The 9th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications
21-23 September, 2017, Bucharest, Romania

Distributed System for Sampling and Analysis of Electroencephalograms

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***Abstract*— Distributed system for sampling and analysis of electroencephalograms is proposed and implemented in alpha state. The system is based on the previously developed database for archiving of the electroencephalograms in Ukrainian National Grid infrastructure. The new components of the system include EEG sensors for laboratory animals, simulations software and data procession algorithms. The first application of the system for data sampling, analysis and simulations of epileptic seizures is performed.**

Keywords—grid, epileptic seizure, distributed system, simulation, detection, prediction, electroencephalography signal

I. Introduction

Epilepsy is a serious neurological disorder characterized by unprovoked seizure attacks. Although epileptic seizures rarely cause death of a patient [1], during generalized seizure attack patients lose control of their behavior and body position, which often results in traumatic injury [2]. While some patients have perceptual disturbance which allow them to predict oncoming seizures (epileptic aura), the majority of people who suffer from epilepsy appear to have unexpected seizures [3]. For decades neurologists considered epileptic seizures as events which occur within few seconds, however quantitative studies of long digital intracranial electroencephalographic recordings from patients being evaluated for epilepsy surgery, have demonstrated that electrographic seizures develop minutes to hours before actual clinical onset [4]. Prediction of epileptic seizures is an important issue in modern neurology not only for injury prevention but also for advancing the patient quality of life. Developing the methods for seizure prediction promises to give a rise to implantable devices which would be able to trigger therapy to manage clinical epileptic attacks [4, 5].

The electroencephalography (EEG) is an important tool for the monitoring brain activity in various clinical applications including monitoring the depth of anesthesia, diagnosis of coma and encephalopathies, etc. The typical EEG data contain a set of signals measured with electrodes placed on the human scalp. An ordinary EEG recording typically lasts for about 30 minutes and usually involves recording from tens scalp electrodes. These signals contain integral information about the activity of the whole brain. The EEG provides unique information about background brain activity and epileptiform discharges. It is strongly required for the correct diagnosis of specific electroclinical syndromes [6].

One of the critical steps in real-time diagnostics based on EEG signals is the measurement of efficient neurophysiologic signal statistics that allows identifying the normal and abnormal physiologic patients' state. Such EEG signals are noisy, non-stationary, complex and multichannel [7]. The EEG signal analysis and classification are essential for medical and health practice and research. It gives significantly better information about whether a spell is an epileptic seizure or not [8]. Therefore brain state recognition from EEG signals requires specific signal processing, preprocessing, features extraction and classification tools [9]. The processing and analysis of EEG signal are the key concepts of normal and abnormal patient's physiologic state classification and is the base of the computer-aided diagnostic systems design.

Computing grids [10] are useful platforms for distributed medical and biological applications [11] that require large number of data to be stored and processed. At the moment Ukrainian National Grid (UNG) infrastructure [12] is extensively used in a number of projects. These projects include distributed sampling, archiving and procession of electrocardiograms [13], computer tomography images [14], molecular biology [15, 16], etc. Here we show the sizable extension of our recently developed GRID-based system for archiving and analysis of EEG data [9]. From now it supports distributed data sensors, new procession algorithms and simulations. The system is applied for study of epileptic seizures in laboratory animals and for archiving and procession of human electroencephalographic data.

II. EXTENSION OF EEG DATABASE

A. Grid services

The database for archiving of EEG data in UNG [9] contains AMGA (ARDA Metadata Grid Applications) service for database queries, storage resources managements system (SRM) to control GRID storage elements (SE) and LCG file catalogue (LFC) service for data replication. The system is accessed via the web interface with X509 authentication. Special importers for data in different formats are used for data insertions. Data storage and outputs are performed in text formats.

B. Four channels EEG sensor for laboratory animals

EEG recordings of laboratory animals are important for study experimental epilepsy models. All EEG data collected in the GRID database were obtained using a conventional animal EEG tethered recorder. Now we are focused on development of wireless laboratory animals' EEG sensor. Wireless EEG sensor for laboratory animals should meet the following requirements: small size and weight; extremely low power consumption; water resistance; coverage radius up to 10 meters; wireless charging (as an optional feature); real time and small delay monitoring.

