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Analysis of Neuroelectric Oscillations of the Scalp EEG Signals

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Abstract: Electroencephalography (EEG) or magneto-encephalography (MEG) are usual methods adopted in clinics and physiology to extract information relative to cortical brain activity. EEG/MEG signals are a measure of the collective neural cell activity on restricted regions of the cortex. The brain activities ensue from the interaction of excitatory and inhibitory populations of neurons. Their kinetics vary depending on a particular task to be fulfilled, on the particular region involved in that task, and in any instant during the task. In order to improve our understanding of EEG/MEG signals, and to gain a deeper comprehension of the neuro-physiological information contained, various mathematical models and methods have been proposed in previous years. Based on these concepts we develop procedures for an optimal, online and hardware based EEG signal processing. EEG recordings are analyzed in an event-related fashion when we want to gain insights into the relation of the EEG and experimental events. An approach is to concentrate on event-related oscillations (EROs). The method suited to analyze the temporal and spatial characteristics of EROs, is the time-frequency analysis namely wavelet transforms. Recently introduced wavelet-based methods for studying dynamical interrelations between brain signals will be discussed.

Keywords: brain-computer-interface (BCI), time frequency analysis, filters, EEG signals, EMG signals, stationarity of signals.

1. Introduction

We propose a novel framework to analyse electroencephalogram (EEG) biosignals from multi-trial visually-evoked potential (VEPs) signals recorded

with a brain-computer interface (BCI). Electromagnetic activities of the neuromuscular system, including electroencephalography (EEG), electro-myography (EMG), and magneto-encephalography (MEG) signals, have been widely used in the study of motor control in humans. VEPs signals contain components of EMG, MEG and EEG [1], [2], [3], [4].

Oscillations are characterized by their amplitude, frequency and phase. The amplitude of a recorded oscillation is typically between 0 and 10 μV. The (cyclic) phase ranges are between 0 and 2π. At every scalp point at every time moment the amplitude and phase of an oscillation can be recorded. The frequency band of the typical recordable cortical oscillations range is usually from 0.1 Hz to 80 Hz (highly correlated to a 256 Hz sampling rate).

Several methods exist to extract oscillations of biologically specific frequency bands from ERO data. Among the most used are band filtering, Fourier analysis, and wavelet analysis. Oscillating potentials derived from a specific scalp surface, originating from the outer layer of cortex (grouped neuron structures in the layer I cortical areas) are called visual-evoked potential (VEP) signals. These signals are related to the brain's response to visual stimulation and have applications in numerous neuropsychological studies. EROs comprise exogenous and endogenous components. Exogenous components are obligatory responses which result on the presentation of physical stimuli. The endogenous components (say P300 component of an ERO signal) manifest the processing activities which depend on the stimuli's role within the task being performed by the subject. Usually, EEG-signals are based on various phenomena like, for example, visual and P300 evoked potentials, slow cortical potentials, or sensory-motor cortical rhythms. The P300 shape is an event related potential, elicited by a generally stochastic, task related stimuli.

2. Materials and methods

We have used a BrainMaster recording system (BrainMaster AT-1 W2.5 Clinical Pro Wideband System, see *Fig. 1*.), battery powered, portable, two channel 2E neurofeedback module hardware, with added cleaning gel and conductive paste. Recordings have been made with 5 gold plated electrodes (2 recording electrodes, 2 reference electrodes and a ground electrode). The used sampling rate was 256 Hz, sufficient for the studied frequency bands.

Recording areas were the left and right hand side of cortical surface at Primary Motor cortex and sometime on Pre-Motor and Supplementary Motor Cortex (Secondary Motor Cortex) on the scalp of young persons. The recorded and sampled signals from two channels (Ch1, Ch2) are stored in text type files and processed using MATLAB (The Math-Works Inc., Natick, MA.) platform. The software package is elaborated by the authors based on concepts presented

in [5]. The test recordings are usually 1 to 1.5 minutes long. The ERO intervals alternate with relax state with a period of usually 10 seconds. The time-frequency method used in this application is the continuous wavelet transform based on Morlet, Paul and DOG ($m = 2$ and $m = 6$) wavelet base functions. The Morlet and Paul bases are providing a complex continuous transform proper for time-frequency component analysis of the recordings. For the subjects of the experiments, during the recordings a deckchair was used to avoid extra EMG noise created by the body stability problems.

