Analysis of the characteristics of the synchronous clusters in the adaptive Kuramoto network and neural network of the epileptic brain

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ABSTRACT

In the paper we study the mechanisms of phase synchronization in the adaptive model network of Kuramoto oscillators and the neural network of brain by consideration of the integral characteristics of the observed networks signals. As the integral characteristics of the model network we consider the summary signal produced by the oscillators. Similar to the model situation we study the ECoG signal as the integral characteristic of neural network of the brain. We show that the establishment of the phase synchronization results in the increase of the peak, corresponding to synchronized oscillators, on the wavelet energy spectrum of the integral signals. The observed correlation between the phase relations of the elements and the integral characteristics of the whole network open the way to detect the size of synchronous clusters in the neural networks of the epileptic brain before and during seizure.

Keywords: Complex network, electroencephalogram, continuous wavelet analysis, oscillatory patterns, phase synchronization

1. INTRODUCTION

One of the most important tasks of modern theory of nonlinear oscillations and synchronization is the study of synchronization modes in the networks of coupled oscillators.[1] The nodes in such networks serve as components of these complex systems, and communication between the nodes represent the interaction between them. Recently, there is an interest to consider network topology is developed and adapted over time, either due to external influences, or in accordance with specific predetermined rules evolution.[2] Such networks are called as the adaptive networks, and their research is of great interest both in terms of the fundamental problems of nonlinear dynamics, and for applications in various branches of natural science, as well as the study of biological, social, economic, and other systems that represent the totality of the large number of agents with different types and intensities of the time-dependent connections between them.[3]

At the same time study of the neural networks of brain is also one of the most important and widespread problems in modern neuroscience, biophysics and and medicine.[4–6] It has significance in the diverse areas of

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science dealing with the diagnostics and treatment of brain disfunctions and the development of brain-computer interfaces.[7] The processes of interaction of million neurons lead to the appearance of the local synchronous modes in different areas of brain or in some cases a global synchronous states, which, obviously define the different types of cognitive or pathological activity.[8]

The recent advances in the electroencephalography (EEG)[9] and magnetoencephalography (MEG)[10] allowed to record the neuron activity with the high resolution in both space and time and gave the access to the high quality recordings of electric and magnetic activity of neurons in brain. The available data in turn gave the scientists a possibility of the identification of the patterns of neuron activity and opened the ways to control its dynamics (e.g. the interruption of the pathological activity during epileptic seizures[11,12]) and to translate neural activity into a continuous movement command via the special brain-computer interfaces (BCI).[11,13]

However, problems related to the diagnosis of synchronous clusters in the neural networks of the brain are of great interest for the study of pathological activities, especially, epileptic ones, and therefore raises an important question of assessing the efficiency of the use for this purpose macroscopic characteristics representing the integral averaged over the ensemble characteristics.[14,15]

In the present paper we consider the network-related phase Kuramoto oscillators,[2] and provide the analysis of the emergence of the synchronous clusters by means of integral characteristics described the dynamics of large-size neuronal ensemble. As the object of research the model of a complex random network with adaptive links is considered to analysis the synchronous dynamic establishment that leads to the appearance of clusters of interacting elements. The dynamics of the network was analyzed using a continuous wavelet transform of integral characteristics of the complex network,[14,15] which allow to diagnose the formation and dynamics of the clusters. Using phase distribution allows to quantify the level of clustering of the model network. Apply analyzed data model of adaptive network EEG signals of pathological activity, for subsequent identification of separate synchronous clusters.

2. NUMERICAL MODEL UNDER STUDY

Recently, various modifications of the model of the coupled phase Kuramoto oscillators network are used extensively for analysis of synchronization processes, including neural networks and social systems. In this report, the model of a complex network with adaptive couplings, proposed earlier in Ref.[2]

The base model under study is a network of Kuramoto oscillators, where each node has a connection with the other nodes with the coupling strength λ:

$$\dot{\varphi_i} = \delta_i + \lambda \sum_{j=1}^{N} \omega_{ij} \sin(\varphi_i - \varphi_j), \qquad i = 1, \dots N, \tag{1}$$

where φ_i is the phase of i–th Kuramoto oscillator, δ_i is the randomly selected frequency circular frequency phase Kuramoto oscillators, N is the number of generators in the network, and ω_{ij} is the weight of the connection between nodes j and i.

