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COMPLEX WAVELET COHERENCE FOR EEG ANALYSIS

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ПРИМЕНЕНИЕ КОМПЛЕКСНОГО ВЕЙВЛЕТ-ПРЕОБРАЗОВАНИЯ ДЛЯ АНАЛИЗА КОГЕРЕНТНОСТИ ЭЭГ-СИГНАЛОВ

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Аннотация. *Существует множество методов анализа функциональной связности областей мозга, активность которых регистрируется посредством электроэнцефалографии (ЭЭГ). Одной из надежных и эффективных метрик для оценки взаимодействия ЭЭГ-сигналов является мнимая часть когерентности, которая основана на преобразовании Фурье. В данной работе предлагается применение непрерывного комплексного вейвлет-преобразования для однозначной оценки взаимодействия сигналов с учетом динамического характера спектральных характеристик ЭЭГ-данных.*

Introduction. Coherence is one of the modern analysis methods that can be used to examine relationships between two time series. It analyses the linear dependence of two signals in time-frequency space. As a standard, coherence is calculated using spectra based on the Fourier transform. However, EEG records are non-stationary signals, meaning that the spectrum changes over time. Therefore, for monitoring the development of spectral density, the continuous wavelet transformation is more suitable [1]. Complex wavelets can be used to calculate the continuous wavelet coefficients, making it possible to distinguish between the real and imaginary part of wavelet coherence. This dichotomy is important for time-frequency analysis of non-stationary signals. As it was shown in the literature [2], imaginary part of coherency enables to avoid spurious results by overcoming the volume conduction problem. The volume conduction problem is related to the nature of EEG signals, where a single generator within the brain is typically observable in many channels. Thus the coherence between two signals may be caused by the same underlying component rather than represent the information transfer. The imaginary part of coherency is only sensitive to synchronizations of two processes which are time-lagged to each other. Since volume conduction does not cause a time-lag, the imaginary part of coherency is thus insensitive to false interactions.

Methods. EEG data were recorded using a 128-channel electrode cap with the sampling rate of 1000 Hz. During the recording session a person was solving multiplication problems. Only trials with correct answers were used. The data was then downsampled to 500 Hz, average-referenced, filtered from 1 to 40 Hz and cleaned from ocular and motor artifacts. For each valid trial, the time interval from -2000 to 2000 ms around the stimulus onset was analysed. The pre-stimulus interval was used as a baseline, and for the post-stimulus interval the complex continuous wavelet transform was applied according to the function (1):

$$C_x(a,b) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{b}\right)dt, \quad (1)$$

where ψ^* is the mother wavelet. We used Morlet wavelet (2) for our data as it was demonstrated to provide the best results for EEG data since its shape most closely matches the shape of the EEG curve:

$$\psi_0(\eta) = \pi^{-1/4}e^{i\omega_0\eta}e^{-\eta^2/2}. \quad (2)$$

The resulting values were then averaged across trials, and the electrodes were grouped according to traditional anatomical partition into 12 lobes. To estimate the significant changes in spectral dynamics, we applied the permutation procedure to the baseline interval and compared it to the post-stimulus interval.

In order to estimate the relations between time series, cross wavelet transform was applied to the signals averaged across frequency bands and brain regions. For each two time series *X* and *Y*, the cross wavelet transform is defined as (3):

$$W^{XY} = W^X W^{Y*}, \quad (3)$$

where * denotes complex conjugation; cross wavelet power is thus defined as $|W^{XY}|$. To estimate how coherent the cross wavelet transform is in time frequency space, the wavelet coherence was calculated according to the formula (4) [3]:

$$R_n^2(s) = \frac{\left|S\left(s^{-1}W_n^{XY}(s)\right)\right|^2}{S\left(s^{-1}\left|W_n^X(s)\right|^2\right)\cdot S\left(s^{-1}\left|W_n^Y(s)\right|^2\right)}. \quad (4)$$

Results. Permutation tests of spectral amplitude revealed significant activity in the theta frequency band, which is a significant marker of working memory processes involved in mental calculations. This effect was especially pronounced in the temporal lobes (Fig. 1), generally associated with verbal working memory, which is one of the cognitive components involved in multiplication problem solving that heavily relates to multiplication table recalling [4].

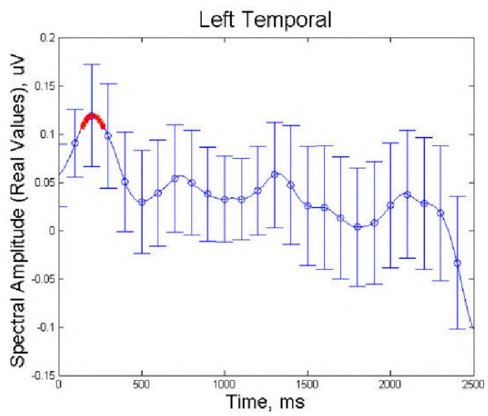

Fig. 1. Spectral amplitude dynamics in the theta frequency band for left temporal lobe. Significant interval is highlighted in red

Figure 2 presents the result of the cross wavelet transform between left and right temporal lobes within the theta frequency band (4–7 Hz). The coherency of the cross wavelet transform is presented on figure 3. The 5% significance level is shown as a thick contour. These results demonstrate the significant difference between coherency based on real and imaginary components. Future analysis with the known interactions between signals may test the effectiveness of real or imaginary wavelet-based coherence.

