FLUCTUATION OF COMPLEX WAVELET COEFFICIENTS AMPLITUDE CORRELATION IN EEG

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ABSTRACT

In this paper, a novel method for detecting the back-loop regulation of coupling and decoupling between cortical neurones from electroencephalogram (EEG) signals is proposed. In this method, a linear time-scale quantifier of the multivariate relationship between simultaneously observed time series takes advantage of unique properties of complex wavelets such as shift invariance, substantially reduced aliasing and non-oscillating magnitude. The quantifier provides correlation between amplitude of complex wavelet coefficients for different frequencies (controlled by the scale factor) at different times (controlled by the time shift). Biological interpretation of this measure is derived from a priori information about presence of inhibitory back-loop connections between cortical neurones in short distance while the long range excitatory connections do not appear to target or effectively excite inhibitory interneurons and analysis of sample pairs of EEG signals.

Index Terms— Dual tree complex wavelet transform, discrete wavelet transform, coherence, EEG

1. INTRODUCTION

The paper is devoted to specific topics of EEG signal processing including its de-noising [1] and analysis [2, 3] including the use of wavelet transform [4, 5, 6, 7].

Approximately 1/5 of the neurons in the cerebral cortex are inhibitory GABAergic interneurons. These cells play a critical role in a number of important functions, including the gating and processing of sensory information, the establishment and plasticity of sensory receptive fields, the synchronization of cortical circuits, the generation of rhythms, and the limiting of seizure activity. A localized excitatory stimulus applied directly to the cerebral cortex can produce a surrounding peri-stimulus inhibitory zone (“Mexican Hat Pattern”). As the network is activated initially, excitation is generated forming the onset-response. Inhibition is then generated, which equilibrates the network. Lateral inhibition between cortical cells is known to play an important role in determining the receptive field properties of those cells. The vast majority of inhibitory synapses targeting neocortical pyramidal cells terminate on the dendrites. While somatic inhibition non-selectively inhibits responses to all stimuli, dendritic inhibition selectively inhibits specific patterns of excitatory inputs. The only method clinically available for evaluating disinhibition in cerebral cortex is transcranial magnetic stimulation. Impaired intracortical inhibition, as found in Amyotrofic Lateral Sclerosis, is also a well-established finding in Parkinson’s disease. Transcranial magnetic stimulation is time consuming expensive method limited to examination of motor cortex. For the frequency domain description of the linear relationship between pairs of time series the coherence function is usually used. The main motivation is its potential in disclosing crucial aspects of functional connectivity in neuroscience. Fluctuation of coherence between pair of electrodes may reflect processes of coupling and decoupling in the neuronal population during information processing. The EEG is a highly composite and substantially nonlinear process. The estimation of coherence based on the Fourier transform assumes that the signal is stationary, for non-stationary signals gives ambiguous results. Correlation of the real wavelet coefficients may reflect similar processes. The main disadvantage of this access is in oscillations of the real wavelet coefficients around singularities, shift variance and aliasing. The solution to these shortcomings is correlation of the complex wavelet amplitude coefficients. Cholinergic activity increases spiking activity in inhibitory GABA interneurons while

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decreasing strength of synaptic transmission from those cels. Those inhibitory interneurons are necessary for brain rhythms and information processing. Cholinergic deficit in Alzheimer's disease (AD) may contribute to cognitivede ficit by modulation of GABA interneurons activity. While information is in the brain transmitted in a rhytmic fashion (rhytm is biological solution for synchrony),flucutations of CoWT coefficients may reflect information processing between neurones.