The main part of EEG sensor is a CC2640 [17] microcontroller unit (MCU) from Texas Instruments. The MCU includes low power processor, random access memory (RAM) and some peripheral devices including analog to digital converter (ADC) and radio-frequency (RF) transceiver compatible with Bluetooth (BT) Low Energy Specification. Having all these units on the same chip makes it very attractive for such applications. Also it should be noted this MCU's package size not exceeds 4-mm × 4-mm.

A temporal separation approach is used in order to utilize the single data receiver for many sensors. Since constant monitoring requires high power consumption a delayed monitoring is applied: the sensor continuously collects data and transmits them once per 4 s.

The structure of wireless EEG system is described in Fig. 1. Four micro-power instrumentation operational amplifiers (OA) INA333 [18] amplify the signal obtained from the electrodes implanted into the animal's brain. After amplification the signal passes to the 12-bit ADC with 2 kHz sampling rate (500 Hz per channel). The signal record of 4 seconds duration has 11.7 Kbytes size that allows storing it in the MCU's RAM. Two 12-bit measurements are stored as one 3-byte value to reduce data size. The CPU0 enters sleep mode between measurements to reduce the power consumption. Every 4 seconds CPU0 activates RF core (CPU1 and BT transceiver) and transmits the collected data. Besides measured EEG data the frame contains check sum, battery voltage, temperature of MCU chip. On successful reception the confirmation is sent.

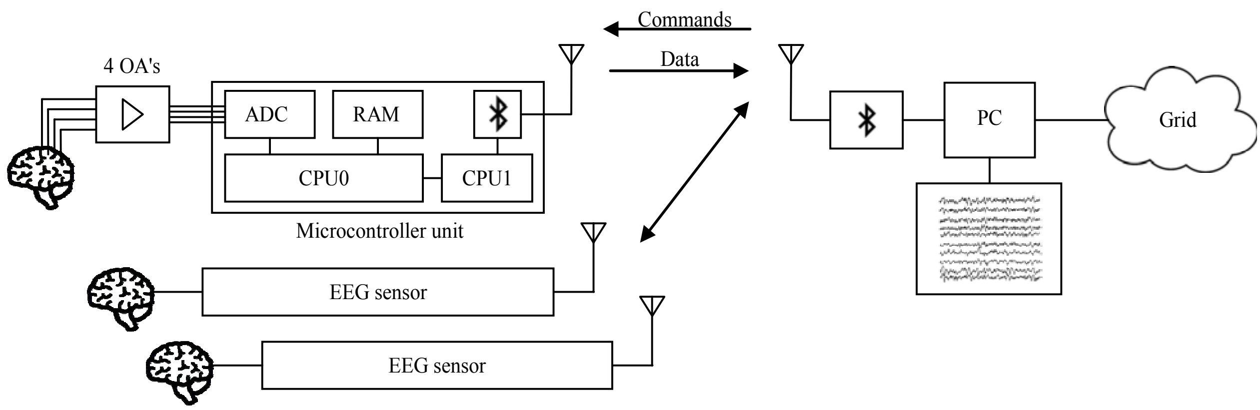

Figure 1. EEG sensors system

Reception of the data is performed by BT module connected to personal computer (PC). Custom PC software controls BT module, receives frames, decodes and saves data for further transfer to GRID, draws plots on the screen. It also supports transmission of commands to certain sensor, such as: switching hibernation/active mode, toggling on/off state, changing transmission period of packets, sampling rate, transmitter power and transmission queue size. The decoder separates one 3-byte value into two 12-bit values and saves them as the separate 16-bit values.

The transmission of the single packet takes about 0.1 s with 1Mbps rate. Estimated operating time of the system is about 65 hours with 20 mA·h Li-ion battery. One BT transceiver on PC can support up to 5 EEG sensors.

Modification of the sensor that can be implanted into the abdomen of the animal requires wireless charging that can be implemented with Qi standard or other methods based on resonant inductive coupling.

