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Research report

A performance study of the wavelet-phase stability (WPS) in 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 this amplitude independent measure, the WPS in extracting the correlates of 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 WPS outperforms the other two measures in discriminating both the attended and unattended single sweep auditory late responses (ALRs). It is concluded that the proposed WPS provides a faster (in terms of less sweeps which are required) and robust objective quantification of selective attention.

1. Introduction

Electroencephalogram (EEG) synchronization provides crucial information to understand the higher cognitive and neuronal processes [14,63,68]. In [59] 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 [59] for a detailed review).

Event-related potentials (ERPs) are widely used in the studies of neuronal synchronization associated with several higher cognitive processes (for example, [9,21,36,39,72]). In contrast to the analysis of averaged potentials, the amplitude information of single sweep event-related potentials turned out to be fragile in some cases [10,30]. For instance, large amplitude fluctuations can easily be introduced by slight accidental changes in the measurement setup over time. Since EEG signals exhibit a high degree of variance from one sweep to another, even robust amplitude independent synchronization measures such as the time-scale entropy, which has been used in an automated detection scheme for the β-wave [65] can hardly be applied to assess the synchronization stability of the EEG sweeps. 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.

The importance of the phase in signals has been emphasized by Oppenheim and Lim [46,20] using the Fourier representation. 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 [16]. Besides that, a statistical interpretation of the usefulness of phase information in signal and image reconstructions has been given [44]. Particularly, authors in [44] have demonstrated that a random distortion of the phases can dramatically distort the reconstructed signal, while a random distortion of the magnitudes will not. Results from these studies reveal that the phase of a signal contains much more important information compared to the amplitude, as a signal can be reconstructed without suffering from a significant degradation of the quality by using solely the phase information.

Methods which make use of phase information have been suggested in examining the synchronization processes related to different cognitive functions. For example, a measure called phase-locking statistics (PLS) or value (PLV) which was proposed by Lachaux has gained much popularity in quantifying the phase coupling over distance (i.e., signals from different sites of the brain) [2,32]. Meanwhile, bi-coherence or cross-frequency phase synchronization indices have been developed to evaluate phase synchronization across different frequencies [45,47,60,62]. In our

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study, the wavelet-phase stability (WPS) is used to analyze the synchronization process that is locked to the onset of the sensory stimulation.

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 [8,28,50,53]. However, the Hilbert phase and Hilbert amplitude have direct physical meaning only for narrow band signals [5,6]. Meanwhile, the wavelet transform can be thought as equivalent to band-pass filtering of the signal, which makes the pre-filtering unnecessary. A review of using wavelets for EEG analysis can be found in [58].

The main goal of this study is to investigate the feasibility of using an amplitude independent measure, i.e., the WPS in extracting large-scale neural correlates of selective auditory attention reflected in auditory late responses (ALRs). Here, a performance comparison of the WPS with the wavelet coherence and correlation coefficient is presented. This is done by examining and comparing the moving mean of the three measures, i.e., moving mean phase stability, moving mean wavelet coherence and moving mean correlation coefficient. It is noted that our study was focused on the N1 wave of the ALR due to its common use in paradigms related to auditory attention [22,25,40,41,70] and it is anatomically associated with the auditory cortex [18,69]. Results show that the phase measure outperforms the others, since significantly fewer sweeps are needed to discriminate the attended and unattended single sweeps ALRs.

2. Methods

2.1. Subjects and experimental setup

A total of 10 student volunteers (with mean age of 26.7 years 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 [34]). 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 min followed by another 10 min 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 right mastoid (Reference), the vertex (EEG channel), and the upper forehead (Ground). Electrodes impedances were strictly maintained below 5 kΩ in all measurements. The 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 50 μV.

2.2. Wavelet-phase stability (WPS)

We employed the time-scale coherence measures based on the complex wavelet transform, which take the non-stationary nature of evoked potentials into account in contrast to conventional coherence based on the frequency information alone, see [32]. This wavelet coherence increases with the correlation of the envelopes between two signals as well as if their phases show smaller variations in time [32]. The quality and stability of the response over the stimulus sequences are evaluated in terms of the time-resolved phase information.

