besides that, a statistical interpretation of the usefulness of phase information in signal and image reconstructions has been given in [12]. The authors demonstrated that a random distortion of the phases can dramatically distort the reconstructed signal, while a random distortion of the magnitudes will not. Taken together, previous studies strongly support that the phase of a signal contains much more important information compared to the amplitude.

Generally, the extraction of the EEG phase can be done via two closely related approaches: the Hilbert transform (or analytic signal approach) and the wavelet transform. As pointed out by most of the studies, the performance of both methods is comparable [13], [14], [15], [16]. However, the Hilbert phase and Hilbert amplitude have direct physical meaning only for narrow band signals [17], [18]. Meanwhile, the wavelet transform can be thought as equivalent to band–pass filtering of the signal, which makes the pre–filtering unnecessary.

The main goal of this paper was to examine the feasibility of using the WPS in extracting large–scale neural correlates of selective auditory attention. In order to accomplish the task, a performance study of the WPS with the other two popular methods, i.e., wavelet coherence and correlation coefficient by means of the moving mean approach was performed. The main interest of this study was to deepen our understanding of the proposed wavelet–phase stability of ALR sequences and to show its potential use as a synchronization measure in analyzing neural correlates of auditory selective attention.

II. METHODS

A. Subjects and materials

A total of 10 student volunteers (with mean age of 26.7 and standard deviation of 2.5, 4 females) from Saarland University entered the study. All subjects were given the informed consent prior to their participation and the experiments were conducted in accordance with the Declaration of Helsinki. The maximum entropy auditory paradigm was used (more details can be found in [19]). For each experiment, subjects performed the attention task (i.e., detecting the target tones in a series of three different tones) for a length of 10 minutes followed by another 10 minutes of relaxing (with no attention).

ALRs were acquired by using a commercially available bioamplifier (g.tec USBamp, Guger Technologies Austria) with a sampling frequency of 512 Hz. Single sweeps (i.e., individual responses to tones) were recorded from the electrodes placed at the left and right mastoid (EEG channels), the vertex (Reference), and the upper forehead (Ground). Electrodes impedances were strictly maintained below 5kΩ in all measurements. Data obtained was bandpass filtered with a FIR filter with cut–off frequencies of 1–30 Hz. An additional artifact filter was used to remove responses that exceeded 50μV.

B. Moving Mean Wavelet–Phase Stability

We employed the time–scale coherence measures based on the complex wavelet transform. The quality and stability of the response over the stimulus sequences are evaluated in terms of the time-resolved phase information. According to [20], the phase stability of a sequence $\mathcal{F} = \{f_m \in L^2(\mathbb{R}) : m = 1, \dots, M\}$ of M sweeps $\Gamma_{s,\tau}$ is defined by:

$$\Gamma_{s,\tau}(\mathcal{F}) = \frac{1}{M} \left| \sum_{m=1}^{M} e^{\imath \arg((\mathcal{W}_\psi f_m)(s,\tau))} \right|. \quad (1)$$

In this study, we used the 4th–derivative of the complex Gaussian function as wavelet. In general, Eq. (1) yields a value in the range of 0 and 1. We have a perfect phase stability for a particular s and τ for $\Gamma_{s,\tau} = 1$ and a decreasing stability for smaller values due to phase jittering.

We defined a moving mean wavelet–phase stability as a function of m sweeps as in the following equation:

$$\Gamma^m_{s,\tau}(\mathcal{F}) = \frac{1}{m} \left| \sum_{n=1}^{m} e^{\imath \arg((\mathcal{W}_\psi f_n)(s,\tau))} \right|, \qquad m = 1, ..., M. \quad (2)$$

C. Moving Mean Wavelet Coherence

Wavelet coherence was first introduced by [21] and has been commonly used in evaluating synchronization in EEG [22], [23], [24]. Furthermore, it has recently been used for a reliable detection of auditory habituation [25]. It is noted that the wavelet coherence measure that we applied here is adopted from [25], which is similar to [21].

For $x, y \in L^2(\mathbb{R})$, the wavelet coherence of two signals x and y, $\upsilon^{\delta,\psi}(\cdot,\cdot)$ with a fixed smoothing parameter $\delta \in \mathbb{R}{>}\, 0$ and the wavelet ψ is defined as the cross–wavelet spectrum of the two signals normalized by their corresponding auto–spectra:

$$(\gamma^{\delta,\psi} x, y)(s,\tau) = \frac{\left|(\rho^{\delta,\psi} x, y)(s,\tau)\right|}{\sqrt{(\rho^{\delta,\psi} x, x)(s,\tau)(\rho^{\delta,\psi} y, y)(s,\tau)}}. \quad (3)$$

Due to the Schwartz inequality, Equation (3) is constrained to a value between 0 and 1.

