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Phase-Based Brain Consciousness Analysis

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Abstract— **This work provides a novel framework for identifying coma and brain death consciousness states by analysing frequency power and phase synchrony features from electroencephalogram (EEG). The proposed analysis of pairs of EEG electrodes using complex extensions of Empirical Mode Decomposition (EMD) permits the extraction of information related to the state of the brain function. Analysis on 34 subjects in the coma and quasi-brain-death states suggests that phase synchrony constitutes a feasible feature to discriminate quasi-brain-death from coma state. Thus, illustrate the effectiveness of the proposed methods for brain consciousness identification. The predictive power of the features extracted is evaluated by building classification models using support vector machine (SVM) and evaluation the models through receiver operating characteristic (ROC) analysis.**

I. INTRODUCTION

The electroencephalogram (EEG) is an important clinical tool for the monitoring of the human brain, due to its non-invasive nature and high temporal resolution. One important topic within such research is related to the identification of brain death, and its implications in the legal and medical communities. The legal definition of brain death is an irreversible loss of forebrain and brainstem functions, however, it is difficult to implement brain death diagnosis precisely, mostly due to clinical issues. Although the diagnosis criteria are different from country to country, repetition of clinical testing is required in a number of countries after initial documentation of clinical signs of brain death. Some of the tests might require the patient be transported out of the intensive care unit (ICU) or temporary be disconnected from important medical care (the respirator), and stress the already compromised vital organs. The diagnosis process requires a preliminary EEG test to determine whether further brain death test, especially those requiring patients to be disconnected from critical life support devices, need to be implemented or not. After the preliminary EEG test, an initial prognosis of quasi-brain-death (QBD) is given; the term "quasi-" means that this is a preliminary decision and the final diagnosis of brain death requires further medical tests. Initial prognosis of quasi-brain-death (QBD) is given based on various methods used for studying brain states using EEG. For example studies have shown that large activity in the alpha band suggests the alertness of a patient [1]. However, standard power spectral density (PSD) based spectral analysis critically ignores all phase information which is considered as an important factor for understanding mechanism for neural integration.

The temporal locking of phase information between different cortical regions of the brain conveys important cognitive information [2]. This is because cognitive operations in the brain require the integration of neuron activation from different brain areas, known as large scale integration. The integration between different brain areas leads to phase locking of the underlying bioelectric signals and is reflected by the EEG signals detected from electrodes. Phase synchrony is used in this work as a measurement of phase locking over a limited period of time. Traditional measures of phase have used the wavelet and Hilbert transform. The wavelet transform is based on a projection onto a fixed set of basis functions which limits its time-frequency resolution and its analysis of nonlinear data. Furthermore, the Hilbert transform is only suitable for phase estimation if the data is first bandpass filtered so that it satisfies narrowband criteria, making the approach sensitive to the a priori selection of filter cutoffs. To address these issues concerning phase synchrony, the recently introduced empirical mode decomposition (EMD) [3] was first applied to measure phase synchrony in [4]. This facilitates highly localized estimation of phase information for analyzing data from nonlinear and nonstationary processes. Furthermore, as illustrated in [5], complex extensions of EMD offer advantages when analysing pairs of sources with shared signal statistics, thus enabling more robust phase synchrony estimation.

We provide a statistically robust framework to test for QBD by using frequency power and EMD-based phase synchrony features obtained from EEG. The proposed analysis thus explores information to charactarise the brain consciousness, and is supported by classification results and sensitivity and specificity analysis on 34 subjects.

II. SENSING - DATA ACQUISITION

The EEG data were recorded in the intensive care unit using the standardized 10-20 system in HuaShan Hospital, Shanghai, China. Electrodes were placed at positions F3, F4, F7, F8, Fp1, Fp2 as well as GND, and also two were

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placed on the ears (denoted by A1 and A2 respectively). The measured voltage signal was then digitized via a portable EEG recording instrument with a sampling frequency of 1000 Hz. Experimental data were obtained from 34 patients (16 female, 18 male) of the ages ranging from 17 to 85 years old; 17 of the patients were in a state of coma, 17 of them were in quasi-brain-death state.

III. SIGNAL PROCESSING AND FEATURE EXTRACTION

In the proposed method, two sets of features were investigated for identifying brain states. One is to use frequency power of the EEG signals as a feature to observe the neuro oscillations. The other feature is the phase synchrony feature as the indication of neural integration in the brain. Algorithms for estimating those features are described in this section.