For the determination of the phase stability, we need an adaptation of the derived phase locking measure between two signals to our problem. Let $\psi_{s,\tau}(\cdot) = |s|^{-1/2}\psi((\cdot - \tau)/s)$, where $\psi \in L^2(\mathbb{R})$ is the wavelet satisfying the admissibility criterion: $0 < \mathcal{C}_\psi = \int_{\mathbb{R}} (|\Psi(\omega)|^2/|\omega|)d\omega < \infty$, where $\mathcal{C}_\psi$ denotes the admissibility constant, $\Psi(\omega)$ is the Fourier transform of the wavelet ψ, $s, \tau \in \mathbb{R}$, $s \neq 0$, and $L^2(\mathbb{R})$ denotes the Hilbert space of all square integrable functions. The wavelet transform $\mathcal{W}_\psi : L^2(\mathbb{R}) \to L^2(\mathbb{R}^2, (dsd\tau/s^2))$ of a signal $f \in L^2(\mathbb{R})$ with respect to the wavelet ψ is given by the inner L^2-product:

$$(\mathcal{W}_\psi f)(s, \tau) = \langle f, \psi_{s,\tau} \rangle_{L^2}. \tag{1}$$

From the equation, we can see that the wavelet transform expands functions in terms of *wavelets* $\psi_{s,\tau}(\cdot)$, which are generated in the form of translations (or time-shift, denoted as τ) and dilations (or scales, denoted as s) of a fixed function called the *mother wavelet* ψ. Note that the scale s can always be associated with a pseudo-frequency F_a in Hz by:

$$F_a = \frac{F_\psi}{s\Delta}. \tag{2}$$

Here Δ is the sampling period and F_ψ is the center frequency of the wavelet ψ [1].

According to [64], the phase stability of a sequence $\mathcal{F} = \{f_m \in L^2(\mathbb{R}) : m = 1, \ldots, M\}$ of M sweeps $\Gamma_{s,\tau}$ is defined by:

$$\Gamma_{s,\tau}(\mathcal{F}) = \frac{1}{M}\left|\sum_{m=1}^{M} e^{\imath \arg((\mathcal{W}_\psi f_m)(s,\tau))}\right|. \tag{3}$$

Eq. (3) 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 jittering. Let us introduce the phase $arg((\mathcal{W}_\psi g)(s, \tau))$ of a virtual reference signal g in Eq. (3) which is constant for all m in scale and time. Then we obtain the phase difference $e^{\imath(\arg(\mathcal{W}_\psi f_m)(s,\tau)) - \arg((\mathcal{W}_\psi g)(s,\tau)))}$ but the result for the stability remains the same. Although this is obvious in a mathematical sense, this experiment easily shows the relation of our stability criteria to phase locking measures of two signals and oscillators as in [57] or [32].

In fact, $\Gamma_{s,\tau}(\mathcal{F})$ measures the degree of clustering of the angular distribution for certain s and τ of M sweeps. Fig. 1 illustrates the concept of the wavelet-phase stability measure. As depicted in the figure, a series of 10 EEG sweeps was simulated according to the phase resetting theory with zero jittering; this is shown in Fig. 1(a). All EEG sweeps were transformed into complex values by using a complex wavelet. Each small circle plotted on the unit circle in Fig. 1(b) represents the complex value of an EEG sweep (from Fig. 1(a)) for $s = 40$ and $\tau = 50$. Since the phase values (the arguments of the complex numbers) are concentrated in a narrow interval, the wavelet-phase stability gives a high value of 0.9701. On the other hand, Fig. 1(c) shows 10 EEG sweeps simulated according to the phase resetting theory with 20 samples jittering. The small circles which are plotted on the unit circle in Fig. 1(d) represent the complex values of the transformed EEGs for $s = 40$ and $\tau = 50$. In this case, the phase values are widely distributed and thus the wavelet-phase stability gives a low value of 0.2501.

In order to observe the evolution of the measure over the sweeps, we defined a moving mean wavelet-phase stability as a function of m sweeps as in the following equation:

$$\Gamma^m_{s,\tau}(\mathcal{F}) = \frac{1}{m}\left|\sum_{n=1}^{m} e^{\imath \arg((\mathcal{W}_\psi f_n)(s,\tau))}\right|, \quad m = 1, \ldots, M. \tag{4}$$

2.3. Wavelet coherence (WC)

Wavelet coherence was first introduced by [31] and has been commonly used in evaluating synchronization in EEG [15,29,33,50]. Furthermore, it has recently been used for a reliable detection of auditory habituation [38]. It is noted that the wavelet coherence measure that we applied here is adopted from [38], which is similar to [31].