The value ω_{ij} changes over time according to the law:[2]

$$\dot{\omega_{ij}}(t) = \omega_{ij}(t)[s_i p_{ij}^T(t) - \sum_{i=1}^{N} \omega_{ij}(t) p_{ij}^T(t)], \tag{2}$$

where

$$s_i = \sum_{j=1}^{N} \omega_{ij} \tag{3}$$

is the total input strength the node i and j.

The degree of coherence $p_{ij}^T(t)$ between the local oscillator i and j are averaged over time interval $[t-T, t]$, which is defined by the equation:

$$p_{ij}^T(t) = \left| \frac{1}{T} \int_{t-T}^{t} e^{\sqrt{-1}[\varphi_j(\tau) - \varphi_i(\tau)]} d\tau \right|. \tag{4}$$

Here, the duration T of averaging window was chosen to be $T = 100$ for all calculations, as in Ref.[2,16]

This model reflects the two key of features of natural networks, namely, scale-free distribution of the weight of bonds and formation of mesoscale structures. These phenomena may be the reason for any of the following mechanisms: "hemophilia" associated with the strengthening of ties between the synchronized nodes, and "homeostasis" — the mechanism of competition, by which increasing a connection from one network element is balanced by the weakening of other bonds of the same node in the network, carried out by imposing conditions:

$$\sum_{j \neq i}^{N} \omega_{ij} = 1 \tag{5}$$

which means that the sum of all the weights within the node is constant at any point in time ω_{ij}–coefficient that which determines the strength of the link connecting the nodes j and i of the network.[2]

In the Refs.[15,17] has shown the ability to detect clusters of adaptive networks based on wavelet analysis of macroscopic dynamics. To analyze the synchronization using the macroscopic characteristics we examined integral signal representing of averaging oscillations over some subset of N_d elements of the network (in this study was considered a signal representing the average over the entire network of $N_d = N$ oscillators):

$$X(t) = \frac{A}{N} \sum_{i=1}^{N} \cos(\varphi_i(t)) \tag{6}$$

where $\varphi_i(t)$ is the phases of oscillators corresponding to i–th node of the network, A is the amplitude of the signals in the model system which was set equal 1.

The signal $X(t)$ was analyzed using a continuous wavelet transform[18]

$$W(s, \tau) = \int_{-\infty}^{\infty} X(t) \psi^* \left(\frac{t - \tau}{s} \right), \tag{7}$$

here $X(t)$ is the integral signal (7), , "*" means the complex conjugation, and $\varphi(s, \tau)$ is the wavelet function, defined for the certain time scale s:

$$\psi(s, \tau) = \frac{1}{\sqrt{s}} \psi_0 \left(\frac{t - \tau}{s} \right), \tag{8}$$

where ψ_0 is the mother wavelet function, t is the time shift parameter, and s is the time scale defining the width of wavelet function (8). In our work we use the Morlet mother wavelet, as it is the most suitable for the task time-frequency analysis and recognition of characteristic patterns in the physiological signals.[18]

$$\psi_0(\eta) = \pi^{-\frac{1}{4}} e^{j\omega_0 \eta} e^{-\frac{\eta^2}{2}}, \tag{9}$$

where ω_0 is the center frequency which was chosen to be $\omega_0 = 2\pi$.

In our consideration we use the absolute value of the complex-valued function $|W(s, \tau)|$ which is proportional to the energy of the signal.

3. RESULTS OF NUMERICAL SIMULATION OF ADAPTIVE NETWORK

Consider the results of numerical simulation of adaptive network of coupled oscillators Kuramoto (1). In our study we investigated the network of 150 oscillators, the value of circular frequency generators Kuramoto were assigned randomly in the range $[0, 2\pi]$, the coupling parameter between the generators will change between $0 \leq \lambda \leq 3.5$ with a constant step $\Delta\lambda = 0.1$.

