

Unconsciousness State Identification Using Phase Information Extracted by Wavelet and Hilbert Transform

Melissa Berthelot¹, Adrien Witon² and Ling Li² .

Abstract—This work aims to determine features for the distinction of coma and quasi brain death (QBD) consciousness states by implementing an algorithm for extracting phase information from EEG data using wavelet convolution and Hilbert transform. The relationship between the EEG data recorded from pairs of different electrodes is then quantified by calculating phase synchrony using Shannon entropy, as a phase synchrony index (PSI). Statistical analysis was used to evaluate the significant pairs of electrodes for the features extracted in the different frequency bands. The findings suggest confirm that both wavelet and Hilbert transform based phase synchrony analysis provide similar results. In particular, Hilbert transform might be a more suitable method for phase synchrony analysis to characterize coma or QBD brain states for lower frequency bands. Using non-parametric statistical tools is reliable and does not require strong assumption on the dataset distribution. The algorithm is not designed to be a diagnosis tool; it rather serves as a secondary test to confirm diagnosis. It also has a potential contribution for the systematic distinction of brain states in other areas of EEG-based research.

I. INTRODUCTION

This work aims to contribute to the knowledge of neuroscience by extracting features from EEG for the distinction of consciousness states. The algorithm and statistical analysis used can be reproduced to be applied to different fields for various applications: from medical purposes to brain computing. Indeed, the logic of the algorithms implementation remains the same regardless of the studied (un)consciousness states, cognitive tasks or mental disease, and can be used to understand brain states and consciousness. The algorithm is based on phase and phase-synchrony detection and quantification: neural assemblies lead to phase-synchronized pattern in order to produce a cognitive action [1]. To detect the neural assemblies involved and analyze how much they are synchronized, many similar signal processing methods can be adapted. From those, it is possible to extract distinct characteristics, construct realistic maps of the connections between the different neural assemblies, of the significant pairs of electrodes included in a specific cognitive action or brain state at a specific frequency range and to compare them.

Particularly, extracting systematic features to distinguish coma and quasi brain death (QBD) states using wavelet convolution or Hilbert transform-based phase synchrony on group analysis EEG records is, to our knowledge, a new area of research. The point is to improve the diagnosis

processes (variant from countries) for brain death by using less intrusive and heavy methods [2]. On a near real time basis, the algorithm can be used to monitor the evolution of the patients brain state and eventually detect significant brain state changes as it is not humanly possible to individually monitor 24/7 each patient in an intensive care unit (ICU). Consequently, assistance can be more quickly provided. It can also be used as a tool to help confirming doctors diagnosis. In this study, the synchrony between pairs of electrodes is evaluated for different frequency ranges (alpha, beta, delta and theta) for coma and QBD brain states. For the phase extraction, wavelet convolution and Hilbert transform are used and compared before the computation of the synchrony via the Shannon entropy. The impact of the use of the Laplacian spatial filter is also analyzed. Finally, the significant pairs allowing the distinction of the states are extracted after statistical analysis and topographically plotted for each frequency range.

II. SENSING - DATA ACQUISITION

The recording of the EEG data took place in an ICU using the standardized 10-20 system in HuaShan Hospital, in Shanghai (China), with a portable NEUROSCAN ESI system set for a sampling rate of 1000Hz. 34 patients were recorded: 16 males and 18 females, from 17 to 85 years old; 17 patients in coma and 17 patients in QBD. All the patients were examined by two independent physicians for the coma test, pupils test and brainstem reflexes. We measured the EEG at this stage. The mean of recording was 17min. Considering that the patients were in bed, only nine electrodes were used for recording with two positioned on the ears (left and right) as reference (A1, A2). The other electrodes (Fp1, Fp2, F3, F4, F7, F8, Cz) were used for data acquisition, with Cz the ground electrode. The corresponding channel numbers for the electrodes were: Fp1 - channel 1, Fp2 - channel 2, F3 - channel 3, F4 - channel 4, F7 - channel 5, F8 - channel 6. Consequently, only 6 channels of data are recorded. Although noise interference is believed to be minimal as the patients remained steady during the data acquisition, smoothing filter was applied on all data before being processed.