For $x, y \in L^2(\mathbb{R})$, the wavelet coherence of two signals x and y, $\gamma^{\delta,\psi}(\cdot, \cdot)$ with a fix 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:

$$(\gamma^{\delta,\psi}x, y)(s, \tau) = \frac{\left|(\rho^{\delta,\psi}x, y)(s, \tau)\right|}{\sqrt{(\rho^{\delta,\psi}x, x)(s, \tau)(\rho^{\delta,\psi}y, y)(s, \tau)}}. \tag{5}$$

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

$$\upsilon_m(\mathcal{F}, s, \tau) = (\gamma^{\delta,\psi}(s, \tau)f_m, f_{m+1}), \quad m = 1, \ldots, M-1. \tag{6}$$

Finally, from the inter-sweep wavelet coherence in Eq. (6) we defined the moving mean wavelet coherence in a similar way to the moving mean wavelet-phase stability:

$$\Upsilon_m(\mathcal{F}, s, \tau) = \frac{1}{m}\sum_{n=1}^{m} \upsilon_n(\mathcal{F}, s, \tau), \quad m = 1, \ldots, M-1. \tag{7}$$

2.4. Correlation coefficient (CC)

Often, the correlation coefficient is more specifically referred to 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 $\mathcal{F} = \{f_m \in L^2(\mathbb{R}) : m = 1, \ldots, M\}$ with M sweeps let $\mathcal{F}_{erp}$ denote the average of the sequence $\mathcal{F}$; the moving mean cor-

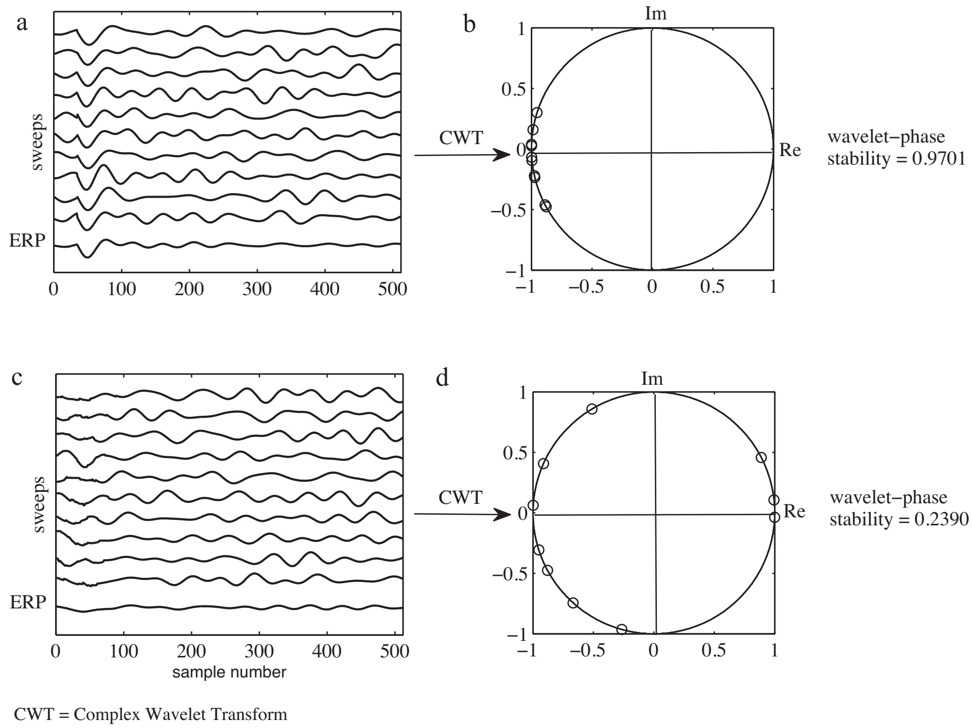

Fig. 1. An illustration of the basic concept of the wavelet-phase stability measure. (a) 10 EEG sweeps were simulated according to the phase resetting theory with zero sample jittering. (b) The small circles which are plotted on the unit circle represent the complex values of the EEG sweeps in (a) for $s = 40$ and $\tau = 50$. The wavelet-phase stability gives a big value of 0.9701. (c) 10 EEG sweeps simulated according to the phase resetting theory with 10 samples jittering. (d) The small circles which are plotted on the unit circle represent the complex values of the EEG sweeps in (c) for $s = 40$ and $\tau = 50$. The wavelet-phase stability gives a low value of 0.2390.

relation 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:

$$r_m(\mathcal{F}) = \frac{cov(f_m, \mathcal{F}_{erp})}{\sigma_{f_m}\sigma_{\mathcal{F}_{erp}}}, \quad m = 1, \ldots, M, \tag{8}$$

where $f_m = (1/m)\sum_{n=1}^{m} f_n$, $m = 1, \ldots, M$.

