Towards Estimating Selective Auditory Attention From EEG Using A Novel Time-Frequency-Synchronisation Framework

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Abstract—**An original experimental design is combined with a novel signal processing approach so as to provide cognitive clues in the study of auditory scene analysis and in the design of auditory brain computer interfaces. Volunteers attended a single auditory stimulus in a perceptually complex auditory environment of speech and music, wherein the experiment aim was to estimate the attended stimulus from recorded electroencephalogram (EEG). Unlike previous studies, the complex nature of the auditory environment does not allow for straightforward analysis that exploits convenient properties of the stimuli. To provide insight, synchronised neuronal activity was analysed within a novel signal processing framework that models energy and phase dynamics independently using empirical mode decomposition. By design, the proposed approach caters for higher order information and is suitable for nonstationary data, both critical properties in the analysis of cognitive activity. The proposed methodology achieved a median classification accuracy of 71% in a series of selective attention experiments with several volunteers.**

I. Introduction

We consider the following question. If a subject is presented with two sound sources, can electroencephalogram (EEG) communicate the attended source? The study of neural mechanisms that convey information about selective attention to auditory stimuli has been the focus of research since the 60's and 70's [1] and has applications in areas such as brain computer interface (BCI). Recent work has shown that accurate binary classification can be achieved when the auditory stimuli are perceptually simple tones. This allows for a clear 'watermark' to be inserted into the stimuli, making it straightforward to identify related phenomena in the EEG. For example, one such study [2] determined the attended stimulus by constructing simple stimuli with a unique rhythm and searching for related structure in the EEG. Another [3], compared modulations present in the EEG with the AM (amplitude modulated) and FM (frequency modulated) content of each tone. We propose an experiment in which the stimuli are 'perceptually complex', music and speech, so as to provide insight into the cognitive mechanisms that govern selective attention in a real-world auditory environment.

The complex nature of the chosen experiment design presents a challenge as it is no longer straightforward to incorporate prior knowledge of the stimuli. Instead it is proposed to identify more general features that are likely to be relevant for a wide range of cognitive applications including BCI. To this end, the degree of neuronal synchronisation within different cortical regions of the brain is modelled, which studies show reflects cognitive processing and conveys selective attention [4]. Specifically, the degree of synchronisation within the gamma band, 30-80Hz, is examined [5].

However standard measures of synchronisation, such as coherence or crosscorrelation, are not appropriate in practice as they combine phase and amplitude information and are limited to the analysis of second order signal properties only. Growing evidence suggests that such signal dynamics should be processed independently [6]. It is thus proposed, in addition to standard spectral features, to combine the following features: asymmetry - the lateralization of spectral power between different brain regions; and phase synchrony - the temporal locking of phases. Individual studies of both asymmetry [7] and phase synchrony [6] demonstrate how the processes reflect cognitive activity. It is natural that a joint study will provide a comprehensive synchronisation measure and an insight into the cognitive mechanisms that govern selective attention.

An additional challenge is that EEG data are often nonlinear and nonstationary [8], making standard measures of asymmetry and phase synchrony unsuitable. For example in previous studies [9], [10], asymmetry was calculated with algorithms based on Fourier theory, such as the periodogram, which project the data on linear basis functions and are therefore not appropriate for processing nonlinear data. In the case of phase synchrony, previous studies have used the wavelet transform [11] and the Hilbert transform [12]. Like Fourier based algorithms, the wavelet transform is limited by its fixed-basis operation which affects its time-frequency resolution and estimation of instantaneous phase. In the case of the Hilbert transform, it is only suitable for phase estimation if the data is first bandpass filtered so that it satisfies narrowband criteria. Thus, the approach relies on the a priori selection of bandpass filter cutoffs. Such constraints make the analysis sensitive to slight changes in experimental conditions, meaning that some synchrony events are likely to be missed [13].

The empirical mode decomposition (EMD) [14] is a fully adaptive algorithm which determines the oscillations inherent to the data without any prior assumptions. By design, the AM/FM decomposition components, called intrinsic mode functions (IMFs), are narrowband and thus the Hilbert transform can be applied directly to obtain highly localised phase and amplitude information. The data-driven and localised nature of the algorithm make it suitable for performing

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spectrum analysis [14] and phase synchrony estimation [13] on nonlinear and nonstationary data [15].