III. FEATURE EXTRACTION

In order to extract features for the distinction of coma and QBD states, we adopted phase synchrony analysis. A strong phase synchrony between two different electrodes can indicate: either 1) a connection between two brain regions where these two electrodes are located; or 2) The biopotential generated by a locally synchronized activity, namely a source

¹Melissa Berthelot is with The Hamlyn Centre, Imperial College London, South Kensington, London UK. email: {meb14@ic.ac.uk} ² Adrien Witon and Ling Li are with the School of Computing, University of Kent, UK. e-mail: {c.li@kent.ac.uk, aw448@kent.ac.uk}

inside the brain, gets propagated to two different electrodes at the scalp. Both scenarios indicate brain activity, thus distinguish coma and QBD.

Two main steps are needed for a phase synchrony analysis. Step 1 is to obtain the phase information, which includes the detection and extraction of a signals phase. Step 2 is the phase synchrony analysis, which evaluates the phase relationship of two signals. The goal is to quantify the similarity of phase using an entropy-based index (phase synchrony index: PSI [1]). The PSI has its value ranging from 0 (no similarity i.e. no synchronization) to 1 (total similarity i.e. total synchronization). Having obtained the PSI for each pair of electrodes, statistical analysis is applied to evaluate the extracted PSI features for the distinction of brain states.

A. Step 1: Phase Analysis for Each Channel of EEG data

There are many existing methods for extracting phase information (i.e. Fourier Transform, Short Time Fourier Transform, Wavelet Analysis, Hilbert Transform). In order to extract phase information from a non-stationary EEG signal, we can use either wavelet analysis or Hilbert transform. In this work, we applied both methods and compared their performance in extracting phase synchrony features.

a) *Wavelet Convolution:* Before conducting wavelet analysis, the signal was segmented by a fixed time window of 1 second. We also chose the length of the wavelet. The length of the wavelet window is determined by a trade-off between the underlying frequency band, the sample frequency of the EEG, and the edges of the convolved signal that might need to be cut to minimize the impact of the edge effect [3]. In order to extract 12Hz (12 cycles per second) information from the EEG time series, it is necessary to have at least a window length of one cycle to be able to extract the signals phase. Conventionally, in order to minimize the edge effect, an empirical time window for a minimum two cycles is used (i.e. 2 seconds for 1Hz) and contains 2000 time points for a signal with a sampling frequency of 1000Hz. Thus, after wavelet convolution, we can remove one cycle of the convoluted signal (half cycle at the beginning, half cycle at the end) that have been convolved with the tapered part of the filter. In fact, when a filter is created, its edges do not usually match those of the ideal filter, consequently we removed those convolved parts as the results are compromised (particularly with the wavelet which creates artefacts on the convoluted signal).

b) *Hilbert Transform:* Data have to be band limited to be able to apply Hilbert Analysis for phase extraction. There are methods that can be used to obtain band limited signals; one standard method is to use band pass filter to restrict the frequency range needed for the analysis. Alternatively, empirical mode decomposition (EMD) [4], or its extensions in complex domain [5] and multivariate domain [6] can be used to automatically decompose signals into a number of band limited signals before applying Hilbert Transform for phase extraction. After constructing the filter, verification on its correctness has to be made by comparing the similarity of the frequency characteristics of the constructed filter with

those of the ideal one [3]. Then, similarly to the wavelet convolution method, the signal was segmented by a fixed time window. To allow an effective comparison, the length of the window will match that of the wavelet convolution. Finally, Hilbert transform is applied on each segmented data.

B. Step 2: Phase Synchrony Quantification Using Entropy

Entropy is the measure of uncertainty in a random variable: it is the amount of information a variable has. Entropy quantifies the expected values of the information contained in the random variable. Therefore, if a result of a variable falls into a range of expected values, the entropy is low, otherwise, it is high. In our study, we used entropy-based phase synchrony index (PSI) [1] to quantify the degree of phase synchrony. If two signals are perfectly synchronized, the phase difference between the two signals remains the same all the time, thus low in entropy. Considering two time series, which have exactly the same shape, but with a slightly delay, the phase difference between the two signals would remain a constant. On the contrary, if two signals are not synchronized, the phase difference would significantly vary and lead to a higher entropy. Therefore, the phase relationship between two signals can be quantified using the following formula.

