PROCEEDINGS OF SPIE

SPIEDigitalLibrary.org/conference-proceedings-of-spie

Detection of different states of sleep in the rodents by the means of artificial neural networks

Viacheslav Musatov, Viacheslav Dykin, Elena Pitsik, Alexander Pisarchik

Viacheslav Musatov, Viacheslav Dykin, Elena Pitsik, Alexander Pisarchik, "Detection of different states of sleep in the rodents by the means of artificial neural networks," Proc. SPIE 10717, Saratov Fall Meeting 2017: Laser Physics and Photonics XVIII; and Computational Biophysics and Analysis of Biomedical Data IV, 107171N (26 April 2018); doi: 10.1117/12.2314957

Event: Saratov Fall Meeting 2017, 2017, Saratov, Russian Federation

Downloaded From: https://www.spiedigitallibrary.org/conference-proceedings-of-spie on 4/30/2018 Terms of Use: https://www.spiedigitallibrary.org/terms-of-use

Detection of different states of sleep in the rodents by means of artificial neural networks

Viacheslav Musatov[ab], Viacheslav Dykin[a], Elena Pitsik[a], Alexander Pisarchik[ac]

[a]REC "Artificial Intelligence Systems and Neurotechnology", Yuri Gagarin State Technical University of Saratov, Politechnicheskaya Str. 77, Saratov, 410056, Russia
[b] Department of Automatization, Control and Mechatronics, Yuri Gagarin State Technical University of Saratov, Politechnicheskaya Str. 77, Saratov, 410056, Russia;
[c] Universidad Politécnica de Madrid, Centre for Biomedical Technology, Calle Ramiro de Maeztu, 7, 28040 Madrid, Spain

ABSTRACT

This paper considers the possibility of classification of electroencephalogram (EEG) and electromyogram (EMG) signals corresponding to different phases of sleep and wakefulness of mice by the means of artificial neural networks. A feed-forward artificial neural network based on multilayer perceptron was created and trained on the data of one of the rodents. The trained network was used to read and classify the EEG and EMG data corresponding to different phases of sleep and wakefulness of the same mouse and other mouse. The results show a good recognition quality of all phases for the rodent on which the training was conducted (80–99%) and acceptable recognition quality for the data collected from the same mouse after a stroke.

Keywords: Electroencephalogram, neurophysiological experiment, artificial neural network, pattern recognition, artificial intelligence

1. INTRODUCTION

Sleep is a neurological dynamic behavior with physical tranquility, reduced interaction with environment and inherence of physical activity in almost all muscles. It is a special condition of the brain associated with processes of recovery of body and mind,[1,2] thus it's quality is significantly important for all biological functions of organism. Yet the actual general function of sleep is not yet fully understood.

Sleep in mammals is actually organized by cycles consisting of two different states: rapid eye movement or fast sleep (REM) and non-rapid eye movement, or deep sleep (NREM), which are so different that scientists describe them as different behavioral states. These stages have different biological manifestations which may have neurological as well as physical nature and correspond to specific types of brain activity, studying which is important for diagnosis of various hidden physical and psychological pathological conditions.[3] In this case EEG proved itself as an effective method of study these types of activity.[4,5] We consider the sleep brain activity of the mice, since rodents are widely used as laboratory animals,[6–11] for which the technology of invasive installation of metal EEG electrodes is widely used.

This paper contains the research of the classification problem of different EEG- and EMG-patterns corresponding to different phases of sleep and wakefulness by the means of artificial neural network.[12]

2. METHODS

EEG and EMG signals were obtained during a series of experiments with rodents equipped with metal screw electrodes that were implanted epidurally (see Figure 1). These EEG and EMG signals were continuously recorded at a frequency of 250 Hz for several days. Activity of mice at this time was divided as different states of sleep: wakefullness (WAKE), paradoxical sleep (REM) and deep sleep (NREM). Recorded files were respectively marked.

Further author information: (Send correspondence to Elena Pitsik)
Elena Pitsik: E-mail: pitsikelena@gmail.com, Telephone: +7 937 144 08 42

Saratov Fall Meeting 2017: Laser Physics and Photonics XVIII; and Computational Biophysics and Analysis of Biomedical Data IV, edited by Vladimir L. Derbov, Dmitry E. Postnov, Proc. of SPIE Vol. 10717, 107171N · © 2018 SPIE · CCC code: 1605-7422/18/$18 · doi: 10.1117/12.2314957

Downloaded From: https://www.spiedigitallibrary.org/conference-proceedings-of-spie on 4/30/2018 Terms of Use: https://www.spiedigitallibrary.org/terms-of-use