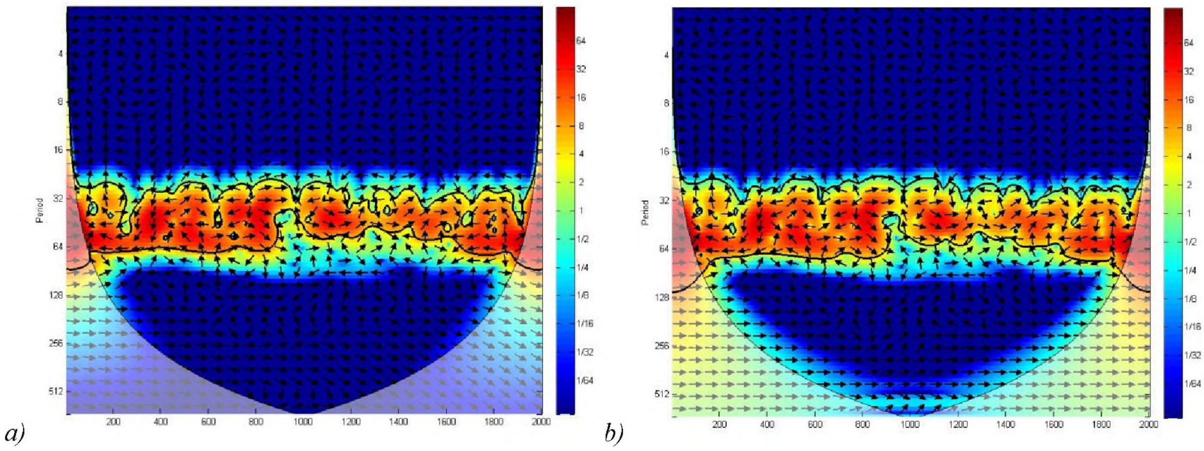

Fig. 2. Cross wavelet transform of the a) real, and b) imaginary part of the signals.

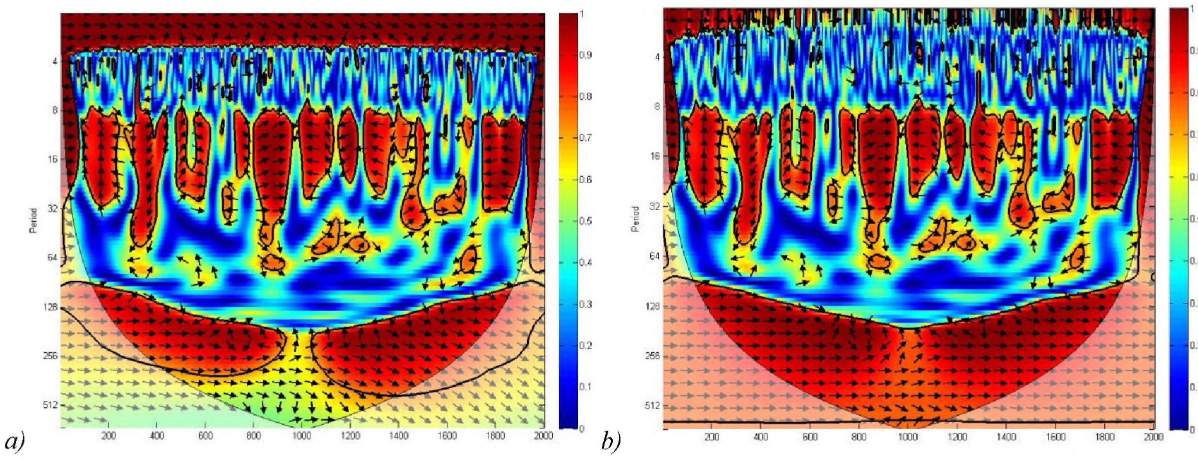

Fig. 3. Squared wavelet coherence between a) real, and b) imaginary part of the signals

Conclusion. The application of continuous wavelet transform enables to track the spectral dynamics of the signal, which is preferable for task-dependent EEG data. Using the imaginary part of coherency between cross wavelet transformations allows to overcome the problem of volume conduction, yielding more reliable results for signal interactions. The combination of continuous complex wavelet transform and imaginary part of coherency thus provides a reliable method to track interactions between signals representing brain activity.

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