The population modeling of neuronal cell fractions for the use of controlling a mobile robot

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Abstract: The population modeling of neuronal cell fractions for the use of controlling a mobile robot is presented in this article. Present models of neuronal cells are compared to describe the problem. Population models which represent fractions (pyramidal cells and interneurons) are compared as well. A population approach to controlling a mobile robot is chosen as a result of this analysis. The process of modeling cell fractions definitely facilitates in laboratory conditions the process of controlling when the concept of brain-computer interface is implemented.

Keywords: modeling, neuronal cells, a mobile robot

1. Introduction

Models facilitate testing an influence of different types of stimuli or changes of model's parameters on its functioning. They also enable to formulate new hypotheses for a modeled system. In order to build a model on the level with the EEG signal, a single dynamics of neurons should be described. Then it is necessary to conduct mutual correlations in a space. It is also possible to work out a model where a single element represents an average reaction of many neurons. This resolution is described in this article. A well constructed model enables to specify details of a very complex nervous system under the analysis. Next research questions are implied during model construction. It enables to specify a description of cases which characterize the model. It is also important to choose right criteria for model classification. The right criteria are: the way of a structure's characteristics, the level of an integration of different aspects of neuron functioning, the complexity of parameters, the accuracy of a biological mapping, etc. Due to the use of modeling, it is possible to confirm many hypotheses about the influence of particular parts of the system on the functioning of the whole. Especially a type and strength of connections between nervous cells are taken into account.

Every model of the neuronal system should be coherent and at the same time it should be considered together with a total approach to the problem. However, it is not possible in case of a human brain and its neurons, mainly because of incomplete biological knowledge, restrictions of research methods and the fact that such a model is very complex.

One of the types of models is a model of low levels which is one or multi-compartment. They can represent one neuron or a part of it. The next type is system models which are created on the basis of an analysis of a structure within neuronal connections and the dynamics of phenomena from the results of neurophysiologic research. At the same time they are easy to be verified. It should be admitted that from the biological aspect, the brain structure does not enable an autonomous control of every muscle. It is determined by the fact that a human mind has to control many subsystems in the human structure like a circulatory system and sustaining of a constant body temperature etc. A human nervous system is characterized by a relatively low speed of an information transmission and a limited computing power in spite of the number of neurons which are counted in milliards.

2. Problems with implementations of neuron models

It is possible to present a neuron in a computer memory as a digital or mathematical model. When a nervous cell and its construction are described, the model is a nonlinear differential equation. The more precisely the construction of the cell is described, the more such equations appear. Their solutions in analytical figures are practically impossible. In such cases it is necessary to do an approximation of the solution by means of numerical methods. Unfortunately, it might cause errors.

When the neuron is modeled, any errors should be taken into account. They might arise in the process of generating a functional potential. The mathematical model of the neuron contains continuous functions such as a diameter of a dendrite tree, resistance of a neuron membrane and a membrane potential.

A spatial digitizing should be conducted during the process of modeling the neuron. The accuracy of an approximation of particular phenomena depends on the digitizing. A similar situation is with time digitizing. When a nervous cell is divided into a big amount of segments, it increases the size of the model. It causes the situation when the model is not practical in terms of its functionality and effectiveness [1]. The complete resistance of the nervous cell is defined by the formula (1):

$$R_{in}(y) = \frac{\Delta V(y)}{\Delta I(y)}, \tag{1}$$

where: y is a specific location in the neuron, $\Delta V(y)$ is the difference of potentials from the current impulses, $\Delta I(y)$ – the difference of impulses from the electrode.

3. The analysis of population models of neurons

In the 1980s *Georgopoulos Apostolos* and his co-workers *Kettner Ron, Schwartz Andrew* and *Johnson Kenneth* supported a hypothesis about a population vector to explain how a neuron population of a moving cortex coded the direction of movement. The basis of the hypothesis was an observation that particular neurons tended to discharge in terms of a definite direction of the movement, so-called a preferred direction for every neuron. This model was proved by the fact that it described coding in the moving cortex correctly. It also enabled to expect new phenomena which were proved in many next research on monkeys.

It is described in many research studies that single neurons are very noisy. For example, when one single neuron of a visual cortex is investigated, it is difficult to reconstruct what an eye of a person under research sees. The information is processed in the brain by a neuron population, and this process is divided into many of them [2]. Every neuron processes only a part of information in many cases. The more neurons take part in the work, the more precise coding of information is. When single neurons have a high coefficient of hum to a signal, a population as a whole creates average hum and as a result the proportion of hum to the signal is slight. A similar effect is used during a registration of evoked potentials from the surface of a skull.