Then, the inter–sweep wavelet coherence of a sequence $\mathcal{F} = \{f_m \in L^2(\mathbb{R}) : m = 1, \dots, M{-}1\}$ of $M{-}1$ sweeps is defined as:

$$\upsilon_m(\mathcal{F}, s, \tau) = (\gamma^{\delta,\psi}(s,\tau) f_m, f_{m+1}), \qquad m = 1, ..., M-1. \quad (4)$$

Finally, we defined the moving mean wavelet coherence in a similar way to the moving mean wavelet–phase stability:

$$\Upsilon_m(\mathcal{F}, s, \tau) = \frac{1}{m} \sum_{n=1}^{m} \upsilon_n(\mathcal{F}, s, \tau), \qquad m = 1, ..., M-1. \quad (5)$$

D. Moving Mean Correlation Coefficient

Correlation coefficient is often referred to more specifically as the Pearson's correlation coefficient, or Pearson Product–moment correlation coefficient. It is a measure of the linear relationship between the two signals and has been used in the EEG synchronization investigations. For a sequence $\mathcal{F} = \{f_m \in L^2(\mathbb{R}) : m = 1, \dots, M\}$ with M sweeps and $\mathcal{F}_{erp}$ is the average of the sequence $\mathcal{F}$, the moving mean correlation coefficient of the sequence $\mathcal{F}$ and $\mathcal{F}_{erp}$ is defined in terms of their covariance cov and standard deviations σ, as seen below:

$$r_m(\mathcal{F}) = \frac{cov(f_m, \mathcal{F}_{erp})}{\sigma_{f_m} \sigma_{\mathcal{F}_{erp}}}, \qquad m = 1, ..., M, \quad (6)$$

where $f_m = \frac{1}{m} \sum_{n=1}^{m} f_n, m = 1, ..., M$.

This gives a value of $[-1, 1]$. If there is no relationship between the two signals then the correlation coefficient will be 0; if there is a perfect positive match it will be 1. If there is a perfect inverse relationship, then the correlation coefficient will be -1. The significance level (i.e., p–value) is calculated by transforming the correlation to create a t statistic having $n-2$ degrees of freedom, where n is the number of subjects.

III. RESULTS AND DISCUSSION

The scale parameter s of the complex wavelet analysis was chosen as 40. Note that the scale can be associated with a pseudo frequency of 6.4 Hz. Regarding the translation parameter τ, we considered the interval of 70–120 ms where the N1 wave appeared.

Figure 1 (a) shows the grand averaged of the normalized moving mean wavelet–phase stability for the target tones from the maximum entropy auditory attention experiments and its corresponding significant test results (i.e., one–way ANOVA). It is noted that the horizonal dashed lines on the right of the figure indicates the significant level $p < 0.05$. As one can observe, only as few as seven sweeps are needed to significantly discriminate the attended and unattended conditions.

Regarding the evaluation which uses the moving mean wavelet coherence, the smoothing parameter δ was set to 20 as in [25] since we study the same interval of interest. The outcome is shown in Figure 1 (b). In general, the performance of the wavelet coherence is not encouraging. Based on the figure, although the wavelet coherence of the target tones shows significance difference at certain sweeps, the difference is fluctuating over the sweeps.

The result of using the correlation coefficient as synchronization measure is illustrated in Figure 1 (c). The graph shows the results for both attended and unattended sweeps and the p–values are computed by using the t–test. At least 23 sweeps are required to differentiate significantly the attended and unattended conditions for the target tones.