2. METHOD

2.1. Algorithm

The method proposed in this paper works on two simultaneously recorded signals $X_{m,k},\ m = 1, 2,\ k \in Z$ which are obtained from two different recording sites. Sampling frequency was 128 Hz. Using a suitable FIR filters, each signal is filtered in the frequency range 0.5 - 60 Hz. A sliding window w of the length of 128 samples (1 s) was moved along the EEG by small shifts of the length equal to one sample with selected results presented in Fig. 1. For each time point k, denoting the beginning of w, the EEG signals inside w was decomposed by CWT into $l = 1, 2...5$ levels. Let $c_{l,k}$ be value of CWT (complex wavelet transform) of the $l-th$ level with shift k for the first channel. Let $c^{+}_{\mathrm{l,k}}$ be the adequate value of CWT for the second channel. Due to complex nature of $c_{\mathrm{l,k}},\quad c^{+}_{\mathrm{l,k}}$ we perform the correlation analysis of absolute values of complex numbers. Standard Pearson's correlation coefficient was used for the independence testing of $c_{\mathrm{l,k}}$ and $c^{+}_{\mathrm{l,k}}$ over all levels and shifts in given time interval. Thus any pair of channels is characterized via correlation coefficients $r_{l,k}$. Correlation fluctuations of the complex wavelet coefficients amplitude $\triangle r_{l,k} = r_{l,k+1} - r_{l,k}$ for $k = 1, 2..., n - 1$.

Magnitude-squared coherence values $Co_{X1,X2}(f, k)$ were computed for frequency bands $f = 1, 2...5$ roughly corresponding to the CWT levels l (33-64 Hz for $l = 1$, 17-32 Hz for $l = 2$, 9-16 Hz for $l = 3$, 5-8 Hz for $l = 4$, 3-4 Hz for $l = 5$), in sliding window of 1 s with the shift k.

$$Co_{X1,X2}(f, k) = \frac{|P_{X1,X2}(f, k)|^2}{P_{X1,X1}(f, k)\ P_{X2,X2}(f, k)} \tag{1}$$

Coherence fluctuations $\triangle Co_{X1,X2}(f, k) = Co_{X1,X2}(f, k + 1) - Co_{X1,X2}(f, k)$ for $k = 1, 2..., n - 1$.

2.2. Data

1. Two pairs of electrodes were compared. The first O1-O2 is known as anatomically connected while the second localization Fp1-O2 are not directly connected. The 20 minutes samples were obtained from 42 healthy volunteers. The noisy and filtered data were compared.

2. Fluctuation of absolute value CoWT coefficients of 63 AD patients has been compared to 63 age matched healthy control subjects. EEG signals from 40 electrode pairs were evaluated in wavelet scales corresponding roughly to frequencies 33-64 Hz,17-32 Hz, 9-16 Hz, 4-8 Hz and 1-3 Hz. The method was applied to a artifact - free data set after denoising, segmentation and automatic artifact recognition.

3. RESULTS

Results achieved are summarized in Tables 1-8 presenting coherence and correlation of original noisy data and the same results achieved after their de-nosing.

Table 1. Coherence - noisy data

Freq.(Hz)	33-64	17-32	9-16	5-8	3-4
O1-O2	0.9190	0.7684	0.8498	0.8781	0.8844
Fp1-O2	0.6935	0.6682	0.6639	0.6804	0.6863

Table 2. Coherence fluctuation - noisy data

Freq.(Hz)	33-64	17-32	9-16	5-8	3-4
O1-O2	0.0074	0.0188	0.0041	0.0032	0.0032
Fp1-O2	0.0105	0.0156	0.0068	0.0066	0.0069

Table 3. Correlation - noisy data

Level	1	2	3	4	5
O1-O2	0.4970	0.5520	0.7991	0.8713	0.9183
Fp1-O2	0.5476	0.5668	0.6329	0.7569	0.7481

Table 4. Fluctuation correlation - noisy data

Level	1	2	3	4	5
O1-O2	0.4353	0.0892	0.2263	0.1623	0.1016
Fp1-O2	0.3467	0.0776	0.1908	0.1558	0.1762

Table 5. Coherence - filtered data

Freq.(Hz)	33-64	17-32	9-16	5-8	3-4
O1-O2	0.8229	0.8286	0.8390	0.8363	0.8056
Fp1-O2	0.3309	0.3250	0.2904	0.1778	0.1412

Fig 1 shows 1 sec. of filtered EEG curve.

Coherence fluctuation for distant non-connected electrodes has higher amplitude, but less average value. Fig 2.

Correlation of CoWT coefficients shows another useful characteristics of non regulated signals - irregularity and frequency instability. Fig 3.