Group of neurons which are not so complicated works in a spinal cord. They control basic automatisms such as a monosynaptic tendon reflex or a reversible neuration of skeletal muscles. They contain both excitatory and inhibitory neurons. On the other hand, own groups of neurons within the spinal which are responsible for a moving coordination of limbs during any movement have a more complex structure. The groups of neurons in the cortex, the cores of a base and a cerebellum are partly recognized nowadays. However, neuroanatomy of these structures is described in detail.

The direction of any neuron movement is represented by neuron populations not by separate cells. Population modeling gives the chance to reconstruct correlation effects on the basis of single neurons. It also enables to examine a reverberation. It is a process of a mutual stimulation of coupled neurons with an average test of reconstructing EEG potentials. A simplification of impulse neuron models which create webs where a dependence on time and the problems with synchronization are disappearing can be seen in the research literature. A hypothesis by Stevens can be used in this case. Impulses from neurons are used only in communication. According to this hypothesis, an activity measure of neurons proportional to a charge on an axon hillock should be used to describe state of the web. The neuron activity is nonlinear in this case and it depends on the sum of input signals. The advantages of population modeling are: comparing the results of the model with signals from experimentations, the use of analytical methods for examining how the model acts, a computable capacity and a simplicity of the model. The advantages of population models are simulating experiments which are impossible to work out in reality and possibility of prediction of complex dynamic actions of neuron population. These models assume that there are many neurons which influence each other in a particular part of a nervous tissue. An arrangement of the neurons in the population and their structural construction are omitted in this case. A human nervous system is very complex, so it is not possible to take into consideration all features of the neurons in one model even with the use of the latest technological devices, especially in terms of modeling complex electroencephalographic signals. That is why many features are stated on average. For example, population models interpret electric features of the neuron as average postsynaptic potentials [5]. In publications there are models which describe a pyramidal cell with 64 compartments.

3.1. A population vector

When a direction of movement is not determined by the action of a single neuron but by specific neuron web, a vector of a population can be observed. Many researches show that almost every direction of the movement is connected with a strong activity of a particular group of neurons. The scientist, *Georgopoulos A.,* proved this fact and described the vector of the population for the first time in 1982. He stated that there was a tendency for discharges in a specific direction of the movement in terms of particular neurons.

Individual neurons in a model of the population vector opt for their preferred directions by frequencies of the discharges. An incidental direction of the movement appears as a result of a vector sum of individual preferred directions multiplied by factors which are measurements of frequency of discharges.

3.2. The Wilson-Cowan Theory

The assumption of the Wilson-Cowan Theory (fig. 1) states that every neuron population acts homogeneously.

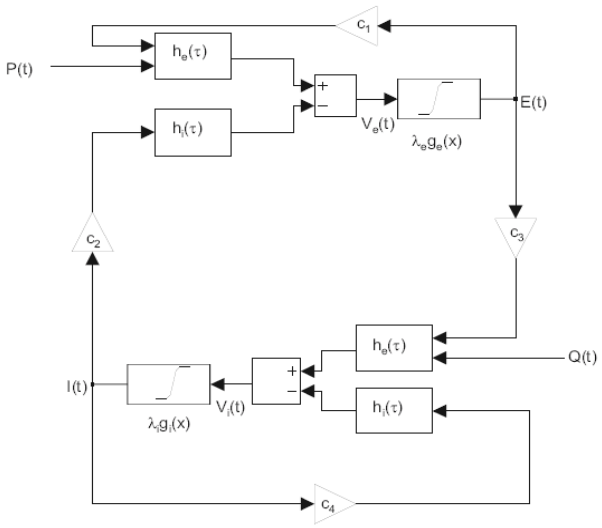

Fig. 1. The Wilson and Cowan Model
Rys. 1. Model Wilsona i Cowana

Wilson and Cowan did not analyze a spatial length of the population. In this model $E(t)$ is a measure for a population of excitatory cells which start functional potentials in an amount of time t, and $I(t)$ is a measure for a population of inhibitory cells. An average membrane potential of the excitatory population $V_e(t)$ and an average membrane potential of the inhibitory cells population $V_i(t)$ can be described by these formulas (2):

$$V_i(t) = \int_0^{\infty}[c_3E(t-\tau)+Q(t-\tau)]h_e(\tau)d\tau - \int_0^{\infty}c_4I(t-\tau)h_ih_i(\tau)d\tau$$
$$V_e(t) = \int_0^{\infty}[c_1E(t-\tau)+P(t-\tau)]h_e(\tau)d\tau - \int_0^{\infty}c_2I(t-\tau)h_i(\tau)d\tau \quad (2)$$