Figure 1: The BrainMaster AT-1 System (Brain Master LTD company product image).

In the EEG–EMG experiments, subjects are trained for two different motor tasks: a left-right or up-down movement of the closed or opened eye balls and right or left hand movement. The scenario of the performed task is recorded in the header of the generated file. The recording technique is a not invasive recording method.

3. Data analysis tools

A period of baseline EEG+MEG was recorded at the beginning of each experiment when the subjects rested. During the offline analysis, signals within an approximately 10 s epoch were selected from the rest period and averaged to obtain baseline EEG. Subsequently, the value of the baseline EEG+MEG was subtracted from the entire EEG+MEG data set to acquire baseline corrected signals. The corrected values were saved into files for further processing.

An important fact is that the magnitudes of cyclic visual-evoked potential components are much more detectable in the 0–10 Hz frequency range. This is important for the further analysis.

From the experimental studies of VEPs, relative to the recorded oscillations, the literature clearly depicts the delta (1–4 Hz) and theta (4–10 Hz) ranges as containing main components of power in frequency domain for the waves. We will consider these bands for further identification of the activity patterns [1]. Now, we are considering the important details of wavelet transform used in these processings.

By decomposing a time series into time–frequency space, one is able to determine both the dominant modes of variability and how those modes vary in time. The first tested method was the Windowed Fourier Transform (WFT). The WFT represents one of analysis tool for extracting local-frequency information from a signal. The WFT represents a method of time–frequency localization, as it imposes a scale or 'response interval' T into the analysis. An inaccuracy arises from the aliasing of high- and low-frequency components that do not fall within the frequency range of T window. Several window lengths must be usually analyzed to determine the most appropriate choice of window size to be sure to contain within the window the main, but unknown basic oscillatory components. To avoid this difficult task, in our analysis finally we have used wavelet transform (WT) methods.

The WT can be used to analyze time series that contain nonstationary power at many different frequencies. The term 'wavelet function' is generically used to refer to either orthogonal or nonorthogonal wavelets. The term "wavelet basis" refers only to an orthogonal set of functions. The use of an orthogonal basis implies the use of the discrete wavelet transform (DWT), while a nonorthogonal wavelet function can be used with either the discrete or the continuous wavelet transform (CWT).

A brief description of CWT is following. Assume that the recorded time series, x_n, is with equal time spacing δt (sampling period) and $n = 0 \ldots N\text{-}1$. Also assume that one has a wavelet function, $\Psi_0(\eta)$, which depends on a non-dimensional 'time' parameter η.

To be 'admissible' as a wavelet, this function must have zero mean and must be localized in both time and frequency space. An example is the Morlet wavelet, consisting of a plane wave modulated by a Gaussian function:

$$\Psi_0(\eta) = \pi^{-1/4} \cdot e^{i \cdot \omega_0 \cdot \eta} \cdot e^{-\eta^2/2} \tag{1}$$

This is a wavelet basis function, where w_0 is the non-dimensional frequency, here taken to be 6 to satisfy admissibility condition.

The continuous wavelet transform of a discrete sequence x_n is defined as the convolution of x_n with a scaled and translated version of $\Psi_0(\eta)$:

$$W_n(s) = \sum_{i=0}^{N-1} x_i \cdot \Psi^* \left[\frac{(i-n) \cdot \delta t}{s} \right], \tag{2}$$

where the (*) indicates the complex conjugate. By varying the *wavelet scale* ***s*** and translating along the *localized time index* ***n***, one can construct a picture showing both the amplitude of any features versus the scale and how this amplitude varies with time. The subscript 0 on Ψ has been dropped to indicate that this Ψ has also been normalized. It is possible to calculate the wavelet transform using (2), and it is considerably faster to do the calculations in Fourier space. By choosing *N* points, the convolution theorem allows us to do all *N* convolutions simultaneously in Fourier space using discrete Fourier transform (DFT). To ensure that the wavelet transforms at each scale *s* are directly comparable to each other and to the transforms of other time series, the wavelet function at each scale *s* was normalized to have unit energy. Normalization is an important step in time-series analysis and is used at each scale *s.*