More recently, it has been illustrated how bivariate extensions of EMD [16] can improve the performance of the algorithm in applications which require multicomponent analysis [17], [18]. The extension facilitates improved component estimation [18] which can enhance the accuracy of the marginal spectrum for each source, critical to the calculation of asymmetry. Furthermore it allows for a scale by scale comparison between pairs of sources and a more localised estimate of phase synchrony [18].

It is proposed to estimate selective attention features by modelling the degree of gamma band synchronisation, both in energy (asymmetry) and phase (phase synchrony), within a unified bivariate EMD framework. By design, the approach is highly localised in both time and frequency and is sensitive to higher order synchronisation properties. The robustness of the nonlinear synchronisation estimation paradigm is illustrated in a selective attention experiment in which the subject alternates their attention between perceptually complex auditory stimuli. Its performance is compared to that of standard synchronisation measures[1].

II. Methods

A. Subjects, Stimuli, Protocol and Recordings

Eight volunteers with healthy hearing participated in the experiment (mean age 30 years, median age 25 years, five males, three females). The auditory stimuli consisted of a segment of speech and a segment of music, each lasting 30 seconds. The speech consisted of a male reading from a passage of text and the music segment was taken from a baroque orchestral piece. Each of the stimuli were continuous and contained no significant pauses.

The subject was seated between two speakers in a quiet environment. For each experimental trial, the speech and music stimuli were played simultaneously, with speech being played from the right speaker (relative to the subject) and music from the left. Before each trial, the subject was instructed to attend one of the stimuli only. Furthermore, the subject was asked a question specific to the attended stimulus so as to help ensure concentration. The attended stimulus was alternated between trials. After each trial, the subject was interviewed to determine the quality of the concentration. If the subject failed to concentrate adequately, the trial was repeated. A total of 10 trials were performed for each subject, with the music and speech stimulus being identical for each trial. So as to reduce the effects of visual stimuli and ocular artifacts on the recordings, the subjects were instructed to close his/her eyes for the duration of the experiment.

EEG was recorded at positions FC3, FC4, FC5, FC6, C3, C4, T7 and T8 and sampled at 256Hz. Recordings were made with reference to the right ear lobe, and amplified and bandpass filtered at 0.5-100Hz using a gMOBIlab+ portable biosignal acquisition system.

[1]There exist some synchronisation dynamics that can be estimated using linear methods (correlation) but not with asymmetry or phase synchrony. However, this shortcoming will be the focus of future work.

B. The EMD Algorithm

Empirical mode decomposition (EMD) [14] is a data driven time-frequency technique which adaptively decomposes a signal, by means of a process called the sifting algorithm, into a finite set of AM/FM modulated components. These components, called "intrinsic mode functions" (IMFs), represent the oscillation modes embedded in the data. By definition, an IMF is a function for which the number of extrema and the number of zero crossings differ by at most one, and the mean of the two envelopes associated with the local maxima and local minima is approximately zero. The EMD algorithm decomposes the signal $x(t)$ as

$$x(t) = \sum_{i=1}^{M} C_i(t) + r(t) \tag{1}$$

where $C_i(t)$, $i = 1, \ldots, M$, are the IMFs and $r(t)$ is the residual. The first IMF is obtained as follows [14].

1) Let $\tilde{x}(t) = x(t)$;
2) Identify all local maxima and minima of $\tilde{x}(t)$;
3) Find an "envelope," $e_{min}(t)$ (resp. $e_{max}(t)$) that interpolates all local minima (resp. maxima);
4) Extract the "detail," $d(t) = \tilde{x}(t) - (1/2)(e_{min}(t) + e_{max}(t))$;
5) Let $\tilde{x}(t) = d(t)$ and go to step 2); repeat until $d(t)$ becomes an IMF.