A. Estimate Frequency and Phase using EMD based Hilbert Transform

The frequency information and phase information were extracted using EMD based Hilbert Transform. The advantage over the tranditional filter based method is that EMD is a data driven technique that adaptively decomposes a signal into a number of zero-mean [3], band limited oscillatory components, therefore fullfill the requirement of applying Hilbert transform for obtaining the frequency and phase information. Those band limited components are called intrinsic mode functions (IMFs). Two steps can be applied for estimating frequency and phase information from a time series. Step 1: to apply EMD for decomposing original time series into band limited signals. Step 2: to apply Hilbert transform for estimating frequency and phase. The algorithm is described below.

1) Algorithm for Step 1: : We first describe how the EMD is applied in real domain, then describe the EMD extension to the complex domain and why we choose to use the complex domain method for obtaining band limited signals. A signal $x(t)$ can be decomposed into IMFs with following steps [3]:

- Obtain the extrema of $x(t)$, including all the local maxima and local minima.
- Construct new a waveform with all the maxima called the upper envelope. Use all the minima to form lower envelope.
- Calculate the average of the upper envelope and lower envelope.
- Subtract the average $m(t)$ from the original signal $x(t)$, represented as $d(t) = x(t) - m(t)$.
- Repeat until $d(t)$ satisfies the conditions of an IMF: the difference between the number of zero crossings and number of extrema is less or equal than one, and the mean of the upper envelope and lower envelope is approximately zero.
- Once the ith IMF $c_i(t)$ is extracted, subtract all the extracted IMFs from $x(t)$ and take the remaining signal as new signal and repeat the above steps until the stopping criteria are satisfied.

After the decomposition, the signal can be represented as: $x(t) = \sum_{i=1}^{n} c_i(t) + r(t)$, where $c_i(t)$ is the ith IMF, n is the total number of IMFs, and $r(t)$ is the residue.

The extension of EMD algorithms to the complex domain $\mathbb{C}$ is particularly important for the analysis of phase-dependent process [1]. Complex extensions of EMD include the Complex Empirical Mode Decomposition (CEMD) [6], Rotation Invariant Empirical Mode Decomposition (RIEMD) [7], and Bivariate Empirical Mode Decomposition (BEMD) [8]. The BEMD is particularly suitable for the analysis of phase synchrony as it operates directly in $\mathbb{C}$ and facilitates enhanced local mean estimation compared to RIEMD [9].

The algorithm for decompositing a complex signal $z(t) = x_1(t) + jx_2(t)$ using BEMD is listed below [8]:

- Project the complex signal in the direction of $\theta(k)$ to obtain K signal projections $\{p_{\theta_k}\}_K^{k=1}$ as: $p_{\theta_k} = \Re(e^{-j\theta_k} z(t)), k = 1, ..., K$, where $\Re(\cdot)$ is the real part of the underlying complex number, and $\theta_k = 2k\pi/K$;
- Find the local maxima of $\{p_{\theta_k}\}_K^{k=1}$ and its corresponding $\left\{t_j^k\right\}_K^{k=1}$. Using spline interpolation to construct the envelope $\{e_{\theta_k}\}_K^{k=1}$ by the maxima.
- Calculate the mean of all evelopes $m(t)$
- Subtract the mean $m(t)$ from the original signal $z(t)$, represented as $d(t) = z(t) - m(t)$.
- Go to step 1), replace $d(t)$ as $z(t)$ and repeat until $d(t)$ becomes an IMF.
- Once the complex IMF is extracted, subtract all the extracted IMF from $z(x)$ and repeat the above steps until all the IMFs are extracted.

2) Algorithm for Step 2: Apply Hilbert transform to the above decomposed IMFs to obtain instantaneous frequency and instantaneous phase. In real domain, as the IMFs satisfy narrow-band criteria of the Hilbert transform $\tilde{x}(t) = \mathcal{H}[x(t)]$ and the analytic signal $z_a(t)$ is given by $z_a(t) = x(t) + j\tilde{x}(t)$, $z_a(t) = a(t)e^{j\theta(t)}$, and the amplitude of instantaneous frequency $a(t)$, instantaneous frequency $\omega(t)$ and the instantaneous phase function $\theta(t)$are given by

$$a(t) = \sqrt{x^2(t) + \tilde{x}^2(t)},$$

$$\theta(t) = \arctan\left(\frac{\tilde{x}(t)}{x(t)}\right) \qquad and \qquad \omega(t) = \frac{d}{dt}\theta(t).$$

In the case of decomposed complex IMF using BEMD, the Hilbert transform is applied to real part and imaginary part of the complex IMF individually for obtain the instantaneous frequency and instantaneous phase. The estimated $a(t)$ and $\omega(t)$ are used for frequency power feature extraction. The estimated instantaneous phase $\theta(t)$ is used for futher analysis of phase synchrony as described below.