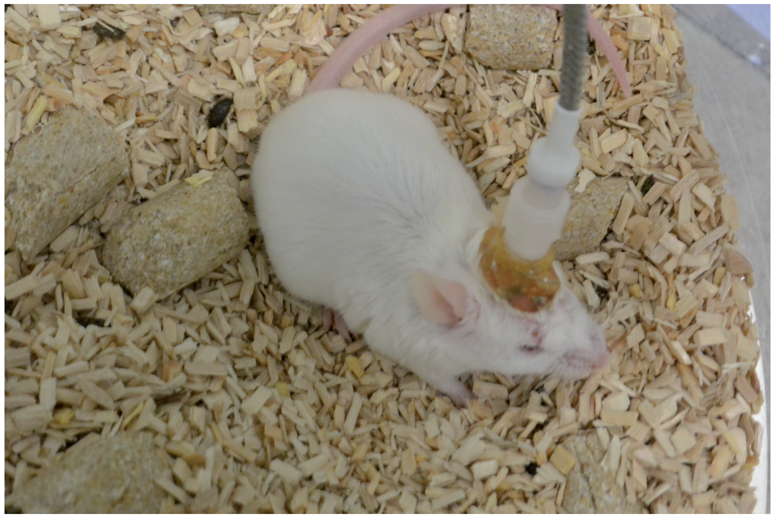

Figure 1. Electrode arrangement for experiments

To detect different stages of sleep in rodents we used feed-forward artificial neural network (which shows good results in human EEG studies[13,14]) with 15 neurons on hidden layer and 3 neurons on output layer, one for each stage: wakefullness, REM and NREM sleep. The schematic architecture of designed neural network presented on Figure 2.

Training was conducted on EEG and EMG data recorded within two days of one of the mice. Training dataset contains EEG and EMG data and time marks corresponding to different states of sleep: WAKE, REM, NREM. Each training sample was presented in frequency domain[15,16] by means of digital preprocessing using discrete Fourier transform (1) and filtered with low-pass filter (20 Hz).

$$X_k = \sum_{n=0}^{N-1} x_n e^{-\frac{2\pi i}{N} k_n}, k = 0, ..., N-1, \tag{1}$$

where N is a number of signal values measured over a period and number of decomposition components; X_k is the measured signal values at discrete time points; k_n is the complex amplitudes of sinusoidal signals composing the original signal.

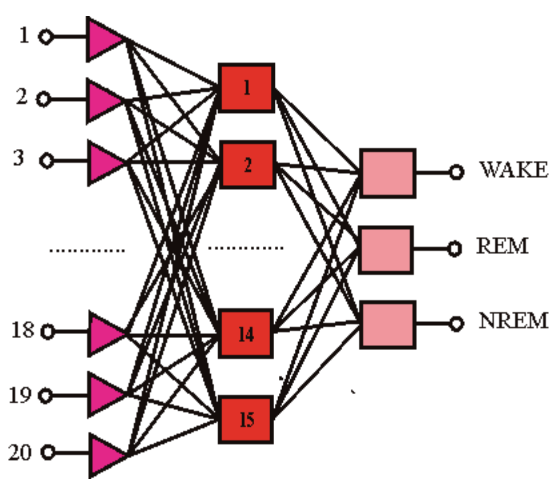

Figure 2. Artificial neural network architecture used in computer experiment

Downloaded From: https://www.spiedigitallibrary.org/conference-proceedings-of-spie on 4/30/2018 Terms of Use: https://www.spiedigitallibrary.org/terms-of-use

3. RESULTS

To build training dataset for neural network we collected every 1000 points on the entire data segment and then selected one data section where there were more phase transitions — about 50,000 points long. One trainig sample contained 250 points, each one was processed by a Discrete Fourier Transform. The first 20 Hz of the Discrete Fourier Transform spectrum of EEG and EMG were combined in one vector and used in calculations.