Morlet wavelet function $\Psi(\eta)$ is a complex function, the wavelet transform $W_n(s)$ is also complex. The transform can then be divided into the real and imaginary part, or amplitude and phase. Finally, one can define the *wavelet power spectrum* as $|W_n(s)|^2$. The *expectation value* for $|W_n(s)|^2$ is equal to *N* times the expectation value for the discrete Fourier transform of the time series. For a white-noise time series, this expectation value is σ^2/N, where σ^2 is the variance of the noise. Thus, for a white-noise process, the expectation value for the wavelet transform is $|W_n(s)|^2 = \sigma^2$ at all *n* and *s*. Based on this knowledge, the same logic is used to calculate the expected value of red noise. The $|W_n(s)|^2 / \sigma^2$ is the measure of the normalized signal value relative to white noise. As the biological background noise is a red noise type, the normalization method is relative to red noise as it is described in [5] (in a way as it was used in the results of this paper).

An important concept of this study is the so called *Cone of influence* (COI). The cone of influence is the region of the wavelet spectrum in which edge effects become important because of the finite length of signal and used window. The significance of the edge effect is defined as the *e*-factor (power spectrum edge drops by a factor e^{-2}) time of wavelet power at each scale. The edge effects are negligible beyond the COI region. This must be considered for an accurate analysis. In each figure, COI is represented at the edge of the wavelet transforms (lighter area in figures).

Another important factor we have added to this analysis is the *significance level* of the correlation studies. The theoretical white/red noise wavelet power spectra are derived and compared to Monte Carlo simulation results. These spectra are used to establish a null hypothesis for the significance of a peak in the wavelet power spectrum (the question to be answered: is a power peak from a wavelet figure the result of biological events or it is a result of stochastic red/white noise effect?).

The null hypothesis is defined for the wavelet power spectrum as follows. It is assumed that the time series has a mean power spectrum, if a peak in the wavelet power spectrum is significantly above this background spectrum, then it can be assumed to be a true feature with a certain percent of confidence. ('significant at the 5% level' is equivalent to 'the 95% confidence interval').

Our application is highlighting the biological events, with surrounding the significant peaks of correlations at the confidence interval of 95%. It is important that in biological studies the background noise can be modeled by a red (or pink) noise. A simplest model for a red noise is the lag-1 autoregressive [AR (1), or Markov] process. In the following figures, all significant localization of a biological event (VEPs) in time-frequency domain is also statistically significant. This is an important result. What is not within a significant area, is not considered in the results. Another important result in our analysis is the representation of the phase relationship between two recordings. In each cross-wavelet spectrum and cross-coherence spectrum the phase relationship is represented with arrows. A horizontal arrow to the right means that in that time frequency domain the two biological signals are in phase (if that domain is significant at 5% level and is not within COI domain). The opposite arrow orientation has the meaning of opposite phase correlation. The angle of arrows relative to horizontal line is showing the phase angle in that time frequency domain. Our application is calculating and is representing all these phase values. The definition of wavelet-cross-correlation and wavelet-cross-coherence are defined in [5] and [6].

4. Results

The following figures are slim examples from our recordings and their analysis. *Fig. 2* is the amplitude/time representation of a channel signal as a recording on the right hand side of the Motor Cortex area when the left hand has been lifted two times during a 50 s recording session. This figure is showing also the application menu created for this WFT type of analysis. *Fig. 3* is the WFT representation of the *Fig. 2* recording in different frequency bands. The vertical axis is for the frequency, and the horizontal one is the time axis. The frequency bands for the different windows are 0.1 – 50 Hz for the top left, 0.1 – 8 Hz for bottom left, 24 – 30 Hz top right window and finally 30 – 36 Hz for bottom right window. The frequency bands are representative for biological events. A color-code represents the intensity of a time-frequency domain for that WFT decomposition (the corresponding color-code is represented at the right hand side of each window). The shape within each window is characteristic for a real time motion recorded as EMG+EEG. *Fig. 4* is similar with *Fig. 3* but it is represented in 3D for a better visual understanding of the

significant domains contained in this time-series decomposition. Based on these figures, it can be concluded that a ‘shape’ in time-frequency domain is related to an arm motion in time domain. The automatic identification of these domains (peaks) in time-frequency decomposition it must be related to the corresponding arm motion what has happened in time domain. For this peak identification one can use a pattern recognition procedure.