This gives a value in $[-1, 1]$. 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.

3. Results

We used the 4th derivative of the complex Gaussian function as wavelet in all analyses. The scale parameter s was chosen as 40. Note that the scale can be associated with a pseudo frequency of 6.4 Hz (based on Eq. (2)). For this scale, the temporal resolution is rather satisfactory and the differences in this frequency band are also clearly noticeable [64]. Regarding the translation parameter τ, we considered the interval of 70–120 ms where the N1 wave appeared. The neural activity reflected in this wave is presumably associated with the auditory cortex [18,69] and it is commonly used in paradigms related to auditory attention [22,25,42,70].

Fig. 2(a) shows the grand averaged of the normalized moving mean wavelet-phase stability for the target tones from the *maximum entropy paradigm* experiments and its corresponding significant test results (i.e., one–way ANOVA). It is noted that the horizontal 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 [38] since we study the same interval of interest. The outcome is shown in Fig. 2(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 a 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 Fig. 2(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.

The outcome from the moving mean wavelet-phase stability measure is very motivating, therefore it is also interesting to observe the time domain signals. Fig. 3(a) shows the normalized wavelet-phase stability for the first seven sweeps and Fig. 3(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, $p < 0.05$).

4. Discussion

The use of the wavelet-phase stability measure which focuses on the phase in evaluating the synchronization of auditory late responses has been reinforced by comparing its performance to the wavelet coherence and correlation coefficient methods. The extraction of the phase in our study was done by employing the complex wavelet transform that provides a view of the scale versus time behavior (so-called time-scale) of the signal and therefore has great potential in analyzing non-stationary brain signals.