B. Quantify Phase Synchrony using Phase Synchrony Index

Phase synchrony provides a measurement of the relationship between two signals in spite of the amplitude of the signal. There are terms used for defining phase relationship, i.e. "in phase", "out of phase", "phase locking". In this work, we follow "phase locking" defined in [2] for the phase synchrony measurement. That is, for signals $s_1(t)$, $s_2(t)$,

and their corresponding instantaneous phase $\phi_1(t)$, $\phi_2(t)$, the phase locking is

$$\phi_{12}(t) = |n\phi_1(t) - m\phi_2(t)| \tag{1}$$

where n, m are integers indicating the ratios of possible frequency locking. We focus on the case $n = m = 1$ for this application. If $\phi_{12}(t)$ is a constant, it means that the events detected by two individual electrodes have a phase locking, therefore indicates there is an interaction within the brain.

Having obtain the phase information from the data, we will be able to quantify the phase difference using statistical method as described below. BEMD provides a unique platform to estimate phase synchrony [5]. For a pair of sources $x_1(t)$ and $x_2(t)$, this can be achieved by firstly applying BEMD to $z(t) = x_1(t) + jx_2(t)$, thus obtaining a set of complex IMFs, $c_i(t)$, $i = 1, ..., n$. The instantaneous amplitudes for the real and imaginary part of each IMF at each time instant $t = 1, ..., T$ are denoted by $\Re\{a_i(t)\}$ and $\Im\{a_i(t)\}$. For the ith IMF, the instantaneous phase difference between the real part and imaginary part is given by phase locking $\phi_i(t)$. In order to statistically quantify the phase synchrony, the deviation of the actural distribution of $\phi_i(t)$ from the δ distribution (perfect synchrony) indicates the degree of phase synchrony. It can be quantified using Shannon entropy by the phase coherence value (PCV) [10]:

$$\rho_i(t) = \frac{E_{max} - E}{E_{max}} \tag{2}$$

where $E = -\sum_{n=1}^{N} p_n \ln p_n$, the Shannon's entropy of the distribution function $\phi_i(t - \frac{W}{2} : t + \frac{W}{2})$ defined by a window of length W, N is the number of bins, p_n is the probability of $\phi_i(t - \frac{W}{2} : t + \frac{W}{2})$ within nth bin [10]. The maximum entropy is $E_{max} = 0.626 + 0.4 \ln(W - 1)$. In the process of evaluating the phase difference distribution, the power of the inputs may also be considered, so as to cater for component relevance, giving

$$\rho_i(t) = \begin{cases} \frac{E_{max} - E}{E_{max}}, & \textbf{if } \Re\{a_i(t)\} \geq \gamma, \Im\{a_i(t)\} \geq \gamma \\ 0, & \textbf{if } \Re\{a_i(t)\} < \gamma, \Im\{a_i(t)\} < \gamma \end{cases} \tag{3}$$

where γ is an appropriate threshold. In this way, the degree of the phase synchrony varies between 0 and 1.

IV. RESULTS AND DISCUSSION

In this section, the effectiveness of the extracted frequency and phase synchrony features are modelled using machine learning (SVM) and evaluated ROC analysis.