Table 6. Fluctuation coherence - filtered data

Freq.(Hz)	33-64	17-32	9-16	5-8	3-4
O1-O2	0.0108	0.0093	0.0070	0.0066	0.0072
Fp1-O2	0.0199	0.0184	0.0163	0.0132	0.0121

Table 7. Correlation - filtered data

Level	1	2	3	4	5
O1-O2	0.6017	0.7147	0.7751	0.7614	0.7255
Fp1-O2	0.0330	0.0211	0.0179	0.0129	0.0754

Table 8. Fluctuation correlation - filtered data

Level	1	2	3	4	5
O1-O2	0.0416	0.0340	0.0313	0.0392	0.0712
Fp1-O2	0.0989	0.0712	0.0737	0.0873	0.1039

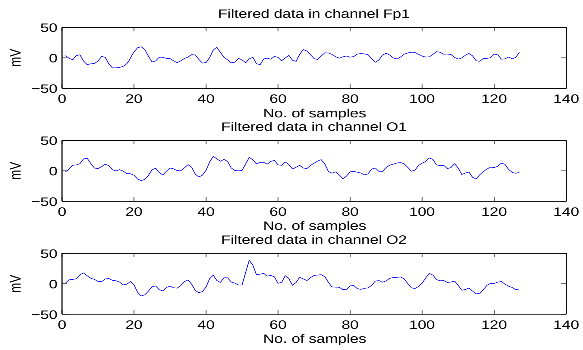

Fig. 1. A sample of data segment one second long

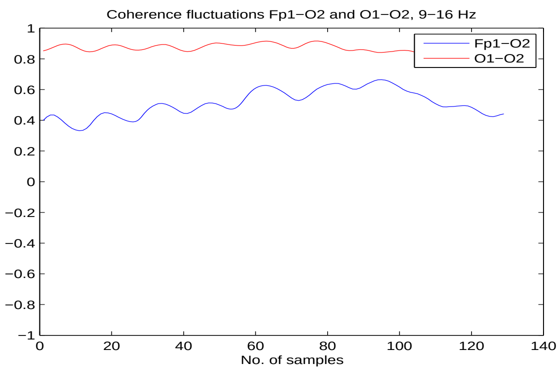

Fig. 2. Coherence fluctuation between selected EEG signals.

Low values of average coherence and CoWT correlations between distant electrodes reflects low information processing comparing close and anatomically connected electrodes. Fig 4 and fig 6.

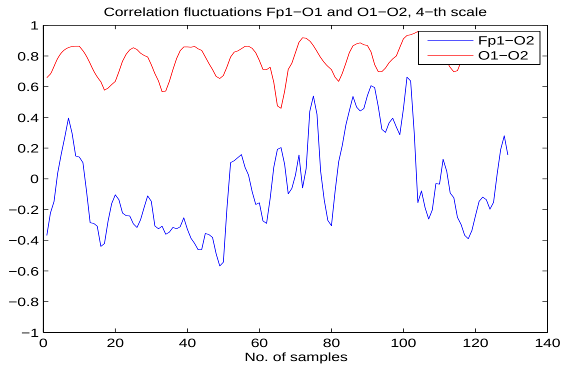

Fig. 3. Differences in CoWT coefficients correlation fluctuation between close and distant electrodes in control group of healthy drivers, 4-th scale.

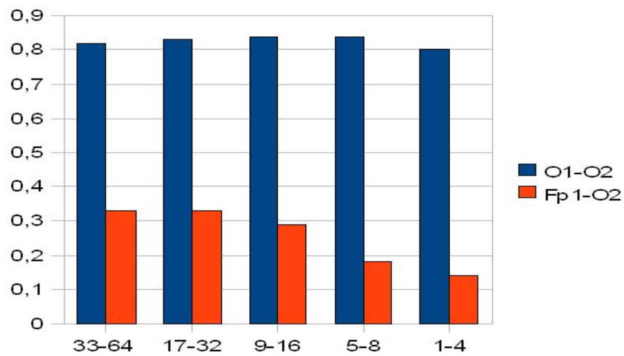

Fig. 4. Average coherence between close and distant electrodes in control group of healthy drivers, 5 scales.