First, calculate the phase difference between the signals: for the signals $s_1(t)$ and $s_2(t)$ and their respective phases $\phi_1(t)$ and $\phi_2(t)$, their absolute difference is:

$$\phi_{12}(t) = |\phi_1(t) - \phi_2(t)| \quad (1)$$

If $\phi_2(t)$ is a constant, the signals $s_1(t)$ and $s_2(t)$ are synchronized (phase-locked). From this differential, it is possible to calculate the PSI for a pair of channels 1 and 2, for each point of the window by sliding the window over the signal [7]:

$$PSI_{12}(t) = \frac{(E_{max} - E)}{E_{max}} \quad (2)$$

with

$$E = - \sum_{n=1}^N pn \ln(pn) \quad (3)$$

the Shannon entropy of $\phi_2(t)$ is calculated using the time window ($t : t + W$), with W the window length, N is the number of phase bins:

$$N = \exp(0.626 + 0.4 \ln(W)) \quad (4)$$

and $E_{max} = \ln(N)$; pn is the probability of $\phi_2(t)$ being obtained within the time window ($t : t + W$).

For each time point, the PSI quantified by entropy is calculated using a time window. Selecting appropriate time window to calculate the PSI is important, as it has a direct impact on the calculation of the number of bins. With too few bins, it will be not sensitive enough to reveal the true distribution of the data and with too many bins, the distribution will be too flat. In both cases, it will not be possible to properly interpret the distribution result. According to equation 4, the length of the time window can be selected. Such parameter selection is detailed in the following section.

C. Parameters Selection

Here is the list of the parameters that we have used in our study:

- Wavelet Transform: We chose the length of the wavelet to be at least 2 cycles for the frequency of interest. This can be a 2s window for the wavelet, centred at 0 with a step of 0.001s, as in our study we focus on the frequency range from 2Hz to 50Hz. Complex Morlet wavelet based on a Gaussian signal is used as the tapered waves at its edges minimized the edge effect and therefore reduce the amount of convolved signal to be removed.
- Hilbert Transform: A plateau-shaped filter is recommended to minimize frequency leakage. We used narrow gate filter with a transition of 0.2 for band pass.
- Shannon entropy: The edges of the bins interval (from 0 to π).

To select the appropriate parameters, a benchmarking was performed, changing one parameter at a time. Different time windows were experimented from 1s to 10s. The overall cut of the convoluted data with wavelet was from 200ms to 3s respectively (with half at the beginning and the other half at the end of the resulted data). Particularly, our study showed that it is necessary to use a phase and phase-synchrony window of 1s to convolute with a wavelet of 2s, cutting 1s as an overall (500ms at the beginning and the end) for removing the edges artefacts when using Wavelet convolution for phase analysis (this selection takes into account the trade-off explained earlier). With a 1s window for the phase analysis, the smallest number of cycle window of period is one which is enough to compute the phase for the low frequency bands. For the phase synchrony analysis, the best suitable time window is 1s, giving 30 bins to perform the distribution of 1000 sample points, which gives a reasonable repartition of the data. These choices have been made according to the theory (mathematical equations and reasoning) and practice (by plotting the intermediate results to understand the behavior of the algorithm according to the parameters and to help finding the appropriate values).

D. Surface Laplacian

The spatial Laplacian filter can be applied on the data before performing phase and phase synchrony analysis: this is a spatial band-pass filter that improves the topographical localization of the connectivity between the sensors by enhancing the high-spatial frequencies (i.e. activities observable at only a small cluster of electrodes) [3]. It is used to deal with the problem of volume conduction, where the electrical field propagates from one electrode to another via scalp/skull. The spatial filter removes the common information shared by channels. In this paper, we also aim to compare the phase synchrony analysis results with or without preprocessing with a spatial filter. Many methods exist for applying the Laplacian filter. We adopted the traditional Perrin et al. (1987) method [8].