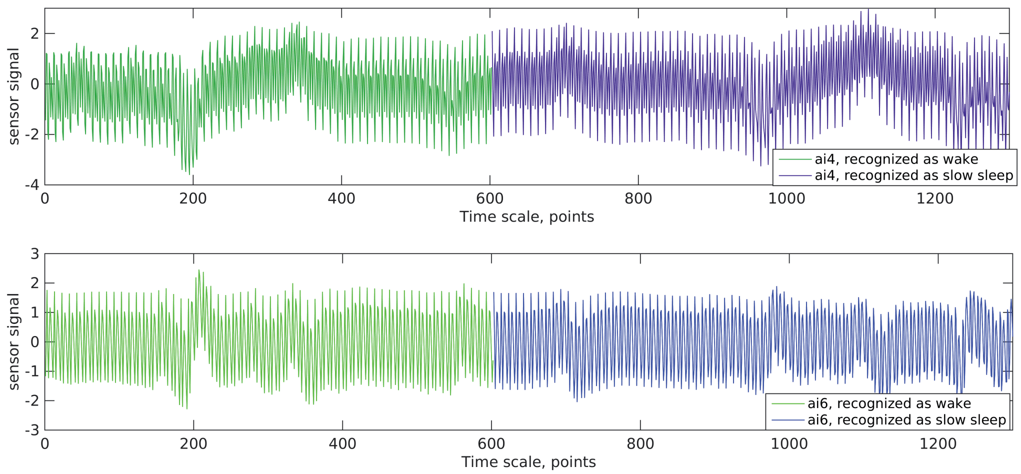

Figure 3. Example of recognized EEG and EMG signals

Examples of different sleep phases recognizing by trained neural network are shown in Figure 3. The average states classification reached sufficient quality: ∼ 80% between REM and wakefullness, >99% between REM and NREM and >99$ between NREM and wakefullness.

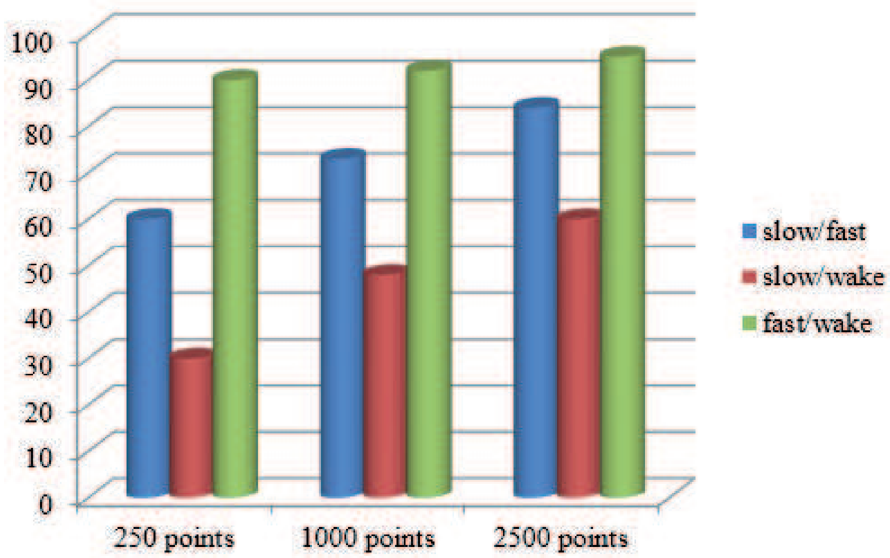

Figure 4. The dependence of the recognition quality on the number of data points for the DFT

Since the EEG data related to the different stages of sleep are widely used in diagnosis of various kinds of illness, we conducted the computational experiment in order to investigate the potential of artificial neuronal

Downloaded From: https://www.spiedigitallibrary.org/conference-proceedings-of-spie on 4/30/2018 Terms of Use: https://www.spiedigitallibrary.org/terms-of-use

networks in classification of the EEG data recorded from the mouse one day after a heart attack. Artificial neuronal network was trained on the data of healthy mouse, and then was made an attempt to predict the states of sleep on the data collected from the same mouse after the infarction. Results are as follows: between REM and NREM: ∼60%, between NREM and wakefullness: ∼30%, between NREM and wakefullness: ∼90%. To improve the recognition quality, as a sample of data for the Discrete Fourier Transform, 1000 and 2500 points of EEG and EMG data were used. The results of the neural network recognition quality of the data thus transformed are shown in 4.

It is seen that an increase of the number of points used for the Discrete Fourier Transform improves the recognition quality.

4. CONCLUSION

Summing up the above, we investigated the potential of multilayer perceptron for recognition EEG and EMG signals corresponding to the sleep and wakefulness phases of laboratory mice. We designed the optimal neural network's structure with 20 inputs, 15 neurons in the hidden layer and 3 neurons at the output, that is capable to obtain the most good quality of classification. Before training the network data for recognition were pre-processed with effective mathematical methods of signal transform. It was shown that this ANN provides high recognition quality of phases wakeful, fast and slow sleep in the training and testing of EEG and EMG data obtained from the same mouse.

In addition, it is established that ANN, trained on the EEG and EMG data of healthy mouse show the ability to recognize the sleep phases of the same mouse after a serious illness — infarction. The quality of recognition is noticeably worse, but it is shown that in order to improve the quality of recognition under such conditions, it is reasonable to use an enlarged data sample — not 250 points, as in the initial case, but 1000 or 2500 points, which allows to increase the quality of recognition from 30–90% to 60–94%. Obtained results allow to judge about the prospects of using ANN for recognition and classification of to EEG and EMG signals corresponding to wakefulness and sleep states of rodents.