Higher amplitude of CoWT and coherence fluctuations in distant electrodes may be related to the absence of an inhibitory back-loops. Fig 5 and fig 7.

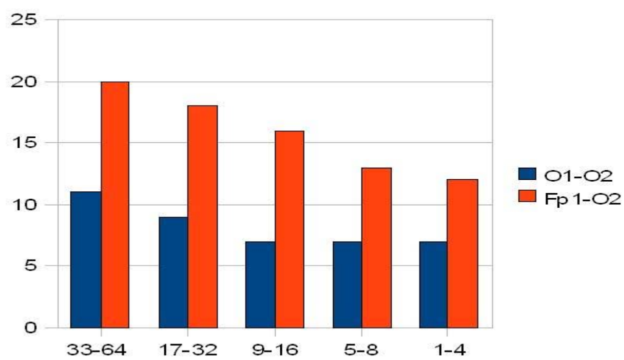

Fig. 5. Coherence fluctuation between selected EEG signals.

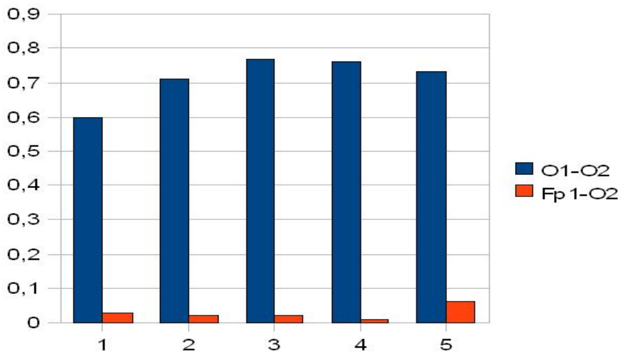

Fig. 6. Average CoWT coefficients correlation between close and distant electrodes in control group of healthy drivers, 5 scales. For distant electrodes is close to zero

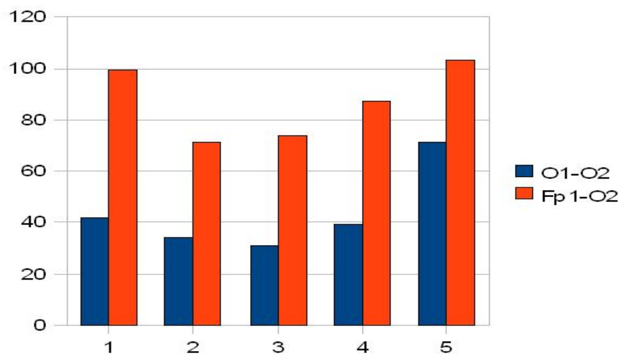

Fig. 7. Average amplitude fluctuation CoWT of coefficients between close and distant electrodes in control group of healthy drivers, 5 scales.

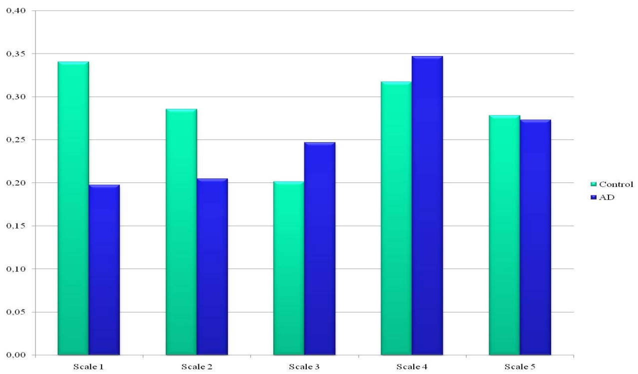

Fig. 8. Average CoWT coefficients in AD patients and healthy controls in all scales (significant differencies for scale 1 and 2)

Differences between fluctuations of CoWTcoefficients in healthy persons and AD patients resemble those betweenclose and distant electrodes in healthy persons. Fig 9, fig 10 and fig 11.