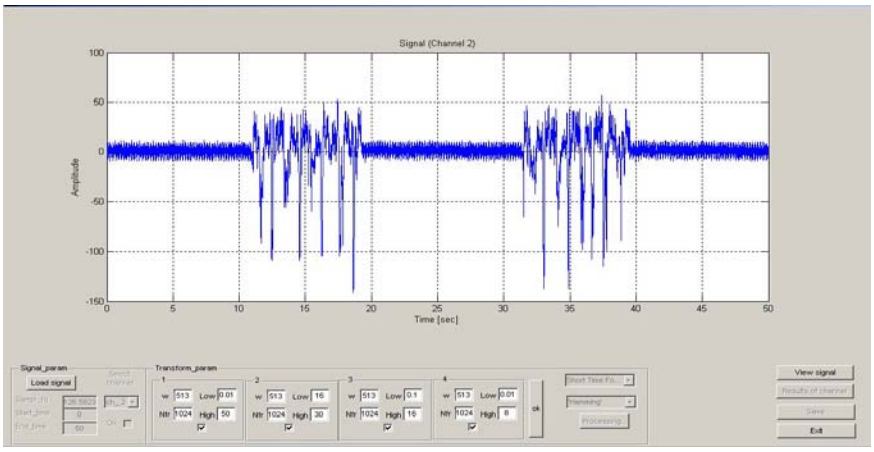

Figure 2: A recorded (right hand side Motor Cortex) amplitude/time representation.

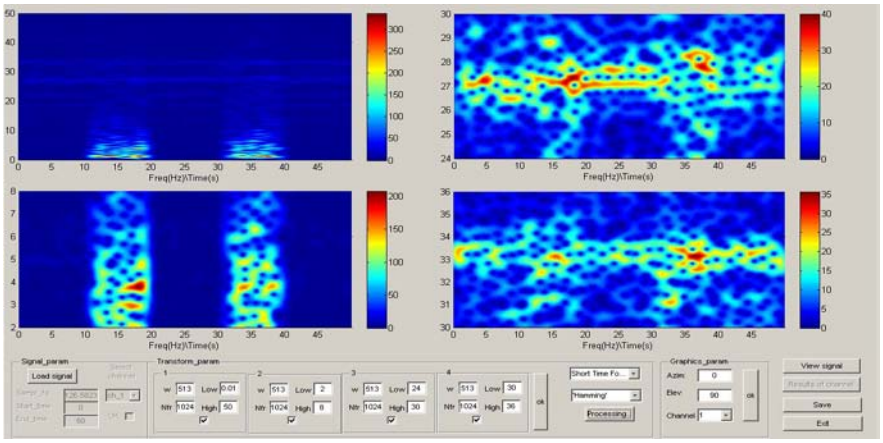

Figure 3: The wavelet Fourier transform (WFT) in four different frequency bands.

As it was mentioned, the same hand lifting time event recording has been done on both cortical sides. The left cortical side recording and decomposition with WFT is not represented here, but it has a similar configuration. *Fig. 5* is the difference in time-frequency domain of the two side signals. It is visible that the two side recordings are not the same as it is known from theory. This

analysis is WFT, and here the COI and significance test was not used. As it was mentioned, the WFT is very sensitive to the window length (T) used in decomposition of the time signal [7], [8]. In the spectrum, not controllable frequency interference is present, but the method is powerful enough to be usable in detection and classification of not very sensitive types of motor actions.

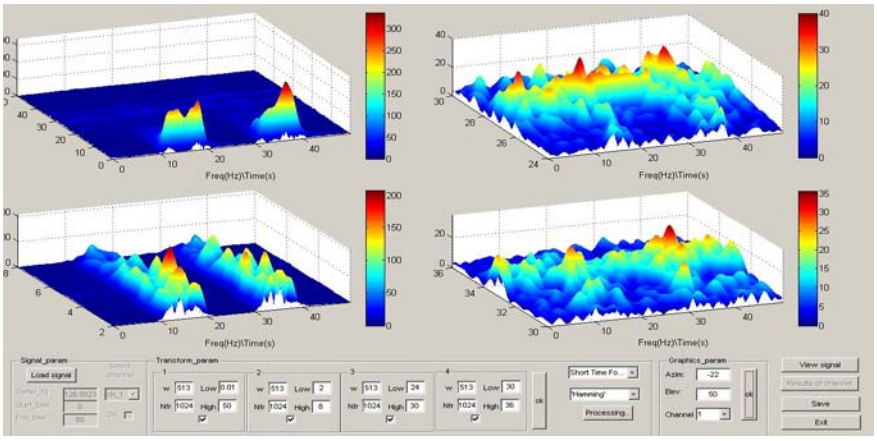

Figure 4: The 3D representation of figure 3 WFT decomposition.