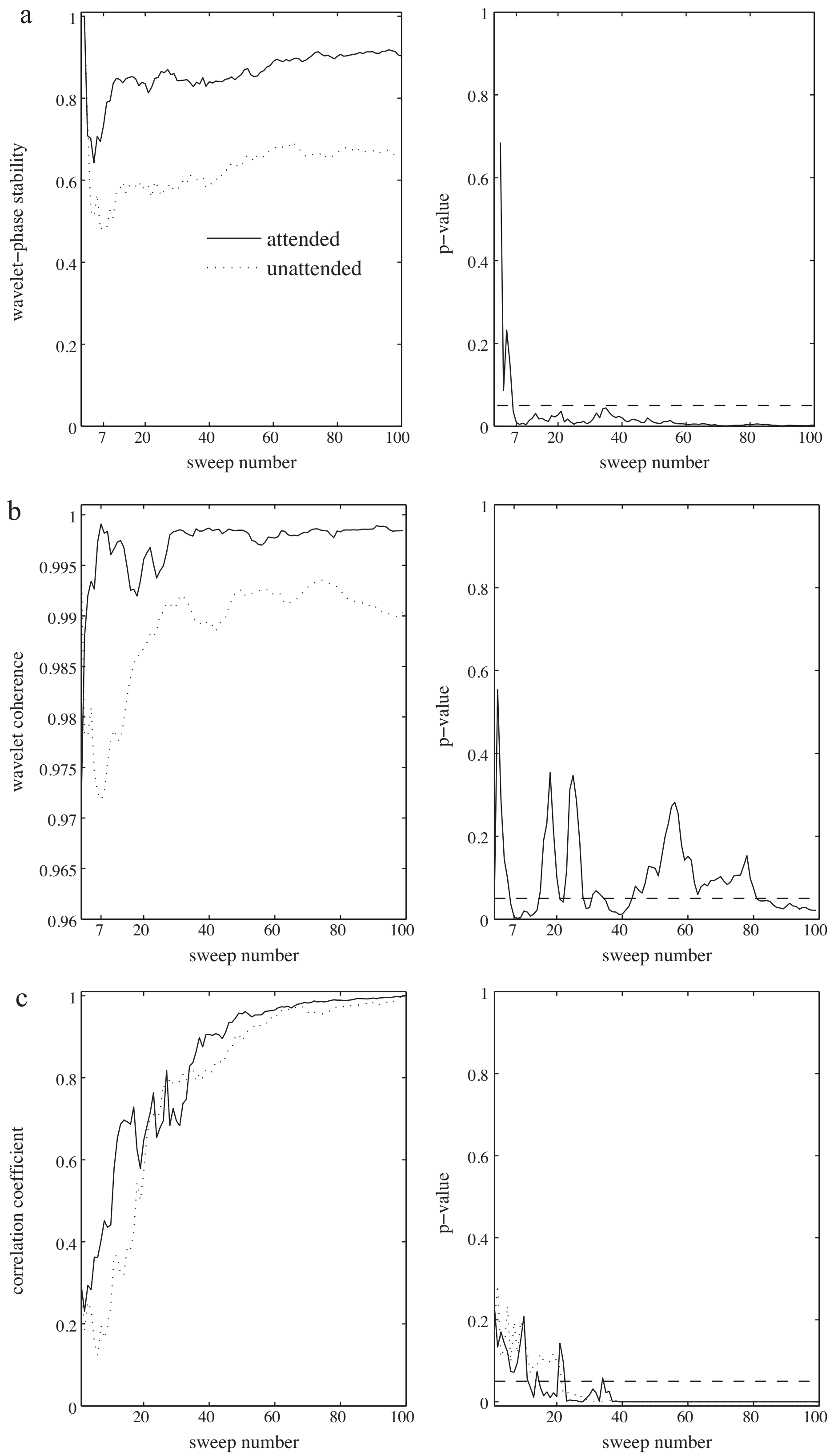

Fig. 2. The grand averaged of the (a) normalized moving mean wavelet-phase stability, (b) moving mean wavelet coherence, (c) moving mean correlation coefficient and their corresponding significance test results for the target tones at the N1 wave. Note that the horizontal dashed line in the figure (right) indicates the significant level $p < 0.05$.

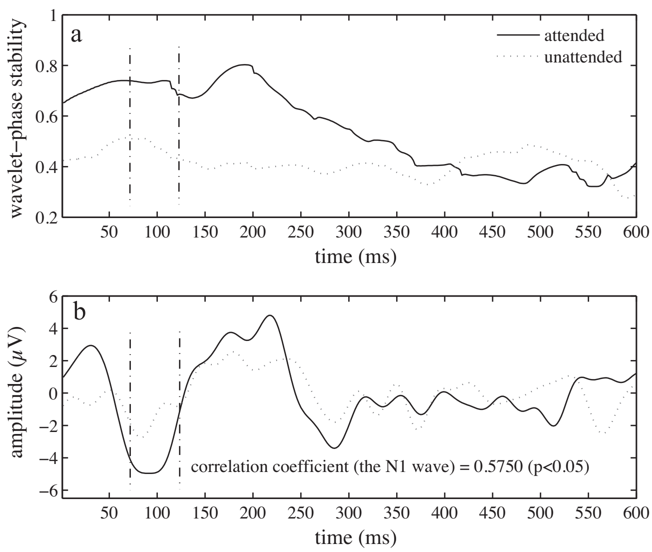

Fig. 3. The grand averaged of the (a) normalized wavelet-phase stability of the target tones for the first seven sweeps, (b) time-domain ERP of the target tones for the first seven sweeps. Note that the correlation coefficient calculated at the N1 wave is 0.5750 (t-test, significant level $p < 0.05$). The interval of the N1 wave is shown in the figure by two vertical dotted lines.