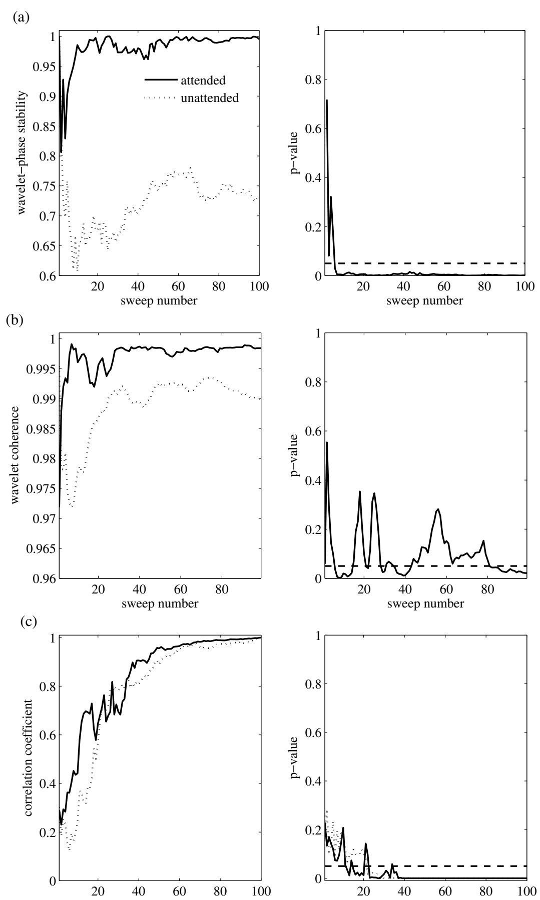

Fig. 1. The grand averaged of the (a) normalized moving mean wavelet–phase stability, (b) moving mean wavelet coherence, (c) moving mean correlation coefficient and their corresponding significance test results for the target tones. Note that the horizontal dashed line on the right side indicates the significant level $p < 0.05$.

On the other hand, it is also interesting to observe the time domain signals. Figure 2 (a) shows the normalized wavelet–phase stability for the first seven sweeps and Figure 2 (b) depicts the averaged of the first seven ALRs. The correlation coefficient of the averaged attended ALRs and averaged unattended ALRs is calculated as 0.5750 and it implies a significant association between these two signals (t–test, $p < 0.05$).

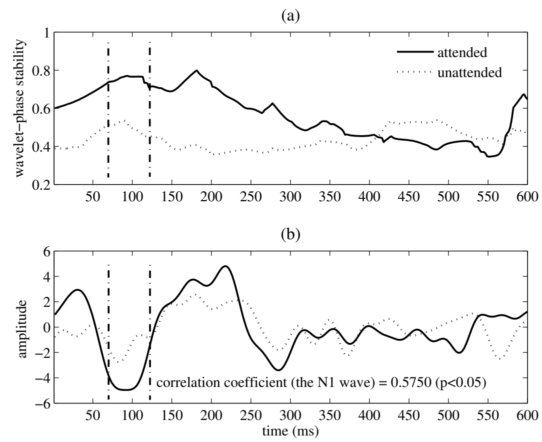

Fig. 2. (a) The grand averaged of the normalized wavelet–phase stability for the first seven sweeps of the target stimuli. (b) The grand averaged of the time–domain ERP for the first seven sweeps of the target stimuli. Note that the correlation coefficient at the N1 wave is calculated as 0.5750 (t–test, significant level $p < 0.05$).

Typically, a large number of ALR sweeps is used in identifying neural correlates of auditory selective attention due to a poor signal–to–noise ratio. The number of sweeps that has been used in those pioneer studies is typically more than 100, some studies even analyzed more than 1000 sweeps (e.g., [26], [27], [28], [29], [30], [31], [32]. This has led to a lengthy EEG recording and processing time. Furthermore, subjects are easily exhausted during the task performing.

A number of studies in the field of EEG synchronization use the coherence measure. However, it is argued that coherence cannot be regarded as a specific measure of synchronization [33], [34], [35]. As we know, coherence does not separate the effects of covariance of the amplitude waveforms and of the phases of two oscillatory signals. Since the core of the synchronization is the adjustment of phases and not of amplitudes, it should be detected by a measure neglecting amplitude variations.

It has been highlighted by the authors in [4] that the EEG phase synchronization reflects the exact timing of communication between distant but functionally related neural populations, the exchange of the information between global and local neuronal networks, and the sequential temporal activity of neural processes in response to incoming sensory stimuli. So, the phase of ongoing EEG oscillations (certain frequencies) must undergo resetting (or realignment) due to the exogenous (i.e., physical properties of the incoming auditory stimulations) as well as endogenous processes (i.e., during the performance of the attentional task). Therefore, methods to analyze the phase of the EEG are more desirable and proper because phase values might contain crucial and meaningful information related to cognitive processes.

IV. Conclusion

We have presented a performance study of using the WPS in identifying neural correlates of auditory selective attention that reflected in single sweeps ALRs. It is shown that the method requires fewer response sweeps to perform the discrimination of the attentional conditions (attended versus unattended) compared to the widely–used wavelet coherence and correlation coefficient methods. It is concluded that the WPS is adequate to be used in an objective evaluation of large–scale neural correlates of auditory selective attention as a synchronization measure.

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