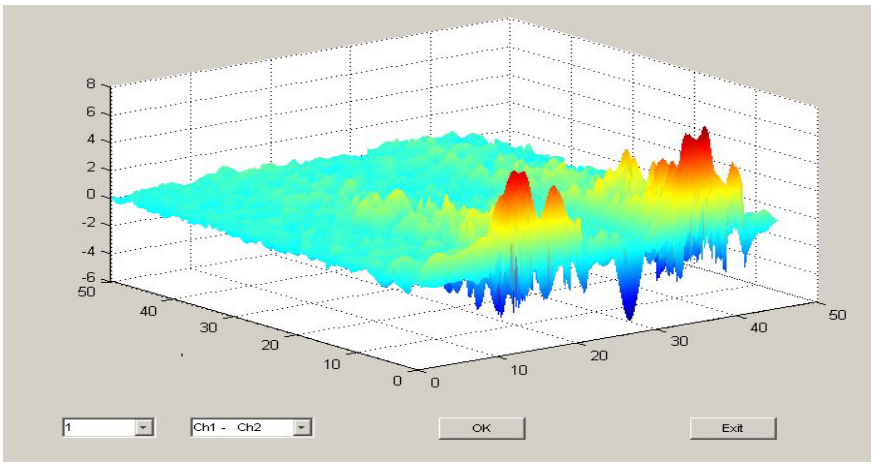

Figure 5: The difference of the two channels recording decomposition by WFT.

A most sensitive procedure is the use of Morlet type of Wavelet transform (WT) with the representation of COI and with significance test of biological events based on wavelet Cross-correlation and wavelet Cross-Coherence [5], [9]. These results are more accurate and with higher resolution in time

frequency in comparison with the previous WFT analysis. The amount of calculation is higher than in case of WFT but optimizing the procedures on hardware based processor units, this method should be very powerful.

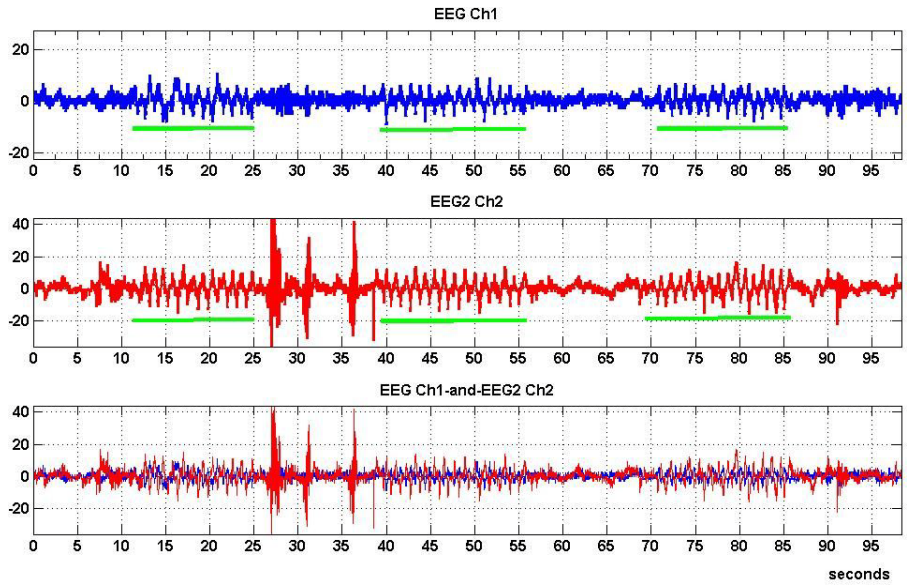

Figure 6: The two channels (Ch1, Ch2) amplitude/time representation of the recordings. The bottom figure is showing the two superimposed signals. The green highlights are the eye movement time sequences (sample size on vertical).