A. Feature Extraction Results

1) Frequency Power Feature: Fig. 1 shows the frequency Power feature from the quasi-brain-death and coma patients, produced by extracting frequency power of the FP1 electrode within the range 0 - 50Hz. The standard deviation for the coma and QBD patients are also shown to assess the degree of feature separation. The analysis was carried out with a window length of ($W = 1000$). In Fig. 1, we know that the

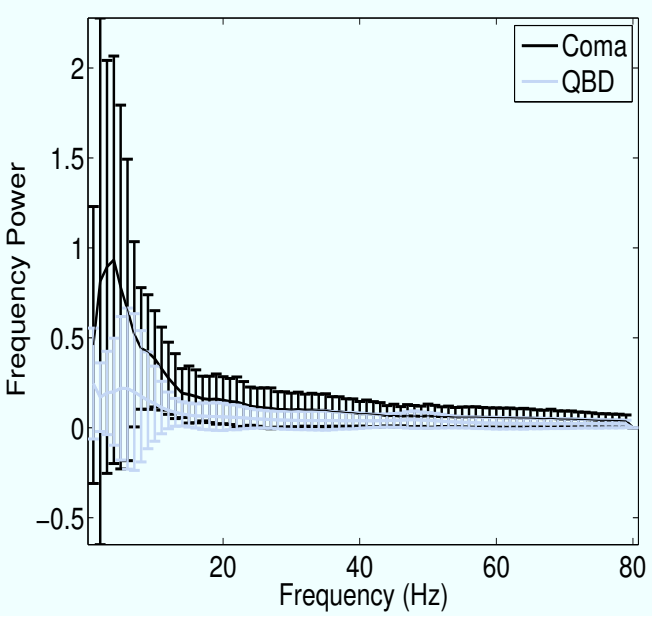

Fig. 1. Frequency power features and error bars (+/- standard deviation).

average power of coma's EEG is higher than that of QBD since coma patients have brain activities which are mainly within the range of 8Hz - 13Hz . Moreover, in the same band, frequency power has a less overlapping error bar leading to slightly separation the coma and QBD patients.

2) Phase Synchrony: Phase locking is generated from the integration between different brain areas. The physical meaning of phase locking is described in Chaos theory: the process of phase locking occurs whenever the chaotic actions of the individual shifts to the ordered actions of a collective system–when individual behavior shifts to a collective behavior [11]. This gives a foundamental background of why phase synchrony is important for understanding the neuron integration, especially why it is particular useful for the identification of coma and brain death state. Coma patients have the ability to shift individual chaotic actions to the ordered actions of a collective system. The chaotic to ordered process can be reflected by phase synchrony, whereas brain death patients do not have the ability to conduct cognitive operations, therefore, phase locking should not be detected, which will lead to low phase synchrony. The feature extraction results confirms about this theory. Phase synchrony features were obtained by applying BEMD to electrodes FP1 and FP2, based on the window length $W = 1000$ and illustrated in Fig. 2. It can be observed that there is a distinctive peak in the phase synchrony index for patients' EEG between 4 Hz and 13 Hz leading to the separation of the coma and QBD patients.

B. Classification Results and ROC Analysis

The adequacy of the extracted features for the diagnosis was modelled using the Support Vector Machine (SVM) classification method. Further more, Receiver Operating Characteristic (ROC) analysis was employed to evaluate

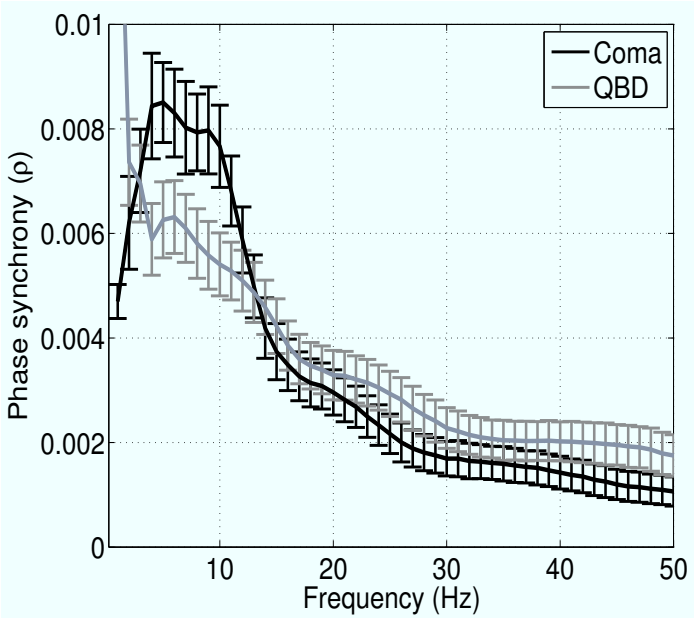

Fig. 2. Phase synchrony feature extracted from coma and QBD patients.