Fig. 1(a, b, c) shows the integral network signals at different values of the parameter λ: $\lambda = 1.5$ (a), $\lambda = 2.5$ (b), $\lambda = 3.5$ (c) and the corresponding wavelet spectra (Fig. 1(d, e, f)). Note that for the small value of $\lambda < 1.3$ we have observed a non-synchronous behavior of the network elements. For $\lambda \geq 1.3$ we have observed the formation of several synchronous clusters, for example, Figs. 1(a, d) obtained for $\lambda = 1.5$ demonstrate the three distinct

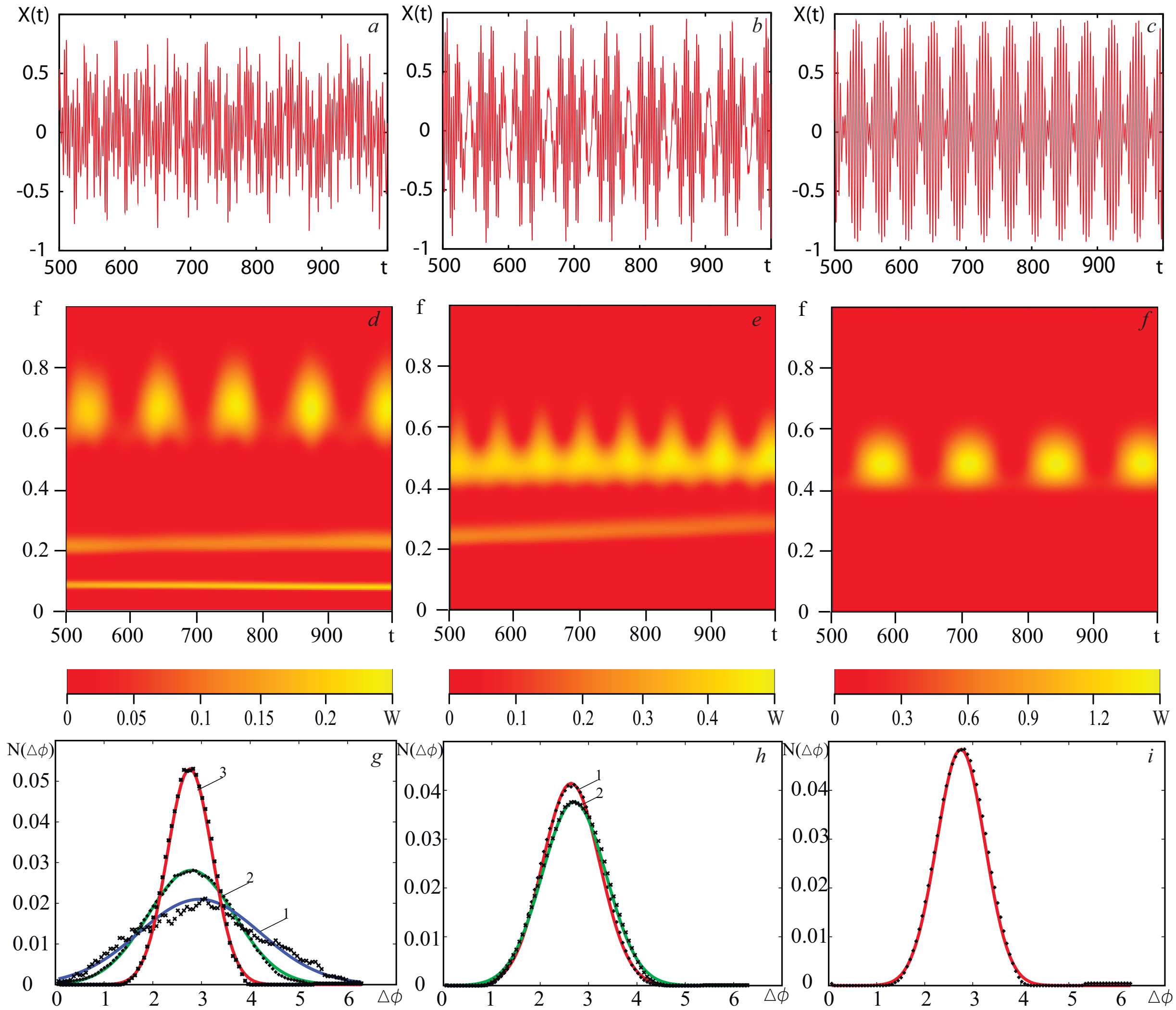

Figure 1. Time dependences of the integral characteristics (6) of the network of $N = 150$ Kuramoto oscillators at different values of the parameter λ: $\lambda = 1.5$ (a), $\lambda = 2.5$ (b), $\lambda = 3.5$ (c); (d, e, f) the normalized wavelet surfaces obtained for the integral characteristics (6) using the continuous wavelet transform (7) for different values of the coupling strength λ, correspondingly; (g, h, i) distributions of the phase differences between Kuramoto oscillators for different values of the coupling strength corresponding different formed clusters in the networks. Solid curves correspond to the Gaussian functions used for the approximation of the distributions