Once the first IMF is obtained, the procedure is applied iteratively to the residual $r(t) = x(t) - d(t)$ to obtain all the IMFs. The extracted components satisfy so called monocomponent criteria and the Hilbert transform can be applied to each IMF separately. This way, it is possible to generate analytic signals, having an IMF as the real part and its Hilbert transform as the imaginary part, that is $x + j\mathcal{H}(x)$ where $\mathcal{H}(\cdot)$ is the Hilbert transform operator. Equation (1) can therefore be augmented to its analytic form given by

$$X(t) = \sum_{i=1}^{M} a_i(t) \cdot e^{j\theta_i(t)} \tag{2}$$

where the trend $r(t)$ is purposely omitted due to its overwhelming power and lack of oscillatory behavior. Observe from (2), that now the time dependent amplitude $a_i(t)$ and phase function $\theta_i(t)$ can be extracted. By plotting the amplitude $a_i(t)$ versus time t and instantaneous frequency $f_i(t) = \frac{d\theta_i}{dt}$ [19], a Time-Frequency-Amplitude representation of the entire signal is obtained, the so called Hilbert–Huang spectrum (HHS). This information can be represented by $H(f,t)$ which denotes the spectrum amplitude at time t and frequency f. The Marginal Hilbert Spectrum (MHS), $h(f)$, can be also defined by marginalizing the amplitude of the HHS over time as

$$h(f) = \int_0^T H(f,t)dt \tag{3}$$

where T is the total data length.

C. Complex Extensions of EMD

In order to obtain a set of M complex/bivariate IMFs, $\gamma_i(t)$, $i = 1, \ldots, M$, from a complex signal $z(t)$ using bivariate EMD, the following procedure is adopted [16]:

1) Let $\tilde{z}(t) = z(t)$;
2) To obtain K signal projections, given by $\{p_{\theta_k}(t)\}_{k=1}^{K}$, project the complex signal $\tilde{z}(t)$, by using a unit complex number $e^{-\jmath\theta_k}$, in the direction of θ_k, as
$$p_{\theta_k}(t) = \Re\{e^{-\jmath\theta_k}\tilde{z}(t)\},\ k = 1, \ldots, K \tag{4}$$
where $\Re\{\cdot\}$ denotes the real part of a complex number, and $\theta_k = 2k\pi/K$;
3) Find the locations $\{t_j^k\}_{k=1}^{K}$ corresponding to the maxima of $\{p_{\theta_k}(t)\}_{k=1}^{K}$;
4) Interpolate (using spline interpolation) between the maxima points $[t_j^k,\ \tilde{z}(t_j^k)]$, to obtain the envelope curves $\{e_{\theta_k}(t)\}_{k=1}^{K}$;
5) Obtain the mean of all the envelope curves, $m(t)$, and subtract from the input signal, that is, $d(t) = \tilde{z}(t) - m(t)$. Let $\tilde{z}(t) = d(t)$ and go to step 2); repeat until $d(t)$ becomes an IMF.

Similarly to real-valued EMD, once the first IMF is obtained, $\gamma_1(t)$, the procedure is applied iteratively to the residual $r(t) = z(t) - d(t)$ to obtain all the IMFs

In our previous work [17], [18], we illustrated that in applications involving a pair of real valued sources, x_1 and x_2, it is advantageous to apply BEMD to the complex signal $z = x_1 + jx_2$. The real and imaginary components of the decomposition can then be viewed as two separate sets of IMFs, corresponding respectively to the real and imaginary components of the input. The advantage of applying this bivariate approach, compared to two individual real valued EMD operations, is that it improves the stability and locality of each set of IMFs. Firstly, this facilitates a more localised phase comparison between the IMFs, thus enhancing the performance of phase synchrony analysis. Secondly, it allows for a more accurate estimate of the marginal spectrum for each source which is critical for a robust calculation of asymmetry.