Factors c_1 and c_2 define an average amount of synapses for an excitatory cell with a $V_e(t)$ potential. Similarly, c_3 and c_4 factors define an average amount of synapses for an inhibitory cell with a $V_i(t)$ potential. $P(t)$ defines an average amount of excitatory impulses reaching a single cell. $h_e(\tau)$ and $h_i(\tau)$ are functions of an impulse answer. A probability that a cell can determine a potential above a threshold is defined as (3):

$$1 - \int_{t-r_e}^{t} E(t')dt', \quad (3)$$

where r_e is a period of an absolute refraction. A particular neuron would be in an excitatory state depending on an average membrane potential which occurs within a particular population. The formulas (4) represent $E(t)$ and $I(t)$ values. Constant values λ_e and λ_i in these formulas define average frequencies of a single cell stimulation in every fraction.

$$E(t) = \lambda_e[1 - \int_{t-r_e}^{t} E(t')dt']f(V_e(t))$$
$$I(t) = \lambda_i[1 - \int_{t-r_i}^{t} I(t')dt']f(V_i(t)) \quad (4)$$

3.3. A comparison of the Lopes da Silva Model and the Jansen-Rit Model

The Lopes da Silva model is a typical population model concerning the formation of oscillations in a brain. Its aim was to present the formation of alfa waves in the human brain. Nowadays it is said to be a model of generating a rhythmical activity of the EEG signal. Similarly as in the Wilson and Cowan model, there are two fractions of hillock-cortex cells and inhibitory interneurons in this model. Cell populations are connected in a loop of a feedback what enables the formation of a rhythmical activity in a model system. The model which is created for an analysis in Matlab/Simulink is presented in the fig. 2.

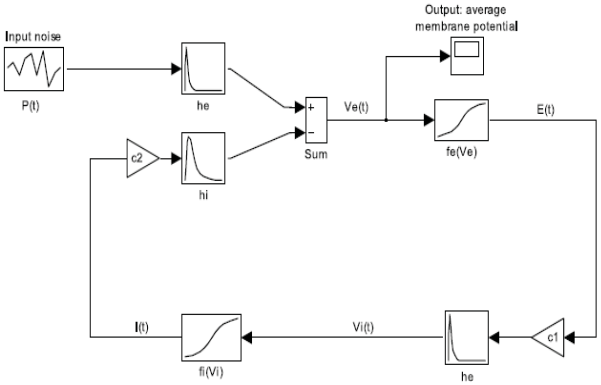

Fig. 2. The Lopes da Silva Model
Rys. 2. Model Lopesa da Silvy

An input signal in the model is described as $P(t)$. In this case neurons of hillock-cortex cells are represented by functions of the impulse answer $h_e(t)$ and a sigmoid $f_e(V)$ which connects the average potential with a frequency of pulsation. The inhibitory neurons are described by functions of the impulse answer $h_i(t)$ and a sigmoid $f_i(V)$. The feedback factor c_1 represents an average amount of inhibitory interneurons and the factor c_2 is an average amount of hillock-cortex cells. The population of the hillock-cortex cells is described by the equation:

$$h_e(t) = A[\exp(-a_1t) - \exp(-a_2t)], \quad (5)$$

whereas of the inhibitory cells by:

$$h_i(t) = B[\exp(-b_1t) - \exp(-b_2t)] \quad (6)$$

while $a_2 > a_1$, $b_2 > b_1$. The sigmoid $f_e(V)$ is formulated by:

$$f_e(V) = f_0 \times \begin{cases} \exp(qV) & \text{dla } V \le 0 \\ 2 - \exp(-qV) & \text{dla } V > 0 \end{cases}, \quad (7)$$

where f_0 – a maximum frequency of firing of activity potentials, q – a gradient of the function f. From the Lopes da Silva model, you can observe that structures located under the cortex have a significant role in generating Alfa rhythms. Their amplitude is definitely higher for the Alfa rhythms than for the Beta rhythms. The Jansen-Rit model was described to understand some phenomena in time and space which occur in the electroencephalographic signal. It expands the Lopes da Silva Alfa waves rhythmic activity model. Every column in this model consists of a population of pyramidal neurons and two populations of both excitatory and inhibitory interneurons. The function of a synaptic stimulation in terms of the Jansen-Rit model was described as:

$$h(t) = \begin{cases} Aate^{-at} & \text{for } t \ge 0 \\ 0 & \text{for } t < 0 \end{cases}, \quad (8)$$

where: A – a maximum amplitude of a synaptic potential, a – time constant features of a postsynaptic membrane. An important feature of this model is the fact that it was

formulated by differential equations. Every function of the postsynaptic potential is represented by the equation:

$$y''(t) = Aax(t) - 2ay'(t) - ay(t)^2 \tag{9}$$

where: y – an output signal, x – an input signal. As the output signal from the model is derived a value of an average potential of pyramidal cell population. The model might generate hum in a low and high stimulation separately, Alfa and Beta signal with hum. It is possible to get results of the simulation in an empirical way in accordance with observed results due to the fact that two columns which represent cortex structures occur in this model especially in terms of a spatial arrangement of Alfa and Beta activities.

4. A suggested population model

The assumption of the population vector which is characterised in section 3.1 of this article is used in the suggested population model. This model represents changes of a synchronization of the electroencephalographic signal which occur during a finger movement. In short, the population model can be used for an analysis of a neuron web's structure, because there are many neurons with identical features in a small area [6].

One of the assumptions is the fact that rhythms with high frequencies are generated by small areas of the cortex. The basic assumption which enables to average the features of thousands of cells is their high density of mutual connections. During the construction of the model two population of cells are assumed to appear. These two cell populations are pyramidal populations and interneurons. Symbols used to work out the model are based on the first population model, the Wilson and Cowan model described in section 3.2. The suggested model represents particular populations of cells by constant values: $E(t)$ – a fraction of pyramidal cells, $I(t)$ – a fraction of interneuron cells. In the model, variables with e index denote the fraction of pyramidal cells connected with EPSP. The variables with i index denote the fraction of interneuron cells connected with IPSP. The notation derives from the first letters of the words *excitatory* and *inhibitory*. A potential which represents particular populations of cells at the moment is also crucial. Due to this fact two variables appear as $V_e(t)$ and $V_i(t)$. The first variable is for the pyramidal cells and the second one is for the interneurons. Neurons are with mutual correlations so for the model two multiplied constant values which represent an average amount of synapses are introduced. The fractions of cells communicate by the synapses. These constants are c_{ei} and c_{ie}. Neurons also communicate within their own fraction so there is a constant c_{ee} as well. $P(t)$ represents an entrance to the fraction of pyramidal cells. There are impulse answers too. They are described as $h_e(t)$ and $h_i(t)$ in the model. It should be admitted that there is a wide range of parameters which are not taken into consideration in the model, because some combinations are highly complex. The combinations can only be described during medical laboratory research when an invasive method of measurement can be used.

4.1. Equations which describe the model

The suggested model does not include structures under the cortex and it is only based on the cortex. An average potential in a population of pyramidal cells (10) is a dominant potential in the signal received by means of an electroencephalograph.

$$V_e(t) = \int_0^\infty \left[c_{ee}E(t-\tau) + P(t-\tau)\right]h_{ee}(\tau)d\tau - \int_0^\infty c_{ie}I(t-\tau)h_{ie}(\tau)d\tau \tag{10}$$

Conjugations between neurons are omitted because they occur very fast. The number of potentials which reach synapses $c_{ei}\ E(t-\tau)d\tau$ in a moment of time $(t-\tau)$ is registered in the mathematical model. The function of time is an effect which is caused by potentials in postsynaptic neurons. It is characterized by a function of an impulse answer $h_{ei.}$

$$V_i(t) = \int_0^\infty c_{ei}E(t-\tau)h_{ei}(\tau)d\tau \tag{11}$$

A reaction of a synapse for a particular stimuli is modeled on a potential which intensifies an amplitude which is typical for particular types of synapses. The shape and the type of an average intensification of the amplitude is modeled by means of a double exponential function:

$$\begin{aligned} h_{ee}(t) &= a\left[\exp(-a_1t) - \exp(-a_2t)\right] \\ h_{ei}(t) &= b\left[\exp(-b_1t) - \exp(-b_2t)\right] \\ h_{ie}(t) &= c\left[\exp(-c_1t) - \exp(-c_2t)\right] \end{aligned}, \tag{12}$$

where: $a_1 < a_2,\ b_1 < b_2,\ c_1 < c_2$. Variables which represent membrane potentials are received as a result of an addition of (10) and (11). They reflect an average type which proves the level of the stimulation that appears in the population. The number of potentials $E(t)$, $I(t)$ which are created in a particular depolarization can be determined when a homogeneous arrangement of synapses in the population is assumed. From this assumption it can be observed that every neuron gets almost similar level of stimulation so the number of all stimulated neurons is formulated in the following formula:

$$f(V(t)) = \int_0^{V(t)} D(V')dV', \tag{13}$$

where $D(V)$ is the arrangement of threshold potentials in a particular population. It is assumed that it is close to a normal one.