C. Human Cognitive Functional EEG sampling automation

Cognitive Functional EEG is used to discern the activities of specific areas of the brain and the relationships between these brain areas. It also facilitates analysis of brain function while participants are involved in cognitive tasks such as playing a videogame or solving a mathematical equation. Investigation of cognitive functions needs not only EEG data but also precise information about the actions performed by subjects. It is also necessary to provide good synchronization between EEG recordings and visual/auditory stimuli as well as cognitive task milestones. All these data should be marked on EEG signal [19]. Some tests like virtual Morris water maze [20] requires synchronization of unique states of the test with EEG signal. In present work we developed the hardware and software that grab the state of the audio and video subsystems of the virtual test (Fig. 2) and transfer them to EEG NEUROCOM [21] recorder for time stamping of EEG records. Synchronization with audio subsystem is performed by detection of certain signal's frequencies with Prony's method [22].

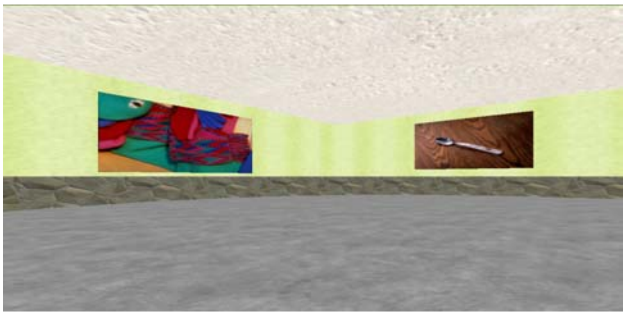

Figure 2. Print screen picture drawing of the virtual Morris water navigation test for subjects.

D. Seizures detection algorithm

In this work the seizures detection algorithm [23] is applied to intracranial EEG data from freely-moving chronic epileptic rats. Electrocorticography (ECoG) or intracranial EEG is a type of electrophysiological brain monitoring that uses recording electrodes placed directly into the brain's cerebral cortex. This recording technique has higher spatial resolution and better signal to noise ratios compared to on-scalp EEG. Furthermore, ECoG is less prone to biological and technical artifacts. So these signals are the best candidates for EEG signal features that can predict the epileptic seizures.

The data processing consists of three main steps: data preprocessing, stationary wavelet transform and post-processing methods [23]. The main steps are wavelet transform applied to the pre-processed data and classification of the detected seizures as epileptic or non-epileptic cases.

The discrete wavelet transform (DWT) is a decomposition of the time series which can be understood as a successive band-pass filtering. The DWT is computationally fast and can be implemented by successive filter banks [24]. Unfortunately, the DWT is not shift-invariant when applied to discrete time series. If the input time series is shifted, the resulting coefficients may become significantly different. The stationary wavelet transform [25] has no such issues. Two wavelets are commonly used for EEG analysis: the Daubechies 4 wavelet and the Symlet 5 wavelet. In this work, the Daubechies 4 (db4) wavelet is used. After detection of rhythmic discharges of specific frequencies the classification procedure is applied for identification of epilepsy seizures. A minimum ictal phase of 5 s and the minimum interictal phase of 10 s are assumed.

E. Seizures prediction algorithm

We focus on developing model predicting the seizure onset based on information about single channel sampled from laboratory animals. According to additional information about seizure onset, for each section we add y value, corresponding to 1 if there is seizure in this section, and 0 otherwise. To be able to predict onset of seizure in advance, we gradually increase risk function y for previous time interval. For each sequence of data points we estimate its risk. As our approach does not describe probability of seizure onset, whereas we want to compare risk of one sequence to another one, we consider regularized ranking algorithm for this task [26], where x is vector of time interval data points, and y is relative risk. To reduce the dimensionality of vector x we apply Principal Component Analysis (PCA) to x append main characteristics of the vector, such as mean, min, max and top coefficients of Fourier transform. Then we apply regularized ranking algorithm in reproducing kernel Hilbert spaces corresponding to different values of regularization parameter and parameter of Gaussian kernel. Finally, we consider ensemble of those outputs with Linear Functional Strategy [27]. Linear Functional Strategy with incremental Nyström subsampling [28, 29] allows effective parallelization of the solver. Finally, performance of aggregated risk ranker is evaluated.

F. Simulations subsystems

Subsystem for simulations of brain functions is based on grid software for simulations in neuroscience [30, 31]. Models and software for simulation of epileptic seizures [32] are also used. This subsystem contains database of jobs. Job agents on computing cluster cluster.univ.kiev.ua periodically checks status, starts and finishes of jobs. Jobs are started on UNG clusters and can access and create data on grid SEs including EEG data records.