D. Phase Synchrony using BEMD

To measure phase synchrony between x_1 and x_2, bivariate EMD is firstly applied to the complex signal $z = x_1 + jx_2$. The instantaneous amplitudes for the real and imaginary components of the decomposition, the $i = 1, \ldots, M$ IMFs at each time instant $t = 1, \ldots, T$, are denoted by $\Re\{a_i(t)\}$ and $\Im\{a_i(t)\}$ respectively. The instantaneous phase difference between each IMF component is given by $\psi_i(t)$. The degree of synchrony is denoted by [18]

$$\phi_i(t) = \frac{H_{max} - H}{H_{max}} \tag{5}$$

where $H = -\sum_{n=1}^{N} p_n \ln p_n$, the Shannon entropy of the distribution of $\psi_i(t - \frac{W}{2} : t + \frac{W}{2})$ defined by a window of length W, N is the number of bins and p_n is the probability of $\psi_i(t - \frac{W}{2} : t + \frac{W}{2})$ within the nth bin [12]. The maximum entropy H_{max} is given by

$$H_{max} = 0.626 + 0.4\ln(W - 1) \tag{6}$$

The value of ϕ is between 0 and 1, 1 indicating perfect synchrony and 0 a non-synchronous state. An additional step can be incorporated to model simultaneously for component relevance.

$$\phi_i(t) = \begin{cases} 0, & \text{if } \frac{\Re\{a_i(t)\}^2}{2} < \epsilon P_r \\ 0, & \text{if } \frac{\Im\{a_i(t)\}^2}{2} < \epsilon P_i \end{cases} \tag{7}$$

where P_r is the power of the original real component (similarly for P_i) and ϵ is an appropriate threshold. The phase synchrony information can be represented by $\Phi(t, f)$, which denotes the phase synchrony at time t and frequency f. Thus the degree of phase synchrony within the frequency range f_1 to f_2 is given by the scalar

$$\alpha_{(f_1,f_2)} = \sum_t \sum_{f=f_1}^{f_2} \Phi(t, f) \tag{8}$$

E. Asymmetry Ratio using BEMD

The asymmetry ratio for a pair of sources, x_1 and x_2, is estimated as follows. Firstly the set of complex IMFs for $z = x_1 + jx_2$ is obtained using bivariate EMD. The real and imaginary components of the decomposition are then separated giving two sets of IMFs and the MHS is calculated for each, $h_1(f)$ and $h_2(f)$ for x_1 and x_2 respectively. The asymmetry ratio, within the frequency range f_1 to f_2, is given by the scalar

$$\beta_{(f_1,f_2)} = \frac{\left|\sum_{f=f_1}^{f_2} h_1(f)^2 - \sum_{f=f_1}^{f_2} h_2(f)^2\right|}{\sum_{f=f_1}^{f_2} h_1(f)^2 + \sum_{f=f_1}^{f_2} h_2(f)^2} \tag{9}$$

F. Normalised Power Spectrum

The normalised power spectrum, $\mathbf{p}(f)$, which characterises the spectrum shape of a source x_1 within the frequency range f_1 to f_2 is given by the vector

$$\mathbf{p}_{(f_1,\, f_2, n)}(f) = \frac{\log(\hat{P}_{\text{PER}}(f)) - \mu_{\hat{P}}}{\sqrt{\frac{\sum_{f=f_1}^{f_2}(\log(\hat{P}_{\text{PER}}(f)) - \mu_{\hat{P}})^2}{n}}} \tag{10}$$

where

$$\mu_{\hat{P}} = \frac{\sum_{f=f_1}^{f_2} \log(\hat{P}_{\text{PER}}(f))}{n} \tag{11}$$

where $\hat{P}_{\text{PER}}(f)$ denotes spectrum power obtained using a periodogram with a Bartlett window, and n is the number of bins between f_1 and f_2.

Standard Fourier analysis was used to obtain the normalised spectrum because the MHS was found to be too sparse for short data lengths and high frequencies, making it unsuitable for obtaining a continuous spectrum shape at discrete frequency intervals within the frequency range 60-80Hz.