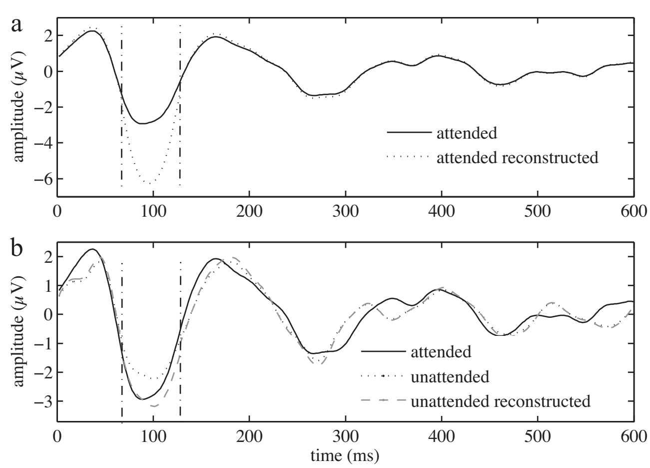

Fig. 4. (a) Amplitude of averaged attended EEGs before and after phase reset at the theta–alpha border (i.e., 6–10 Hz). This frequency range is closely related to auditory attention. Note that the phases of the EEGs have been reset at around 100 ms where the N1 wave is located. (b) Amplitude of averaged EEGs after the phase reset of unattended data to the mean phase of attended data at the theta border (at the N1 wave duration). It is shown that the amplitude of the N1 wave is enlarged and it resembles the attention data. The interval of the N1 wave is shown in the figure by the two vertical dotted lines.

We have recently shown that the wavelet-phase stability of ALR sequences provides an objective quantification of the tinnitus decompensation and allows for a reliable discrimination between a group of compensated and decompensated tinnitus patients [64]. For control subjects, the measure is able to distinguish between the groups of attention and no-attention [34]. In the present study, a performance comparison of the wavelet-phase stability with the well-known wavelet coherence and widely used correlation coefficient using the experimental data acquired from the control subjects is demonstrated. Results reveal that the proposed phase measure performs better than the other two measures by means of less sweeps which are required to differentiate the attentional conditions.

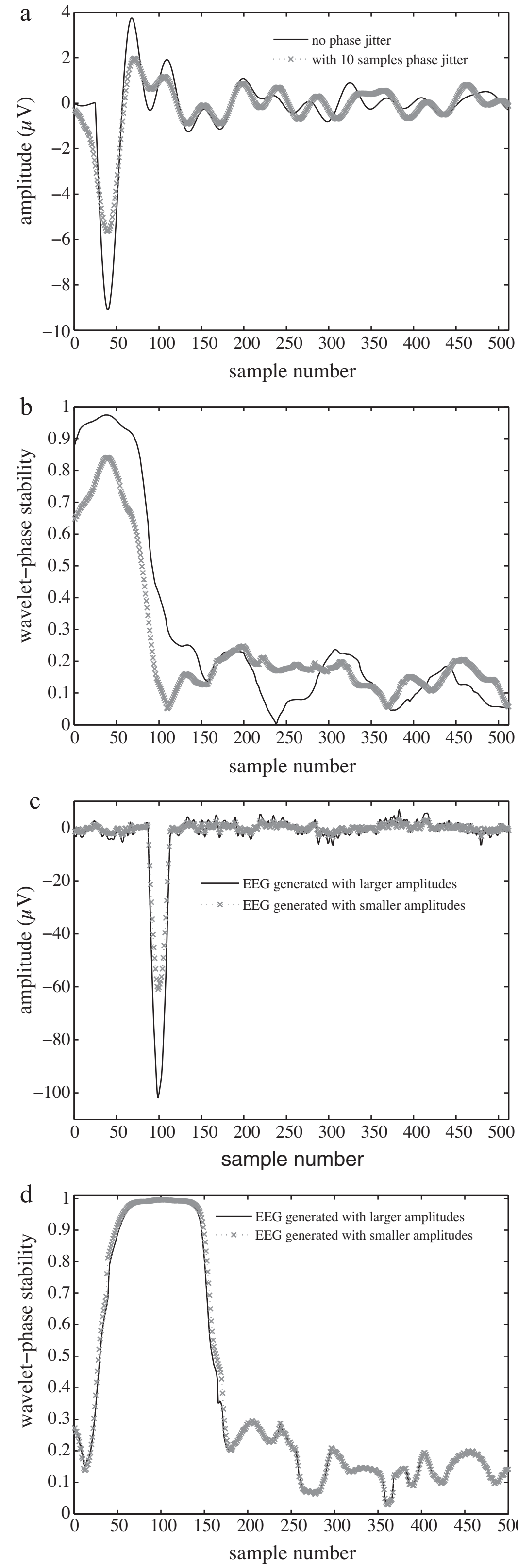

Fig. 5. Demonstration of the phase stability measure on the simulated EEG data. (a) EEG data generated based on the phase reset theory. (b) Phase stability of the data in (a). (c) EEG data generated according to the additive theory with different amplitudes. (d) Phase stability of the data in (c).