E. Statistical Analysis

For each patient, we obtained a matrix of average PSI. Each element in the matrix indicates the degree of synchrony across all the segments for this patient. In our analysis, PSI was deduced for each pair of channels of EEG data. For 6 channels, there will be 15 pairs of combinations for calculating PSI. The PSI results for all possible combinations can be both plotted over time for each pair of channels or plotted over 2D matrices showing the quantitative degree of entropy between all pairs for a particular time-windowed slot or using statistics [7]. Our statistical analysis was performed on all patients and 17 matrices were obtained for QBD patients and 17 for coma patients. To further investigate the statistical power of the phase synchrony results obtained, permutation test is performed on the 34 matrices for coma and QBD groups. Significant pairs of electrodes for the distinction of the consciousness states are selected at significance level of 5%.

IV. RESULTS

Fig 1 shows the topographical representations of the significant pairs of electrodes that allow the distinction between coma and QBD brain states found from the permutation tests (see section III.E). 16 subplots of the map of the significant pairs of electrodes found in the permutation test. The statistically significant connections are shown with blue lines between red dots: AHilbert transform; BLaplace filter and Hilbert transform; Cwavelet convolution; DLaplace filter and wavelet convolution, with four frequency ranges (alpha, beta, delta and theta) explored. The six EEG recording channels are marked as red dots, following the 10-20 system. The links of the significant pairs of electrodes extracted from the permutation test are shown in blue in the figure. In addition to the topographical representation, Table I gives the number of significant pairs of electrodes for each frequency bands and methods used.

TABLE I: Final results of the permutation tests. For each method used and frequency bands, the table gives the overall number of significant pairs.

Number of Significant Pairs of Electrodes	Frequency Bands			
	α	β	δ	θ
Hilbert Transform	7	6	10	9
Wavelet Convolution	7	5	8	8
Laplace Filter & Hilbert Transform	9	11	14	6
Laplace Filter & Wavelet Convolution	5	11	3	5

V. DISCUSSION & CONCLUSION

We built a method for the extraction of features to distinguish coma and QBD brain states. The method is based on the connectivity analysis between pairs of

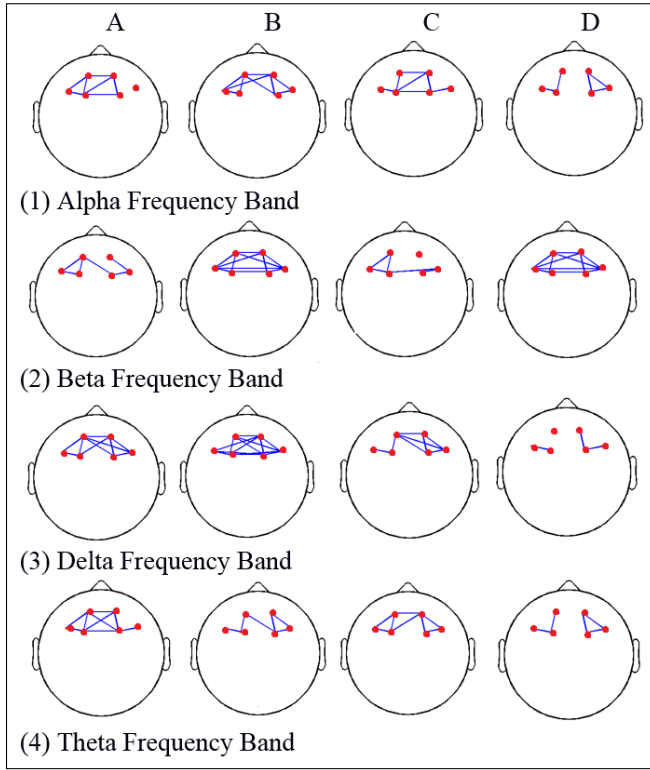


Fig. 1: Topographical representation of the significant pairs of electrodes extracted from permutation test for the four respective frequency bands. The results are divided into four columns according to the computational method used: A: Hilbert transform; B: Laplace filter & Hilbert transform; C: wavelet convolution; D: Laplace filter & wavelet convolution.