G. Correlation

The correlation between two signals, x_1 and x_2, within the frequency range f_1 to f_2 is given by

$$r_{(f_1,f_2)} = \frac{\sum_{t=1}^{T}\left(h_b\{x_1(t)\} - \overline{h_b\{x_1\}}\right)\left(h_b\{x_2(t)\} - \overline{h_b\{x_2\}}\right)}{\sqrt{\sum_{t=1}^{T}(h_b\{x_1(t)\} - \overline{h_b\{x_1\}})^2}\sqrt{\sum_{t=1}^{T}(h_b\{x_2(t)\} - \overline{h_b\{x_2\}})^2}} \tag{12}$$

where $h_b\{\cdot\}$ denotes a bandpass Butterworth filter operation that admits frequencies between f_1 and f_2 and $\overline{h_b\{x_1\}}$ denotes the sample average of $h_b\{x_1\}$ (similarly for $\overline{h_b\{x_2\}}$ and $h_b\{x_2\}$).

H. Support Vector Machine

Feature classification was achieved using a Gaussian kernel support vector machine (SVM), the code of which was obtained from [20].

I. Statistical Analysis

For a given subject, trial and EEG electrode, each 30s data segment was divided into a set of 6 subsegments each of length 4s[2]. Thus, for each subject and electrode, there were a total of 60 (6×10) subsegments available for analysis.

Analysis was performed individually for each subject and each electrode pair. The analysis for subject 'A', for the electrode pair FC5/FC6 was performed as follows. For each corresponding electrode subsegment pair, that is subsegments from FC5 and FC6 recorded during the same time interval, a 1×4 feature vector, reflecting the degree of higher order synchronisation, was calculated as

$$\xi = [\alpha_{(30,45)}, \beta_{(30,45)}, \alpha_{(60,80)}, \beta_{(60,80)}]^T \tag{13}$$

where $(\cdot)^T$ denotes the matrix transpose. Note that the feature ξ denotes synchronisation in the gamma band only, excluding the frequency band dominated by the electronic interference (45-60Hz). For comparison, a 1×2 feature vector containing second order synchronisation information only (correlation) was calculated as

$$\zeta = [r_{(30,45)}, r_{(60,80)}]^T \tag{14}$$

An additional feature, ρ', relating to the normalised gamma band spectrum of one of the electrodes in the electrode pair (FC5) was also included in analysis. ρ' was obtained by applying principal component analysis to reduce the dimensionality of the 1×37 vector $\rho = [\mathbf{p}_{(30,45,16)}(30,\ldots,45), \mathbf{p}_{(60,80,21)}(60,\ldots,80)]^T$ to a 1×3 feature vector.

Thus for a given electrode subsegment pair, the complete 1×7 feature vector containing normalised spectrum power[3] and nonlinear synchronisation is given by $F_{\text{nonlin}} = [\xi, \rho']^T$ and the 1×5 feature vector containing linear second order information only (normalised spectrum power and correlation) is given by $F_{\text{lin}} = [\zeta, \rho']^T$.

Features for 20 of the 30 attended music subsegments and 20 of the 30 attended speech subsegments were used to train the SVM and classification was performed on the remaining subsegments. The selection of the subsegments used for training was performed in a random fashion. In this way, the SVM was retrained and used to perform classification a total of 50 times. The classification performance was taken to be the average of these 50 outcomes.

This same analysis was repeated, including a full retraining of the SVM, for other electrode pairs and subjects.

III. Results

Classification performances for correctly estimating the attended stimulus (speech or music) for the eight subjects, for linear and nonlinear synchronisation features, are given for various electrode pairs in Table I.

The highest classification performance was obtained by analysing the degree of nonlinear synchronisation between the electrode pair FC5/FC4, which gave a median classification performance of 71%. The median classification performance using linear synchronisation was 64.5% for the same electrode pair. On average for all electrode pairs, the median performance of the nonlinear synchronisation features was 4.3% higher than the linear synchronisation features. It is additionally worth noting that although the average performance obtained with T7/T8 was the lowest of all considered electrode pairs (67% using nonlinear synchronisation features), it facilitated a significant peformance increase (compared to FC5/FC4) for the subject 'H' (88%). This suggests that the cortical locations of neuronal synchronisation related to selective attention can be unique to the subject.