Fig. 6 is representing left-right movement of eye balls with a relax time between them. It is visible the time sequence of left and right hand cortical side EMG+EEG. The whole recording length is about 100 seconds. The high amplitude signals in 25-37 seconds interval in Ch2 recording is an extra EMG, a noise from the experiment point of view. The time sequence is containing three eye movement events. These are between (12, 25) sec, (39, 55) sec and finally (71, 85) seconds. These are highlighted by green line segments. In the third (bottom) window it is visible that the Ch1 and Ch2 recordings are in opposite phase. But this will be obvious from cross correlations calculated and represented in *Fig. 9*.

The next two figures (*Fig. 7* and *Fig. 8*) are the representation of Morlet WT of these channel recordings. The COI and the significant areas are represented. Domains of the signal within these closed contours are significant, outside are not significant (should not be considered biological events). We are considering the two parallel lines delimiting roughly the (0.75 – 1.5) Hz frequency interval. Within these limits we can consider the events of eye movement left-right-left in the detected time intervals. It is very obvious the presence of significant

domains, and they can be easily identified. In *Fig. 8*, in 25 sec to 37 sec interval, the EMG 'noise' is there, but the basic components are present also at much higher frequency domains.

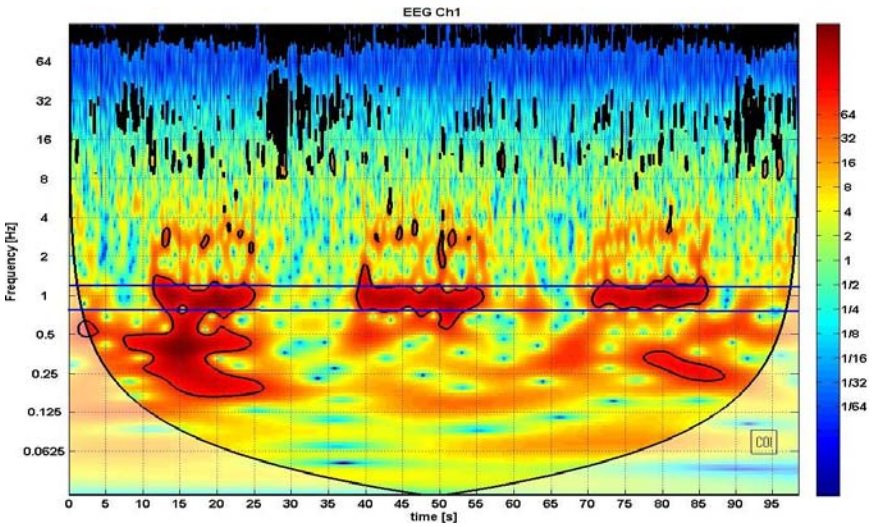

Figure 7: Morlet WT of Ch1 recording with localization of eye left-right movement.

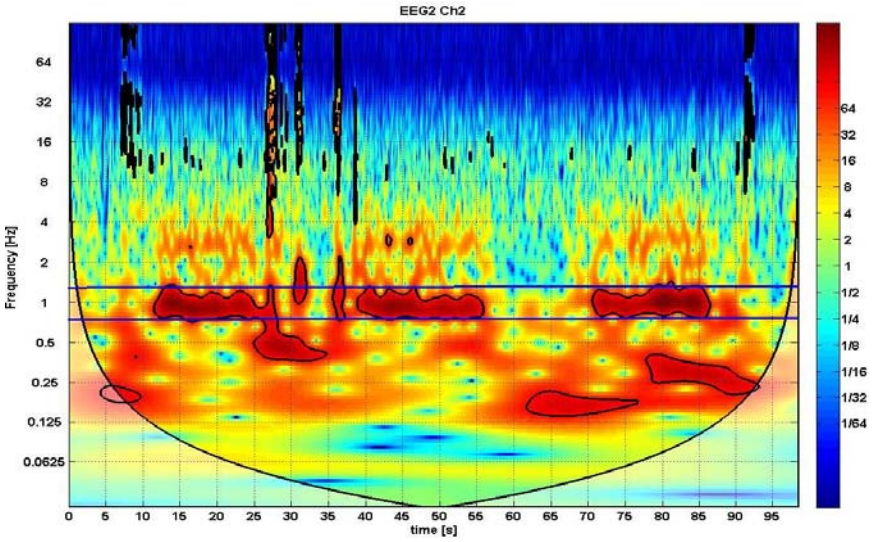

Figure 8: Morlet WT of Ch2 recording with localization of eye left-right movement.