electrodes. A robust statistical analysis is also introduced to deal with the multiple comparison problem; this problem often occurs for multivariate analysis. Hilbert transform and wavelet convolution were both used to extract phase synchrony information and results, after applying Shannon entropy, were compared for all frequency bands (see Table I). We also compared the results with and without applying the Laplacian filter before performing the phase synchrony analysis (see Table I). The Laplacian filter is used to tackle volume conduction issue. Without applying the highest numbers of extracted features are for the δ and θ frequency bands using the Hilbert transform and the Shannon entropy. Those results concur with the fact that while in coma or QBD, no or very few cognitive tasks are performed. After applying the Laplacian filter, for the β frequency band, the number of significant connections increased from 6 and 5 to 11 for both Hilbert transform and wavelet convolution. On the contrary, after applying the Laplacian filter, for the θ frequency band, the number of significant connections decreased from 9 and 8 to 6 and 5 for Hilbert transform and wavelet convolution respectively. Except in the θ frequency band, generally, the number of significant connections increased for Hilbert transform after applying Laplacian filter, whereas the

significant connections decreased for wavelet convolution. This confirms the finding stated by Cohen et al. [3] that local signals have been overshadowed by volume conducted effects and once removed, more significant synchronization between electrodes have been found. When the number of features extracted using the Laplacian filter is lower, the outstanding significant pairs of electrodes found without the Laplacian filter should be consequent to volume conducted effect. Differences between methods for phase synchrony analysis can be diminished by increasing the number of trials and the recording time included in the application of the algorithm. Quantifying the phase-locking value (PLV), which determines the phase-differences across channels (similar to the standard deviation), can also reduce the significant pairs differences between Hilbert transform and wavelet convolution methods [9]. We can therefore conclude that both methods are relevant for extracting features for the distinction of consciousness states and give highly similar results. The results of this research show the general effectiveness of using EEG for the identification of unawareness state, particularly in the cases of coma and QBD.

As LeVanQuyen et al. states [9], for scalp EEG recordings segmented by short window of time, Hilbert transform and wavelet convolution give very different Shannon entropy results (and therefore PSI findings) for the same frequency band. The results obtained when using the wavelet convolution seem to be more narrowed [9]: the number of significant pairs of electrodes is smaller to that when using Hilbert transform, for both with and without the Laplacian filter (see Fig. 1 and Table I). Similarly to the results of LeVanQuyen et al. [9], the synchrony is sharper (less synchrony) at low frequency ranges when using wavelet convolution for phase synchrony analysis. However, when increasing the threshold of the permutation test by 10%, the significant pairs of electrodes are the same for Hilbert transform and wavelet convolution with and without the Laplace filter applied for all frequency bands except for θ - which can be explained by the sharp synchronies found when using wavelet convolution for phase synchrony analysis at low frequency bands.

Future work should focus on 1) lower frequency bands (from delta to alpha) to extract features to distinguish the states of coma or QBD as not many cognitive actions are performed. The preferable method used should therefore be based on Hilbert transform, which is more suitable for phase analysis on low frequency signal. Applying the Laplacian filter in this case might not be sufficient to have a proper interpretation of the connectivity between regions of the brain. 2) Exploring other synchrony detection methods such as mutual information based methods could give a better understanding of the extracted features according to the parameters changing across methods. 3) Similarly, the statistical tests (based on mean, median, proportion or correlation) for the ultimate extraction of features should carefully be explored in order to consistently qualify the

significant pairs of electrodes that allow the distinction of brain states. More than having a large number of features to distinguish the states, it is necessary to find the most reliable ones, as reviewed by Dauwels et al. [10] in the application of Alzheimer's disease. The datasets used in this paper have previously been used to explore brain-state detection using phase analysis on a subset of channels [11]. Applied here on all available channels, a better redundancy is found with a higher number of significant pairs. This is encouraging for others analysis using graph measures, *i.e.* small world network [3], between the different brain states. 4) Using collaborative adaptive filter on the different states can be used as a preprocessing method [12] before applying connectivity measures.