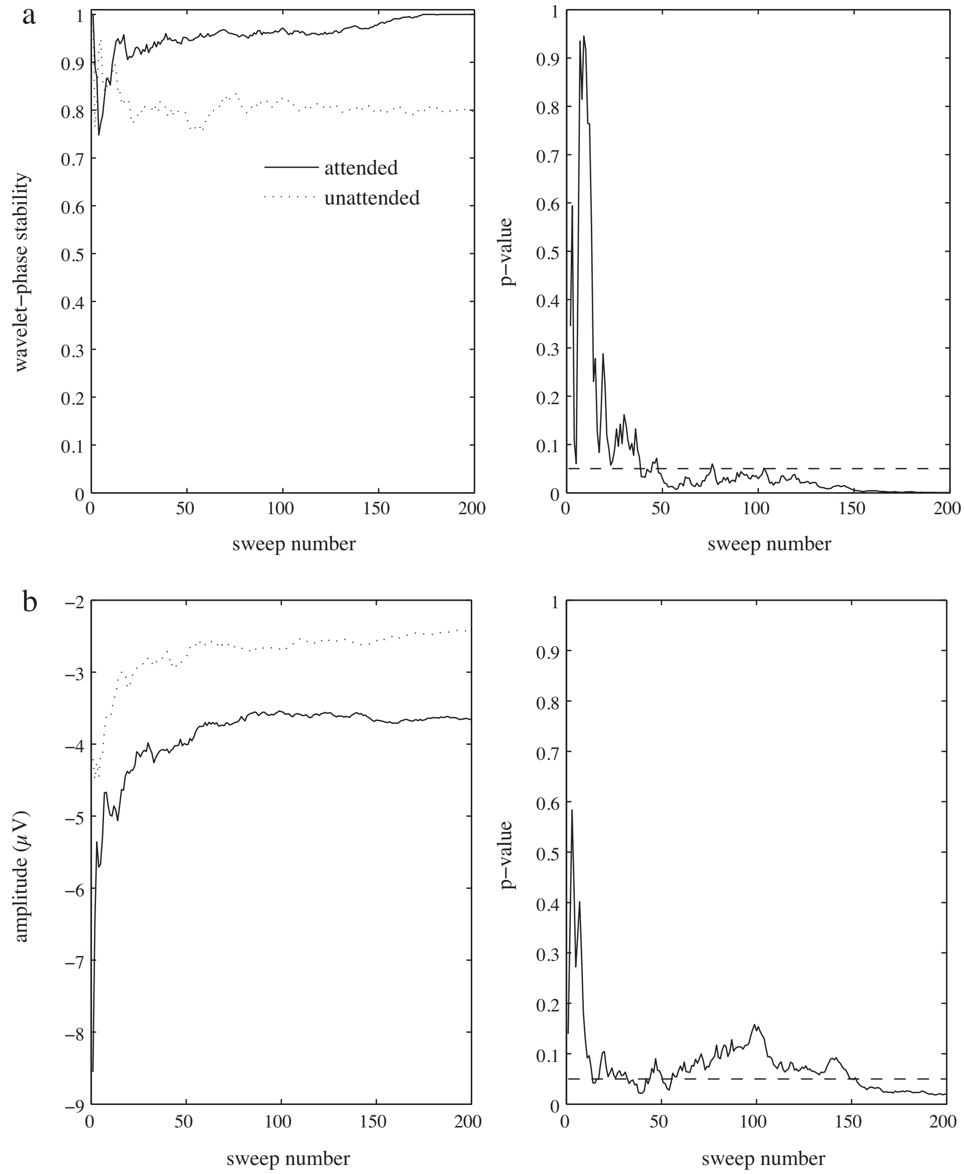

Fig. 6. The grand averaged of the first 200 stimulus for both attended and unattended conditions and its corresponding significant test results by using the (a) normalized moving mean wavelet-phase stability, (b) moving mean amplitude of the N1 wave. Note that the horizontal dashed line in the figure (right) indicates the 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. For example, in studies that were conducted by the groups of Picton [48], Keating [27], Hillyard [22–24], Näätänen [41,42], and Woldorff [70,73,71], as well as other recent studies, e.g., [9,36,43], the number of sweeps that has been used is typically more than 100. Some studies even analyzed more than 1000 sweeps. This has led to a lengthy EEG recording and processing time. Furthermore, subjects are easily exhausted during the task performing.