III. First Application Results

The proposed system is implemented in alpha state. All described components are implemented, tested and provides some preliminary results. The dataset of 14 electrophysiology recordings were sampled. The recordings contain from 258 to 1324 sections, with 4096 data points each, where points are obtained with sampling interval 2.4 ms.

A. *Detection of seizures in laboratory animals' signals*

The described above algorithm for epileptic seizures detection was applied to the data mentioned above. The obtained results are described in Fig. 3. All epileptic seizures are marked in red rectangles; also non-epileptic signal is detected in time period from 780 s to 1587s. Thus the SWT methods provide the sufficient accuracy for epileptic seizure detection from ECoG datasets. Proposed algorithm may be applied for further development of seizure prediction techniques.

B. *Seizures predictions in laboratory animals' signals*

The described above algorithm is tested on the dataset with onset of seizure is known. To be able to predict onset of seizure in 1 minute in advance, we gradually increase risk function y for previous 60 seconds (i.e. 25000 data points). Now for each sequence of 4096 data points we want to be able to estimate its risk. PCA with 64 components gives explained variance ratio over 83%. Finally, performance of aggregated risk ranker is evaluated in terms of mean squared error 0.1, and area under of the receiver operation characteristic curve (ROC AUC) 0.8, and accuracy 84% (values are calculated for the ranker comparing to characteristic function for seizure onset in the current section or following 30 seconds).

As we use ranking algorithm it allows estimating the risk of seizure as well as its time-horizon. Therefore it is interesting to consider accuracy of prediction in terms of time-horizon of seizure onset. Corresponding result is presented in Fig. 4. The prediction accuracy exceeds 84% for time moments preceding seizures up to 50 seconds. For longer term prediction accuracy decreases that may be referred to 60 seconds signals' time window.

C. *Simulation of epileptic seizures in neuronal networks*

In addition to previously obtained results [30, 31] realistic simulations of cortical neuronal network was performed using described system. The effect of Mg^{2+} concentration and Na^{+} ion channel potential on pathological synchronization of neurons was studied, as shown in Fig. 5. Order parameter of the network was computed for 350 dynamics trajectories of 2000 neurons. Order parameter characterizes the relative number of synchronized neurons. It is interesting to note that pathological synchronization is absent in certain range on Mg^{2+} ions concentration.

IV. CONCLUSIONS AND PLANS

The described distributed system for sampling and analysis of electroencephalograms extends features of the grid database for electroencephalograms in Ukrainian National Grid [9]. This system provides the possibility to extend interdisciplinary research in the field of neuroscience and to obtain novel scientific results. Additionally, system provides the possibility to integrate new sampling, data analysis and simulation techniques. Preliminary scientific results in epileptic seizure investigation and predications were obtained.

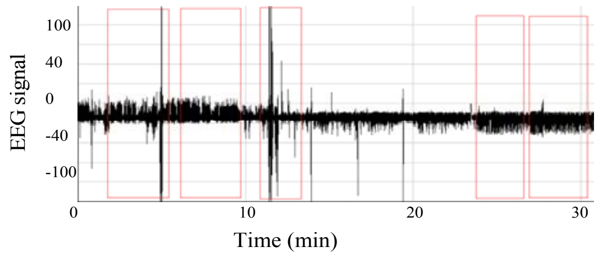

Figure 3. Epileptic seizures detection (detected seizures marked in red rectangles)