We can also consider that although this algorithm has been developed for off line brain state differentiation, it can be proposed as a systematic near real-time analysis to follow the evolution of patients in ICUs and eventually help diagnosing brain states. However, to achieve such goal, preliminary research should be conducted on 1) predictive models for the characteristics of brain states remain to be established. In general, the approach used can be applied for the characterization or distinction of cognitive tasks, brain states or mental diseases. 2) More tests with longer data acquisition are required to investigate the efficiency rate of the algorithm and eventually extract more reliable features for the distinction of coma and QBD brain states or the diagnosis of other consciousness states while studying physiological signals. However, as patients are lying on bed, the number of electrodes cannot be much more increased; 3) cross-frequency analysis can be performed to evaluate the implication of different frequency bands for the extraction of distinctive features while overcoming the reduced number of electrodes. 4) The time window length used for the phase computation can also be adapted to the frequency band(s) studied. 5) Monitoring EEG activity in response to external stimuli, such as audio, could induce more cognitive response and better brain state distinction. It as been shown that different levels of irregularity in the stimuli can be use to distinguish different states between patients in the coma [13]. A similar experiment applied to coma and QBD states could be promising.

Other considerations involve the application of this algorithm on other mental conditions; it could help understanding the behavioral activities and support drugs treatment. It could also serve brain computing purposes by improving brain computer interface applications.

ACKNOWLEDGEMENT

The authors wish to thank Prof. Jianting Cao (the Lab for Advanced Brain Signal Processing, RIKEN Brain Science Institute and Department of Electronic Engineering, Saitama Institute of Technology, Japan) for providing the data.

REFERENCES

- [1] F. Varela, J.-P. Lachaux, E. Rodriguez, and J. Martinerie, "The brainweb: phase synchronization and large-scale integration," *Nature reviews neuroscience*, vol. 2, no. 4, pp. 229–239, 2001.
- [2] E. F. Wijdicks, "The case against confirmatory tests for determining brain death in adults," *Neurology*, vol. 75, no. 1, pp. 77–83, 2010.
- [3] M. X. Cohen, *Analyzing neural time series data: theory and practice*. MIT Press, 2014.
- [4] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, 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," in *Proceedings of the Royal Society of London A: mathematical, physical and engineering sciences*, vol. 454, pp. 903–995, The Royal Society, 1998.
- [5] T. Tanaka and D. P. Mandic, "Complex empirical mode decomposition," *IEEE Signal Processing Letters*, vol. 14, no. 2, pp. 101–104, 2007.
- [6] N. Rehman and D. P. Mandic, "Multivariate empirical mode decomposition," in *Proceedings of The Royal Society of London A: Mathematical, Physical and Engineering Sciences*, p. rspa20090502, The Royal Society, 2009.
- [7] L. Li, A. Witon, S. Marcora, H. Bowman, and D. P. Mandic, "Eeg-based brain connectivity analysis of states of unawareness," in *Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE*, pp. 1002–1005, IEEE, 2014.
- [8] F. Perrin, J. Pernier, O. Bertrand, M. Giard, and J. Echallier, "Mapping of scalp potentials by surface spline interpolation," *Electroencephalography and clinical neurophysiology*, vol. 66, no. 1, pp. 75–81, 1987.
- [9] M. Le Van Quyen, J. Foucher, J.-P. Lachaux, E. Rodriguez, A. Lutz, J. Martinerie, and F. J. Varela, "Comparison of hilbert transform and wavelet methods for the analysis of neuronal synchrony," *Journal of neuroscience methods*, vol. 111, no. 2, pp. 83–98, 2001.
- [10] J. Dauwels, F. Vialatte, and A. Cichocki, "Diagnosis of alzheimer's disease from eeg signals: where are we standing?," *Current Alzheimer Research*, vol. 7, no. 6, pp. 487–505, 2010.
- [11] L. Li, D. Looney, C. Park, T. Tanaka, J. Cao, and D. P. Mandic, "Phase-based brain consciousness analysis," in *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*, pp. 1032–1035, IEEE, 2012.
- [12] L. Li, Y. Xia, B. Jelfs, J. Cao, and D. P. Mandic, "Modelling of brain consciousness based on collaborative adaptive filters," *Neurocomputing*, vol. 76, no. 1, pp. 36–43, 2012.
- [13] T. A. Bekinschtein, S. Dehaene, B. Rohaut, F. Tadel, L. Cohen, and L. Naccache, "Neural signature of the conscious processing of auditory regularities," *Proceedings of the National Academy of Sciences*, vol. 106, no. 5, pp. 1672–1677, 2009.