IV. Discussions and Future Work

The sources of uncertainty in this study include the poor resolution recording facilities (only 256Hz sampling frequency), limited number of trials per recording session (only 10 per subject), and limited number of subjects (eight in total). This only gave 60 segments of 4s in duration, as an input to the classifier; due to the small size of the statistics the classifier was trained by randomly choosing 70% of the segments for training and 30% for testing (a rather high ratio). The observed differences in attention to speech and music were derived based on the gamma band, which has a low SNR.

Future work will consider synchronisation among multiple electrodes using recent multidimensional extensions of EMD [21], together with higher precision recording. This will help generate sufficient statistics for other classification paradigms, investigating both inter-trial and inter-subject variability (e.g. trial-wise rather than segment-wise). Future work will also consider synchronisation dynamics which cannot be estimated using asymmetry and phase synchrony.

[2]The initial 5s and final 5s of each recording were discarded so that any EEG response caused by the sudden introduction/cessation of the stimulus was discarded

[3]The normalised spectrum power was calculated for the first electrode in the electrode pair.

V. Conclusion

A novel framework for estimating synchronised neuronal activity has been presented. This has been achieved using bivariate extensions of empirical mode decomposition, facilitating highly adaptive and localised multicomponent analysis to calculate phase synchrony and asymmetry. The approach has been shown to be suitable for higher order synchronisation in EEG, and has been applied to a novel selective attention auditory experiment. We have achieved a 4.3% increase in the classification performance compared to standard synchronisation measures. Future work is necessary to fully establish the full statistical significance of experiment findings regarding selective attention, however, the proposed framework has showed clear potential in the design of advanced BCI.

TABLE I

The classification rates for 8 subjects using linear (F_{LIN}) and nonlinear synchronisation features (F_{NONLIN}).

Subject	Feature / Electrode pair	F_{lin}	F_{nonlin}
A	FC5/FC6	**81.3**	77.4
	FC5/FC4	**80.9**	77.1
	FC5/C4	78.8	**79.1**
	FC5/T8	77.7	**79.1**
	T7/T8	64.4	**68.1**
B	FC5/FC6	55.9	**64.7**
	FC5/FC4	54.1	**60.9**
	FC5/C4	57.4	**70.9**
	FC5/T8	55.8	**64.8**
	T7/T8	55.5	**57.2**
C	FC5/FC6	**67.3**	66.1
	FC5/FC4	68.2	**68.8**
	FC5/C4	**68.3**	67.1
	FC5/T8	**70.1**	66.3
	T7/T8	52.4	**54.2**
D	FC5/FC6	61.9	**70.6**
	FC5/FC4	60.4	**69.3**
	FC5/C4	61.9	**68.8**
	FC5/T8	63.1	**73.1**
	T7/T8	65.8	**68.2**
E	FC5/FC6	58.1	**61.7**
	FC5/FC4	59.6	**82.1**
	FC5/C4	60.2	**66.1**
	FC5/T8	60.2	**64.5**
	T7/T8	65.8	**66.7**
F	FC5/FC6	**81.4**	76.7
	FC5/FC4	**78.8**	72.9
	FC5/C4	**82.8**	72.4
	FC5/T8	**79.1**	71.3
	T7/T8	**58.5**	53.9
G	FC5/FC6	70.3	**82.0**
	FC5/FC4	64.8	**76.1**
	FC5/C4	71.3	**76.8**
	FC5/T8	66.0	**74.6**
	T7/T8	73.0	**77.4**
H	FC5/FC6	58.5	**67.2**
	FC5/FC4	**64.2**	54.1
	FC5/C4	58.1	**58.9**
	FC5/T8	59.2	**59.7**
	T7/T8	64.1	**88.3**

References

[1] S. A. Hillyard, R. F. Hink, V. L. Schwent, and T. W. Picton, "Electrical signs of selective attention in the human brain," *Science*, vol. 182, no. 4108, pp. 177–180, 1973.

[2] N. J. Hill, T. N. Lal, K. Bierig, N. Birbaumer, and B. Schölkopf, "An auditory paradigm for brain-computer interfaces," *Advances in Neural Information Processing Systems 17*, pp. 569–576, 2005.

[3] M. G. J. Kallenberg, "Auditory selective attention as a method for a brain computer interface," M.S. thesis, Master's thesis at the Department Music, Mind, Machine at the NICI, Radboud University, Nijmegen, 2006.