TABLE I
SVM CLASSIFICATION RESULTS

Features	SVM accuracy(%)	AUC
Periodogram 1-13Hz	88.8889	0.9250
Periodogram 1-30Hz	88.8889	0.9625
Periodogram 8- 13Hz	83.3333	**0.9875**
Phase Synchrony 1-13Hz	83.3333	0.9750
Phase Synchrony 1-30Hz	**94.4444**	**0.9875**
Phase Synchrony 8-13Hz	**94.4444**	0.9750

the specificity and sensitivity of the classification for brain consciousness state between 'coma' and 'QBD' in different frequency ranges, i.e., 1 - 13 Hz (delta, theta, and alpha bands), 1 - 30 Hz (covers most the EEG frequency bands), 8 - 13 Hz (alpha band only).

In our work, SVM was applied using a Gaussian kernel and Quadratic Programming (QP) algorithm [12] as a soft margin classifier. The conditioning parameter set for the QP algorithm was 0.000001. The sample vector used contained 13 column (1-13Hz), 30 column (1-30Hz), and 6 column (8-13Hz). The classification accuracy was evaluated on all the 34 patients (2/3 of the data as training data, 1/3 as test data) each time; the mean accuracy of 10 times cross-validation. The best model is choosen for classification and the results are shown in Table I. Phase synchrony features gave the enhanced accuracy over PSD and the phase synchrony feature (1-30Hz) and (8-13Hz) provides the best classification accuracy (94.4444%).

The Area Under the ROC curve (AUC) was used for the evaluation of the possibility of correctly estimating the two brain states in terms of sensitivity and specificity. The ROC curve was plotted by adjusting the threadhold of SVM output, distance from classification hyperplane. It can been seen from Table I that the standard PSD at 8-13 Hz has an AUC value of 0.9875, whereas the phase synchrony method at 1-13 Hz showed a significant the same AUC value, suggesting the effectiveness of both features in identifying two brain states.

V. CONCLUSION

This paper presents a statistically robust framework to detect the presence of brain death by analyzing PSD and phase synchrony features extracted from EEG signals. The standard frequency power analysis on EEG data can be used to characterize brain activity, however, other feature such as phase synchrony can also be used for such purpose. The analysis presented suggests a great potential of identifying different consciousness states using the EMD-derived phase synchrony features. This leads to future invesgitation of novel methods for neuro-marker discovery.

REFERENCES

[1] D. P. Mandic, M. Golz, A. Kuh, D. Obradovic, and T. Tanaka, *Signal Processing Techniques for Knowledge Extraction and Information Fusion*. Springer, 2008.

[2] E. R. F. Varela, J.P. Lachaux and J. Martinerie, "The brainweb: Phase synchronization and large-scale integration," *Nature Reviews Neuroscience*, vol. 2, pp. 229–239, 2001.

[3] 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.

[4] 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, pp. 79–111, 2007.

[5] D. Looney, C. Park, P. Kidmose, M. Ungstrup, and D. P. Mandic, "Measuring phase synchrony using complex extensions of EMD," *Proceedings of IEEE 15th Workshop on Statistical Signal Processing(SSP2009)*, pp. 49–52, 2009.

[6] T. Tanaka and D. P. Mandic, "Complex empirical mode decomposition," *IEEE Signal Processing Letters*, vol. 14, pp. 101–104, 2007.

[7] M. Altaf, T. Gautama, T. Tanaka, and D. P. Mandic, "Rotation invariant complex empirical mode decomposition," *Proceedings of the International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, vol. 3, pp. 1009–1012, 2007.

[8] G. Rilling, P. Flandrin, P. Gonalves, and J. Lilly, "Bivariate empirical mode decomposition," *IEEE Signal Processing Letters*, vol. 24, pp. 936–939, 2007.

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

[10] P. Tass, M. G. Rosenblum, J. Weule, J. Kurths, A. Pikovsky, J. Volkmann, A. Schnitzler, and H.-J. Freund, "Detection of $n : m$ phase locking from noisy data: Application to magnetoencephalography," *Physical Review Letters*, vol. 81, no. 15, pp. 3291–3294, 1998.

[11] F. D. Peat and J. briggs, Eds., *Turbulent Mirror: An Illustrated Guide to Chaos Theory and the Science of Wholeness*. HarperCollins Publishers Inc., 1990.

[12] A. Rakotomamonjy, "Analysis of SVM regression bounds for variable ranking," *Neurocomputing*, vol. 70, no. 7-9, pp. 1489–1501, 2007.