clusters present. In Refs.[15,18] it has been shown that increase of the strength of the coupling leads to formation of synchronous clusters in the network and each of cluster is characterised by the own oscillatory rhythm, detected by the continuous wavelet transform due to the separate peaks in the wavelet spectrum corresponding to the different clusters. In the case of $\lambda = 1.5$ we have observed three peaks in wavelet spectrum and correspondingly three clusters with typical frequencies $f_1 = 0.65$, $f_2 \approx 0.22$ (frequency of this cluster increases slowly in time due to adaptation process) and $f_3 = 0.12$. With the coupling strength λ growth in the adaptive network number of formed clusters is reduced from three clusters to the regime of global phase synchronization in the full network and, as a result, to formation of a single cluster with typical frequency $f = 0.45$ including all elements of the analyzed adaptive network (see Fig. 1(b, e and Fig. 1(c, f).

Figs. 1 (g, h, i) illustrate the phase distributions of the formed clusters for different λ–values. One can see that the phase distributions are approximated very well by the Gaussian functions. The wavelet spectra and phase distributions allow to quantitatively determine the relative number of oscillators combined in clusters in the adaptive network. Let us consider the case of weak coupling $\lambda = 1.5$. In this case we observe 3 clusters which correspond 3 peaks in the wavelet spectrum with following frequencies, f_i, amplitudes, A_i, and dispersions of phase distributions, σ_i: (1st cluster) $f_1 = 0.08$, $A_1 = 0.17$, $\sigma_1 = 1.13$; (2nd cluster) $f_2 = 0.22$, $A_2 = 0.09$, $\sigma_2 = 0.46$; (3rd cluster) $f_3 = 0.63$, $A_3 = 0.07$, $\sigma_3 = 0.89$. The relation between amplitudes of different clusters in wavelet spectrum can be considered as evaluation of relative number of nodes in the different clusters. In other words, $A_i/A_j \sim N_i/N_j$, where N_j is the number of nodes in the j–th cluster. Such estimation gives the following numbers of cluster sizes: $N_1/N_3 = 2.42$ and $N_2/N_3 = 1.03$. At the same time, taking into account the dispersions of phase distributions (see details in Ref.[15]) we can obtain the relative number of nodes in different clusters as $N'_1/N'_3 = 2.78$ and $N'_2/N'_3 = 1.24$. The obtained from numerical calculations of adaptive network values of the number of nodes in the each cluster are the following: $N_{pv1} = 89$, $N_{pv2} = 31$, $N_{pv3} = 30$, that is $N_{pv1}/N_{pv3} = 2.42$ and $N_{pv2}/N_{pv3} = 1.28$.

The same situation is observed for coupling strength $\lambda = 2.5$. In this case we observe 2 clusters with the following parameters $f_1 = 0.26$, $A_1 = 0.14$, $\sigma_1 = 0.66$, $N_{pv1} = 71$ and $f_2 = 0.17$, $A_2 = 0.27$, $\sigma_2 = 0.58$, $N_{pv2} = 79$. Accordingly, the relative number of elements in the cluster is $N_1/N_2 = 0.96$ and taking into account the dispersions $N'_1/N'_3 = 0.91$. The obtained from numerical calculations relative number of nodes in the first and second clusters is $N_{pv1}/N_{pv2} = 0.9$. So, we can conclude that there is possibility of a reasonably accurate estimation of the relative number of nodes in the synchronous clusters by analyzing the amplitudes of wavelet spectrum amplitude.