It is very important to discuss, what *Fig. 9* represents. The COI is present as the not significant domain, but also a phase relationship between the two signals is calculated. The arrows' orientation within the significant area is to the left

(0.75 – 1.5Hz). This means that the correlation between the two channels, in this frequency band is in opposition. In the recordings with half way eye movement (left to middle, or right to middle) the phase shift is not opposite but is around of 90/270 degrees. These phase events permit the detection of the direction of eye movements. *Fig. 9* bottom image is the normalized version of the same cross-correlation, the so-called cross-coherence between the two channels. This information about the interrelation of the two recordings is more relevant to characterize the ERO contained visual evoked potentials.

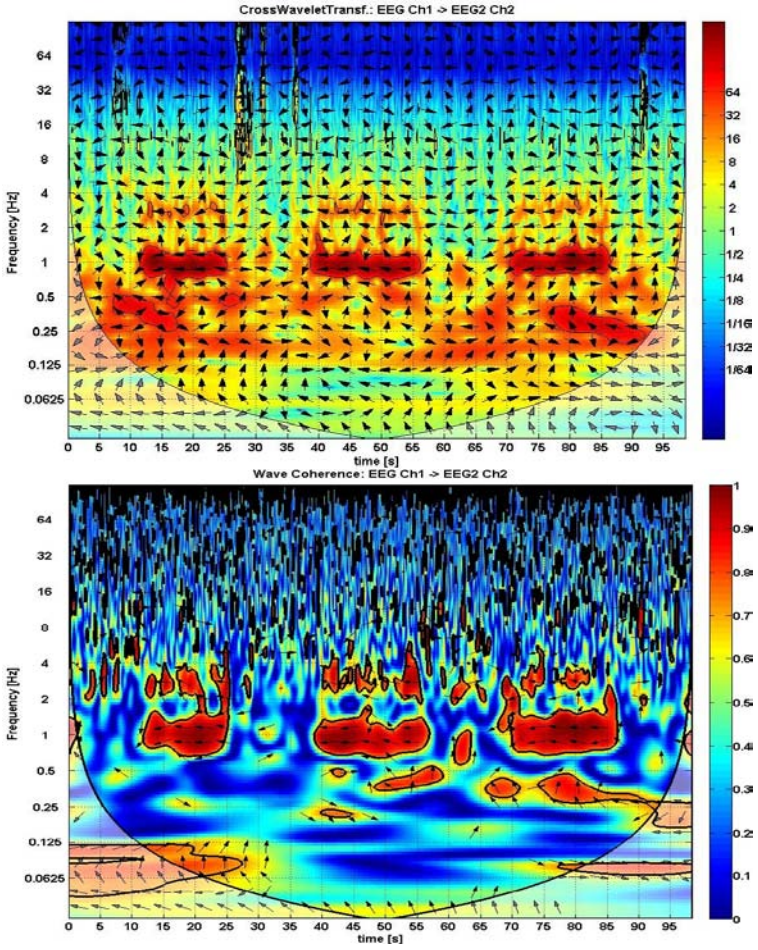

Figure 9: The cross-correlation (up) and the cross-coherence of the two channels signals.

The same analysis has been made also for the up-down eye movement direction. The results are very similar with the left-right movement conclusions,

and are not presented in this paper, but can be considered for technical applications based on EEG+MEG recordings. The cross-coherence matrix is processed to extract the information (signals) for further control tasks.

5. Conclusions

Every characteristic information of EROs (extracted numeric values of the processed VEPs) is usable for further signal processing tasks. Detecting motion related, EEG+MEG signal configuration, the possibly extracted information is usable in external system control tasks. The sensitivity of the electrodes is not the subject of this paper. It is obvious that with a much higher sensitivity of electrodes, it should be possible to record much more detailed signals with deeper correlations. The ideas used in this study are at the beginning of more event sensitive identification and complicated command possibilities [8], [10], [11]. We must also consider the effect of so called grid cells in the cortical area which display regular responses to the position in a virtual, internal 2-D space. This study should be possible using multichannel (>2) recordings, a next step in our research.

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