5. ACKNOWLEDGMENTS

This work has been supported by the Ministry of Education and Science of Russia Federation (project 3.861.2017/4.6) and President Program of Leading Scientific School Support (Grant NSH-2737.2018.2).

REFERENCES

[1] Nicolau, M., Akaârir, M., Gamundí, A., González, J., and Rial, R., "Why we sleep: the evolutionary pathway to the mammalian sleep," *Prog. Neurobiol.* **62**, 379 (2000).

[2] Rechtschaffen, A., "Current perspectives on the function of sleep," *Perspect.Biol.Med.* **41**(3), 359 (1998).

[3] Pavlov, A. N., Hramov, A. E., Koronovskii, A. A., Sitnikova, Y. E., Makarov, V. A., and Ovchinnikov, A. A., "Wavelet analysis in neurodynamics," *Physics-Uspekhi* **55**(9), 845–875 (2012).

[4] Destexhe, A., Contreras, D., and Steriade, M., "Spatiotemporal analysis of local field potentials and unit discharges in cat cerebral cortex during natural wake and sleep states," *J Neurosci* **19**(11), 4595 (1999).

[5] Kudrimoti, H., Barnes, C., and McNaughton, B., "Reactivation of hippocampal cell assemblies: Effects of behavioral state, experience, and eeg dynamics," *J Neurosci* **19**, 4090 (1999).

[6] Datta, S., "Avoidance task training potentiates phasic pontine-wave density in the rat: A mechanism for sleep-dependent plasticiti," *J Neurosci* **20**, 8607 (2000).

[7] O'Hara, B., Turek, F., and Franken, P., "Genetic basis of sleep in rodents. in principles and practice of sleep medicine: Fifth edition," *Elsevier Inc.* **180**, 161–174 (2010).

[8] van Luijtelaar, E. L. M., Hramov, A., Sitnikova, E., and Koronovskii, A., "Spike-wave discharges in WAG/Rij rats are preceded by delta and theta precursor activity in cortex and thalamus," *Clinical Neurophysiology* **122**, 687–695 (2011).

[9] Hramov, A., Koronovskii, A., Midzyanovskaya, I., Sitnikova, E., and Rijn, C., "On-off intermittency in time series of spontaneous paroxysmal activity in rats with genetic absence epilepsy," *Chaos* **16** (2006).

Downloaded From: https://www.spiedigitallibrary.org/conference-proceedings-of-spie on 4/30/2018 Terms of Use: https://www.spiedigitallibrary.org/terms-of-use

[10] Maksimenko, V. A., Luttjohann, A., Makarov, V. V., Goremyko, M. V., Koronovskii, A. A., Nedaivozov, V. Runnova, A. E., van Luijtelaar, G., Hramov, A. E., and Boccaletti, S., "Macroscopic and microscopic spectral properties of brain networks during local and global synchronization," *Phys. Rev. E* **96**, 012316 (2017).

[11] Maksimenko, V. A., Heukelum van, S., Makarov, V. V., Kelderhuis, J., Luttjohann, A., Koronovskii, A. A., Hramov, A. E., and Luijtelaar van, G., "Absence seizure control by a brain computer interface," *Nature Scientific Reports* **7**, 2487 (2017).

[12] Haykin, S., "Neural networks: A comprehensive foundation.," *Prentice Hall PTR Upper Saddle River* (1998).

[13] Musatov, V., Pchelintseva, S., Runnova, A., and Hramov, A., "Patterns recognition of electric brain activity using artificial neural networks," *Proc. SPIE.* **10337**, 1033714 (2017).

[14] Pchelintseva, S., Runnova, A., Musatov, V., and Hramov, A., "Recognition and classification of oscillatory patterns of electric brain activity using artificial neural network approach," *Proc. SPIE.* **10063**, 1006317 (2017).

[15] Sitnikova, E., Hramov, A. E., Koronovskii, A. A., and Luijtelaar, E. L., "Sleep spindles and spike-wave discharges in EEG: Their generic features, similarities and distinctions disclosed with fourier transform and continuous wavelet analysis," *Journal of Neuroscience Methods* **180**, 304–316 (2009).

[16] Sitnikova, E., Hramov, A. E., Grubov, V., and Koronovsky, A. A., "Time-frequency characteristics and dynamics of sleep spindles in WAG/Rij rats with absence epilepsy," *Brain Research* **1543**, 290–299 (2014).

Downloaded From: https://www.spiedigitallibrary.org/conference-proceedings-of-spie on 4/30/2018 Terms of Use: https://www.spiedigitallibrary.org/terms-of-use