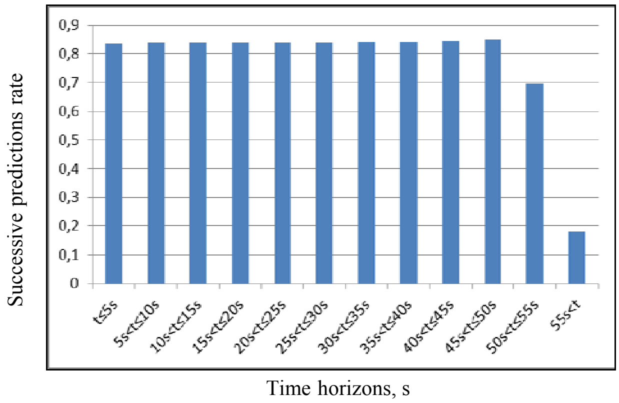

Figure 4. Accuracy of seizure prediction depending on prediction of time-horizon

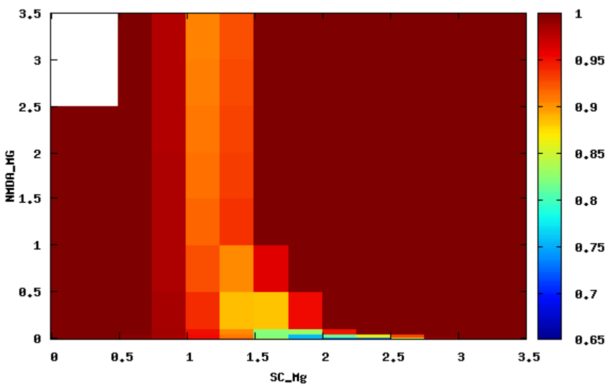

Figure 5. Dependence of network order parameter on Magnesium concentration (SC_MG) and ion channel activation potential (NMDA_MG)

Future plans include the extension of the proposed algorithms and models as well as the usage of the experimentally sampled data for models identification.

ACKNOWLEDGMENT

We thank Ukrainian National Grid for providing of the computing resources. Computations were performed on computing clusters of Information and Computer Center

National Taras Shevchenko University of Kyiv and Scientific Center for Medical and Biotechnical Research, NAS of Ukraine.

REFERENCES

[1] Berg A. Mortality in Epilepsy. Epilepsy Currents. 2001;1(1):28. doi:10.1046/j.1535-7597.2001.00007.x.

[2] Nguyen R, Téllez Zenteno JF. Injuries in epilepsy: a review of its prevalence, risk factors, type of injuries and prevention. Neurology International. 2009;1(1):e20. doi:10.4081/ni.2009.e20.

[3] Dugan P, Carlson C, Bluvstein J, Chong DJ, Friedman D, Kirsch HE. Auras in generalized epilepsy. Neurology. 2014;83(16):1444-1449. doi:10.1212/WNL.0000000000000877.

[4] Litt, Brian, and Javier Echauz. "Prediction of epileptic seizures." The Lancet Neurology 1.1 (2002): 22-30.

[5] Wang L, Guo H, Yu X, et al. Responsive Electrical Stimulation Suppresses Epileptic Seizures in Rats. Boraud T, ed. PLoS ONE. 2012;7(5):e38141. doi:10.1371/journal.pone.0038141.

[6] Alotaiby, T.N., Alshebeili, S.A., Alshawi, T. et al. EEG seizure detection and prediction algorithms: a survey. EURASIP J. Adv. Signal Process. (2014) 2014: 183. doi:10.1186/1687-6180-2014-183.

[7] Nolan MA, Redoblado MA, Lah S, etal. Memory function in childhood epilepsy syndromes. J Paediatr Child Health. 2004 Jan-Feb. 40(1-2):20-7.

[8] Nei, M., Lee, J.-M., Shanker, V. L. and Sperling, M. R. (1999), The EEG and Prognosis in Status Epilepticus. Epilepsia, 40: 157–163. doi:10.1111/j.1528-1157.1999.tb02069.x.

[9] Gaidar, V.O., Sudakov, O.O. Archiving and analysis of electroencephalograms in Ukrainian Grid: The first application. // Proc. of the 2015 IEEE 8th International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications, IDAACS 2015 - p. 961-965.

[10] I. Foster and C.Kesselman, The Grid: Blueprint for a New Computing Infrastructure. Morgan Kaufmann, 1999.

[11] Ardizzone, Valeria, Roberto Barbera, Antonio Calanducci, Marco Fargetta, E. Ingrà, Ivan Porro, Giuseppe La Rocca et al. "The DECIDE science gateway." Journal of Grid Computing 10, no. 4 (2012): 689-707.

[12] Zynovyev, M., Svistunov, S., Sudakov, O., & Boyko, Y. (2007, September). Ukrainian Grid infrastructure: practical experience. // *4-th International Workshop on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications*. Dortmund, Germany, September 6-8, 2007 pp. 237-240.

[13] Salnikov, A., Vishnevskey, V., Boretskyi, O. Palform as a service for inercative analisys of medical data. Mathematical Machines and Systems. 2015 -1 pp 53-64. In Russian. («ПЛАТФОРМА КАК СЕРВИС» В ГРИД ДЛЯ ИНТЕРАКТИВНОГО АНАЛИЗА МЕДИЦИНСКИХ ДАННЫХ).