On the other hand, 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 [2,32,66]. Related to this, a phase synchronization concept introduced by [56] states that a small coupling of the oscillators[1] causes an adjustment of their phases, while the amplitudes remain uncorrelated and chaotic. This concept is based on the well-known fact that weak coupling first affects the phases of oscillators, not their amplitudes. 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. In signal processing, it has been shown that the phase in signals plays a crucial role in the signal representation and reconstruction by using the Fourier transform [20,46], the continuous wavelet transform [16], and statistics methods [44]. Altogether, the related literature strongly suggests that the phase information is prevailing over amplitude.

Critical discussions among the researchers about the ERP genesis have led to the emergence of a theory called *oscillatory model*. This theory argues that the ERP is not independent from ongoing cortical processes, but rather, is generated by phase synchronization and partial phase resetting of ongoing activities

[1] Neurons are weakly coupled non-identical oscillators [11–13,49].

[3,4,17,19,26,37,51,52,61,67]. This is in contrast to the traditional assumption that the ERP is generated by time-locked, stimulus-locked, and synchronized activity of a group of neurons that added to the background EEG. For example, the spectral power of unaveraged EEG data appears to be independent of auditory stimulation, suggesting that ERRs result from reorganization of ongoing activity rather than from additional activity being triggered by the stimulus [61]. Furthermore, the power of cortical oscillations at 8–13 Hz has been shown to correlate with the amplitude of ERRs [7,55,54].

More important, it is highlighted by the authors in [59] 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.

In relation to this, we reinforced the important role of the EEG phase in the generation of ALR through an inverse time-scale analysis [35]. The results are reproduced and shown in Fig. 4. In part (a) the grand averaged of the original attended data as well as its phase-modified reconstruction is depicted. The phases of the EEGs at the *theta–alpha border* (6–10 Hz) were stabilized. As illustrated in the figure, an enlargement of the N1 wave for attended data after the phase stabilization is apparent and it is significantly different from the original signal ($p < 0.05$). In addition, the relationship between attended data and unattended data was studied by resetting the phase of unattended data at the theta border to the mean phase of attended data at the same frequency range. We found that the amplitude of the N1 wave is enlarged and the result looks similar to the attended data. This is shown in Fig. 4(b).

In order to gain more insights of the phase-stability measure, we evaluated the measure using signals with known properties. Hence, we generated the EEG data based on two well-known theories of the ERP genesis: phase reset and additive (also known as evoked) models. To recapitulate, the additive model articulates that the independent responses (i.e., those which are triggered by the experimental events of interest) are added to the ongoing EEG (that is considered as “noise”). On the other hand, the phase-resetting theory states that the experimental events reset the phase of ongoing oscillations. Fig. 5 shows the simulated ERPs and the corresponding phase stability evaluation results. We observe that the phase stability decreases with a larger phase jittering of single sweeps (Fig. 5(a) and (b)). Meanwhile, EEGs with different amplitudes have the same phase behavior (Fig. 5(c) and (d)). These indicate that the phase stability measure is sensitive only to the phase of the data, but not to the amplitude changes. In addition, by using the obtained EEG data, we compared the evaluation of the WPS with the amplitude for the first 200 ALR sweeps. The result is depicted in Fig. 6. It is observed that p-values of the WPS are more stable and always less than 0.05 (after 48 sweeps). This shows that the WPS is more reliable than the amplitude in discriminating the two attentional conditions. This is in line with the fact that we have mentioned before that the amplitude information of single sweep event-related potentials turned out to be fragile in certain cases. Therefore, it is not suitable and not efficient to be used as a synchronization measure. More importantly, the finding again shows that the WPS is a measure which is independent from the influence of signal amplitude fluctuations.

5. Conclusion

The proposed measure based on the phase information constructed from the complex wavelet transform can be used in extracting the large-scale neural correlates of auditory selective attention. In particular, the wavelet-phase stability of ALRs allows for a reliable discrimination of the attentional conditions compared to the widely used wavelet coherence and correlation coefficient methods. The number of response sweeps that are needed to perform the differentiation is largely reduced by using the proposed measure especially for the target tones. The findings highlight the significance of the phase information from brain activities as it might reveal considerably useful hints about the neural activity related to cognitive processes per se. It is concluded that the wavelet-phase stability is feasible to be used as objective evaluation of the large-scale neural correlates of auditory selective attention as a synchronization measure.

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