4. THE ANALYSIS OF NEURONAL NETWORK OF EPILEPTIC BRAIN BY MEANS OF INTEGRAL SIGNAL (CORTEX AND THALAMIC EEG)

Using the method developed for the cluster size determination by means of the analysis of the adaptive network of coupled oscillators Kuramoto, we can proceed to examine the epileptic brain by means ECoG signals of WAG/Rij rats having the genetic predisposition to absence epilepsy.[19]

ECoGs were recorded in 8 male WAG/Rij rats (one year old, body weigh 320–360 g).[20,21] Animals were born and raised at the laboratory of Biological Psychology, Donders Institute for Brain, Cognition and Behavior of Radboud University Nijmegen (The Netherlands). The experiments were conducted in accordance with the legislations and regulations for animal care and were approved by the Ethical Committee on Animal Experimentation of the Radboud University Nijmegen. Distress and suffering of animals were kept to a minimum. A recording electrodes were implanted epidurally over the frontal cortex and thalamus, VPM, for the reason that ECoG hallmarks of epileptic seizure (spike-wave discharge, SWD) showed their amplitude maximum in these zones. Ground and reference electrodes were placed over the two symmetrical sides of the cerebellum. Multichannel EEG recordings were made in freely moving rats continuously during a period of 2 h. ECoG signals were fed into a multi-channel differential amplifier via a swivel contact, band-pass filtered between 0.5 and 100 Hz, digitized with 1024 samples/s/per channel (CODAS software).[15]

For the analysis we take into account the two signals of multichannel ECoG, taken from the different parts of the rat's brain (frontal cortex and VPM nucleus of thalamus) during the emergence of absence epileptic seizure. In Refs.[22] we have carried out the a first study towards precursor activity in WAG/Rij rats based on a frontal and thalamic ECoG signals. Cortical and thalamic ECoG records were examined 3 s before the onset of SWD and during SWD. The wavelet coefficients at each time point and frequency in ECoG epochs prior and during SWD was examined by means of continuous wavelet transform with complex Morlet mother wavelet, and it was found that SWDprecursors consisted of several frequency components in the range from 2 to 12 Hz. The typical ECoG recordings and corresponding wavelet spectra and skeletons are shown in Fig. 2 for cortical and thalamic channels, respectively. The two most powerful rhythmic components in the frequencies 3–5 and 7–12 Hz immediately preceded the onset of SWD, considering their predominance and close proximity in time to the onset of SWD (see Fig. 2).

Our analyses shown that the dominant frequency of delta and theta/alpha precursor activity in the thalamus is similar to that in the cortex. However, the duration of theta precursor activity was slightly longer in the thalamus than in the cortex and also the duration of cortical delta precursor activity was longer than the cortical theta

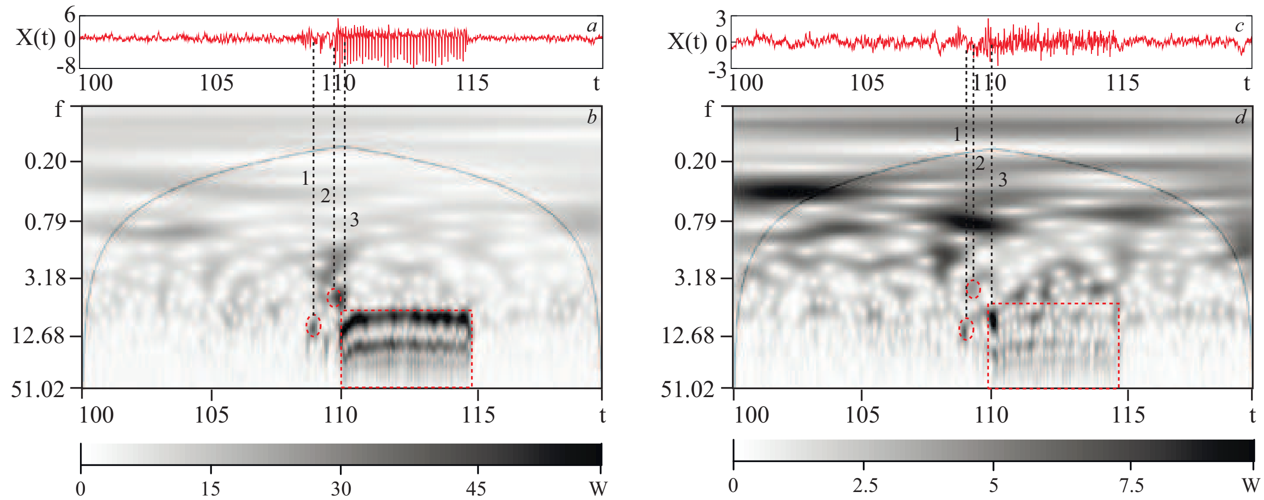

Figure 2. The time series and wavelet spectra of ECoG signals containing SWD simultaneously recorded at frontal cortex (left panel) and thalamus, VPM (right panel). The onset of the SWD was preceded by 9.8 Hz (theta/alpha) and 4.2 Hz (delta) in frontal cortex and by 9.7 Hz (theta/alpha) and 3.87 Hz (delta) — in thalamus (shown by ellipses). ∩-shaped curve on the wavelet surfaces marked the area of boundary effects.[18] The vertical dotted lines indicate the onset of SWD. Ellipses and dashed lines 1 correspond to theta/alpha-precursors, ellipses and dotted line 2 — delta-precursors. Boxes indicate the beginning and end of epileptic seizure