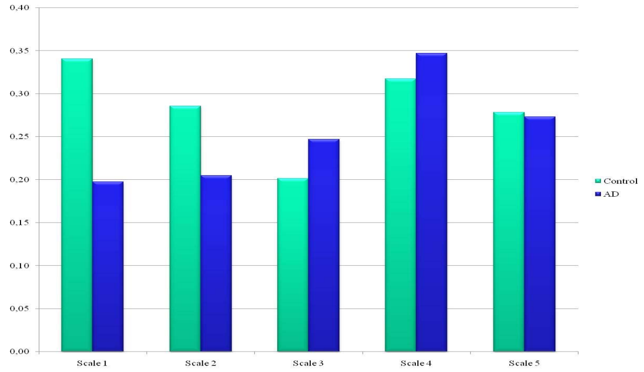

Fig. 9. Average fluctuation CoWT coefficients in AD patients and healthy controls in all scales (significant for scales 2-5).

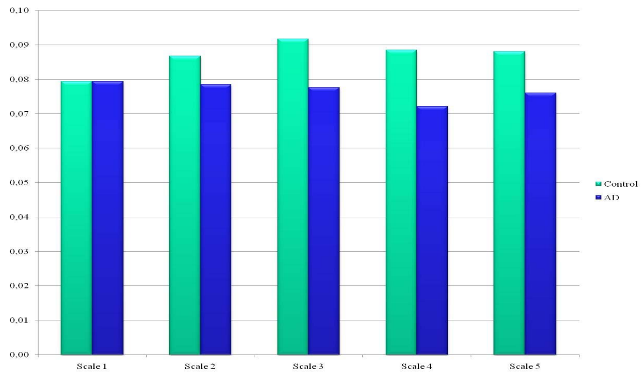

Fig. 10. Fluctuation of correlation CoWT coefficients for electrode pair Fp1-F3 in healthy control and AD patient.

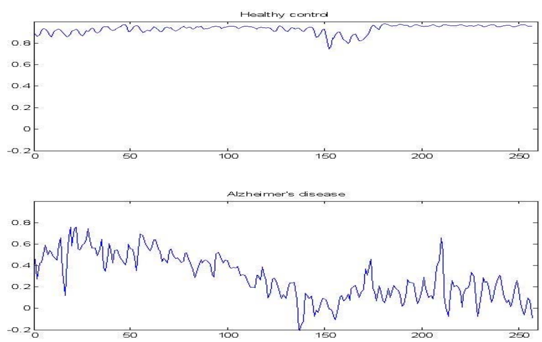

Fig. 11. Coherence fluctuation between selected EEG signals

4. DISCUSSION

In this study we proposed a novel algorithm for the detecting of the communication between EEG channels. Our results demonstrate that comparing coherence correlation of complex wavelet coefficients amplitude is more sensitive to the communication between neurones. Coherence is more robust in the presence of the noise. Higher fluctuation of both coherence and correlation in more distant electrodes may be the final result of the missing back loop connection between them. Again, fluctuation of correlation of complex wavelet coefficients is more significant comparing coherence in filtered signals. This new approach can significantly improve the detection of communication between different cortical areas. It may probably quantify quality intracortical inhibition, which is impaired in some neurodegenerative diseases. Changed activity of inhibitory GABA interneurons due to cholinergic deficit may influence regulation of cortical oscillations. Recent findings indicate that neural network oscillations support temporal representation and long-term consolidation of information in the human brain. Thus changes in fluctuation of CoWT coefficients may reflect cholinergic and cognitive deficit in Alzheimer's disease. A further study will verify its diagnostic usefulness in the clinical practise.

5. CONCLUSION

In this paper we proposed a novel method for the measuring a new quality of communication between different parts of the brain cortex. It may reflect back loop inhibitory regulation of the brain activity. The results confirm that our method is more sensitive then coherence fluctuation in filtered signals. The results further indicate that mean value of correlation of complex wavelet coefficients outperforms mean value of coherence as a measure of brain neurone network communication. In practice it may contribute to the diagnosis of some neurodegenerative diseases.

6. ACKNOWLEDGMENT

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