[4] T. Womelsdorf and P. Fries, "The role of neuronal synchronization in selective attention," *Current Opinion in Neurobiology*, vol. 17, pp. 154–160, 2007.

[5] J. Fell, G. Fernandez, P. Klaver, C. E. Elger, and P. Fries, "Is synchronized neuronal gamma activity relevant for selective attention?," *Brain Research Reviews*, vol. 42, pp. 265–272, 2003.

[6] F. Valera, J.-P. Lachaux, E. Rodriguez, and J. Martinerie, "The brainweb: phase synchronization and large-scale integration," *Nature Rev. Neurosci.*, vol. 2, pp. 229–239, 2001.

[7] J. R. Knott and T. D. Tjossem, "Bilateral encephalograms from normal speakers and stutterers," *Journal of Experimental Psychology*, vol. 32, pp. 357–362, 1943.

[8] T. Gautama, D. P. Mandic, and M. M. Van Hulle, "On the indications of nonlinear structures in brain electrical activity," *Phys. Rev. E*, vol. 67, no. 4, pp. 046204, Apr 2003.

[9] A. Akrami, S. Solhjoo, A. Motie-Nasrabadi, and M. Hashemi-Golpayegani, "EEG-based mental task classification: Linear and nonlinear classification of movement imagery," in *Proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference*. IEEE, September 2005.

[10] Z. A. Keirn and J. I. Aunon, "A new mode of communication between man and his surroundings," *IEEE Transactions on Biomedical Engineering*, vol. 37, pp. 1209–1214, 1990.

[11] J. Lachaux et al, "Estimating the time-course of coherence between single-trial brain signals: an introduction to wavelet coherence," *Clinical Neurophysiology*, vol. 32, pp. 157–174, 2002.

[12] P. Tass et al., "Detection of n:m phase locking from noisy data: Application to magnetoencephalography," *Physical Rev. Letters*, vol. 81, no. 15, pp. 3291–3294, 1998.

[13] C. M. Sweeny-Reed and S. J. Nasuto, "A novel approach to the detection of synchronisation in EEG based on empirical mode decomposition," *Journal of Computational Neuroscience*, vol. 23, no. 1, pp. 79–111, 2007.

[14] N. E. Huang, Z. Shen, S. R. Long, M. L. Wu, H. H. Shih, Z. Quanan, N. C. Yen, C. C. Tung, and H. H. Liu, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Proceedings of the Royal Society A*, vol. 454, pp. 903–995, 1998.

[15] T. M. Rutkowski, D. P. Mandic, A. Cichocki, and A. W. Przybyszewski, "EMD approach to multichannel EEG data - the amplitude and phase components clustering analysis," *Journal of Circuits, Systems, and Computers (JCSC)*, vol. 19, no. 1, pp. 215–229, 2010.

[16] G. Rilling, P. Flandrin, P. Goncalves, and J.M. Lilly, "Bivariate empirical mode decomposition," *IEEE Signal Processing Letters*, vol. 14, pp. 936–939, 2007.

[17] D. Looney and D. Mandic, "Multi-scale image fusion using complex extensions of EMD," *IEEE Transactions on Signal Processing*, vol. 57, pp. 1626–1630, 2009.

[18] D. Looney, C. Park, P. Kidmose, M. Ungstrup, and D. P. Mandic, "Measuring phase synchrony using complex extensions of EMD," in *Proceedings of the IEEE Statistical Signal Processing Symposium*, 2009, pp. 49–52.

[19] L. Cohen, "Instantaneous anything," in *Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 1993, vol. 5, pp. 105–108.

[20] S. Canu, Y. Grandvalet, V. Guigue, and A. Rakotomamonjy, "SVM and kernel methods Matlab toolbox," Perception Systemes et Information, INSA de Rouen, Rouen, France, 2005.

[21] N. Rehman and D.P. Mandic, "Multivariate empirical mode decomposition," *Proceedings of the Royal Society A*, vol. 466, no. 2117, pp. 1291–1302, 2010.