precursor activity. Delta precursor activity in the frontal cortex was found in 90% of all SWD,and theta/alpha precursor activity in 92%. High percentages were also found in the thalamus (VPM): 82% and 83%, respectively, for delta and theta/alpha precursors. There were no differences in the percentages of SWD that were preceded by delta and theta/alpha precursors in cortex and thalamus. The average duration of precursor activity was approximately equal to 0.5 s that gives the possibility to correct and precise identification of precursor activity by means of Morlet-based continuous wavelet transform.

Applying our developed approach of integral network signal processing to ECoG signals we can estimate the size of neuronal population involved in the formation of precursor activity. First, we can suggest that precursor activity is defined by the formation of synchronous clusters in neuronal subnetworks of cortex and thalamus. Second, we can assume that the phase distributions of different synchronous clusters are characterized by the approximately equal values of dispersions as well as the distributions in the adaptive network for large values of coupling strength (see Fig. 1 for $\lambda > 2.0$). In the framework of these suggestions we can define the relative size of neuronal populations involved in formation of (i) theta/alpha precursor, (ii) delta precursor, and (iii) SWD activity by means of estimation of amplitudes of corresponding rhythms in wavelet spectra of ECoG signals registered in cortex and thalamus.

Descriptive statistics of relations between wavelet spectrum components corresponding to delta and theta/alpha precursors, SWD activity in the beginning of epileptic seizures in cortex and thalamus are given in Table 1. We have considered about 30 SWD for each analyzed rat. In Table $\delta_\theta = |W_\theta|/|W_{SWD}|$ is the relative averaged amplitude of theta/alpha precursor $|W_\theta|$ in the wavelet spectrum, $\delta_\Delta = |W_\Delta|/|W_{SWD}|$ — the relative averaged amplitude of delta precursor $|W_\Delta|$, $|W_{SWD}|$ is the averaged amplitude of spike and wave oscillations in the beginning of SWD.

We have obtain that relative size of neuronal ensemble involved in the formation of delta precursor activity in the frontal cortex is about 8–25% of number of neurons in ensemble taking part in SWD formation, and relative size of neuronal ensemble of theta/alpha precursor is about 25–40%. High percentages are also found in the thalamus (VPM): 17–48% and 28–44%, respectively, for delta and theta/alpha precursors.

Table 1. Relations between amplitudes of wavelet spectrum components corresponding to delta and theta/alpha precursors, SWD activity in the beginning of epileptic seizures for cortex and thalamic ECoG signals

Rat #	Cortex channel		Thalamus (VPM) channel	
	δ_θ	δ_Δ	δ_θ	δ_Δ
01	0.34 ± 0.12	0.24 ± 0.2	0.45 ± 0.19	0.42 ± 0.2
02	0.29 ± 0.17	0.26 ± 0.17	0.48 ± 0.18	0.39 ± 0.3
03	0.25 ± 0.16	0.15 ± 0.1	0.32 ± 0.13	0.48 ± 0.19
04	0.4 ± 0.2	0.08 ± 0.07	0.28 ± 0.17	0.17 ± 0.08

5. CONCLUSION

We consider the identification of synchronization in adaptive network of phase Kuramoto oscillators by means of studying the wavelet spectra of integral signals. We have verified our approach by means of analyze of synchronous clusters and evolution of the phase difference distributions in the observed synchronous clusters. It is shown that investigation of wavelet spectra of integral network signals gives the correct qualitative and quantitative description of the processes of clustering with increasing of coupling strength between nodes in an adaptive network. This approach allows you to determine how much the oscillator is in a separate cluster. The practical significance of these results is related to the application of the developed approach to the analysis of real-world objects, consisting of a large number of nodes, where experimental data are limited to the use of integral characteristics: signals EEG and MEG, biological populations of a species, social networks.

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