[14] Sudakov, O., Kononov, M., Sliusar, I., Salnikov, A. User clients for working with medical images in Ukrainian Grid infrastructure. 7-th EEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications September 6-8, 2013, September 12-14, 2013Berlin, Germany. pp. 705-709.

[15] Salnikov, A.O., Sliusar, I.A., Sudakov, O.O., Savytskyi, O.V., Kornelyuk, A.I. MolDynGrid virtual laboratory as a part of Ukrainian Academic Grid infrastructure // Proc. 5th IEEE International Workshop on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications, IDAACS'2009., pp. 237-240.

[16] Savytskyi, O.V., Sliusar, I.A., Yesylevskyy, S.O., Stirenko, S.G., Kornelyuk, A.I. Integrated tools for molecular dynamics simulation data analysis in the MolDynGrid virtual laboratory // Proc. 6th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications, IDAACS'2011, pp. 208-211.

[17] http://www.ti.com/lit/ds/swrs176b/swrs176b.pdf

[18] http://www.ti.com/lit/ds/symlink/ina333.pdf

[19] A. Cherninsky, S. Kryzhanovsky, I. Zyma. Human brain electrophysiology: practical guide. Mavis, Kyiv, 2011, https://books.google.com.ua/books?id=Olq_ivxHxIUC&printsec=frontcover&hl=uk#v=onepage&q&f=false (in Ukrainian).

[20] Hori, S., Matsumoto, J., Hori, E. et al. Alpha- and Theta-Range Cortical Synchronization and Corticomuscular Coherence During Joystick Manipulation in a Virtual Navigation Task. Brain Topogr (2013) 26: 591. doi:10.1007/s10548-013-0304-z

[21] Digital spectral analysis: with applications /S. L. Marple, Jr. Englewood Cliffs, N.J. Prentice-Hall, 1987.

[22] Scientific-technologic Center of radioelectronic medical devices and technologies XAI-Medica of National Aerospace University, XAI-MEDICA-EEG systems. https://xai-medica.com/en/neurocom/neurocom.htm.

[23] V.O. Gaidar, O.O. Sudakov Automatic epilepsy detection using wavelet transform// 11th International conference on scientific computing in electrical engineering, pp. 93 – 94 – October, 3-7, 2016, Wolghang Austria.

[24] Mertins A. Die Wavelet-Transformation// Springer Vieweg: Signaltheorie, - 3rd edition, - 2013, pages 301–354.

[25] Nason G.P. The Stationary Wavelet Transform and some Statistical Applications/ Nason G.P., Silverman B.// Wavelets and Statistics: Lecture Notes in Statistics, - V. 103, - p. 281 – 299.

[26] Kriukova. G., Pereverzyev S.V., Tkachenko P., "On the convergence rate and some applications of regularized ranking algorithms", Journal of Complexity, 33, 2016, pp. 14-29.

[27] Kriukova G., Panasiuk O., Pereverzyev S.V., Tkachenko P., "A linear functional strategy for regularized ranking", Neural Networks, 73, 2016, pp. 26-35.

[28] Rudi A., Camoriano R., Rosasco L., "Less is More: Nyström Computational Regularization", Advances in Neural Information Processing Systems, 29, NIPS 2016.

[29] Kriukova G., Pereverzyev S., Tkachenko P., "Nyström type subsampling analyzed as a regularized projection", Inverse Problems, Special Issue on learning and Inverse problelms, In Press (Accepted: 04 May 2016).

[30] Andrii Salnikov, Roman Levchenko, Oleksandr Sudakov Integrated Grid Environment for Massive Distributed Computing in Neuroscience // Proc. 6th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications 15-17 September 2011, Prague, Czech Republic . - p. 198- 202.

[31] Levchenko, R. I.; Sudakov, O. O.; Maistrenko, Yu L. Parallel software for modeling complex dynamics of large neuronal networks. In: Proc. 17th International Workshop on Nonlinear Dynamics of Electronic Systems, Rapperswil, Switzerland. 2009. p. 34-37.

[32] Golomb D, Shedmi A, Curtu R, Ermentrout B. Persistent synchronized bursting activity in cortical tissues with low magnesium concentration: a modeling study // J. Neurophysiol. published 19 October 2005, 10.1152/jn.00932.2005