4.2. Definitions of potentials on synapses

Potentials on synapses which occur between pyramidal cells (KP) and interneurons (KI) are described on the

basis of scientific research by *A. Thomson*. It is presented in tab. 1. The shape of PSP is adequate regarding frequency of the stimulation on the synapse. Values of parameters for synapses are presented in the tab. 2 concerning the assumption $a_1 < a_2$, $b_1 < b_2$, $c_1 < c_2$.

Tab. 1. The shape of the postsynaptic potential
Tab. 1. Kształt potencjału postsynaptycznego

Synapse	Amplitude [mV]	Period with accumulation of the potential [ms]	Period when the value of potential is higher, it is 0.5 of an amplitude [ms]
KP → KP	1.4±1.1	1.9±0.7	14±6
KP → KI	0.5±0.5	1.0±0.5	6.5±2
KI → KP	–1.2	2.7±0.6	15±4

Tab. 2. The values of parameters for synapses
Tab. 2. Wartości parametrów dla synaps

Synapse	a/b/c [mV]	a1/b1/c1 [Hz]	a2/b2/c2 [Hz]
KP → KP	1.2/0/0	70/0/0	714/0/0
KP → KI	0/1.2/0	0/179/0	0/1050/0
KI → KP	0/0/2	0/0/78	0/0/490

Tab. 3. Values of parameters for pyramidal cell and interneuron populations
Tab. 3. Wartości parametrów dla populacji komórek piramidalnych i interneuronów

Synapse	Potential [mV]	Diversity of stimulating thresholds [mV]
KP population	7	2.2
KI population	10	4.2

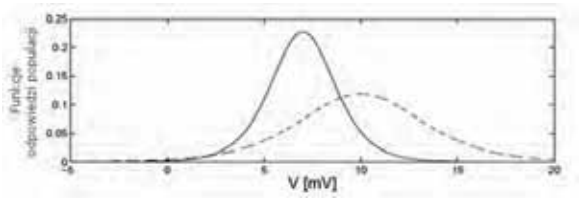

Fig. 3. The functions of answers from the populations f_e and f_i
Rys. 3. Funkcje odpowiedzi populacji f_e oraz f_i

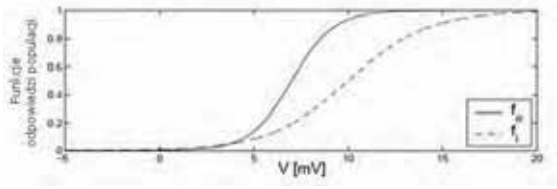

Fig. 4. Distribution of the stimulation thresholds of the population f_e and f_i
Rys. 4. Rozkład progów pobudzenia populacji f_e oraz f_i

Average values of depolarization are stated on the basis of scientific research by *A. Thomson*. They are necessary to stimulate both pyramidal cells and interneurons. This fact is presented in the tab. 3 but with one exception for the second fraction. Interneuron cells are very diverse in the brain structure. That is why it is necessary to diversify stimulating thresholds in this case. There are stimulating thresholds available in many publications. For example, a stimulating threshold for the population model of Lopes da Silva's Alfa rhythm is stated as 7 mV. However, scientists like *Rennie C.J., Wright J.J., Robinson P.A.* define the threshold as 10 mV.

Functions of answers from the population $f(V)$ both for pyramidal cells and interneurons are presented in the fig. 3.

The arrangement for the stimulation thresholds of particular populations of brain cells is presented in the fig. 4.

The model can generate different groups of nervous cell fractions. There is a lack of synchronization when a stochastic activity appears. When the EGG signal vibrates, a big synchronization appears. Exemplary results for changes of the dominant potential during simulations of Alfa, Beta and Gamma rhythms are presented on diagrams (figs. 5, 6 and 7). Time is on the horizontal axis and voltage is on the vertical axis.

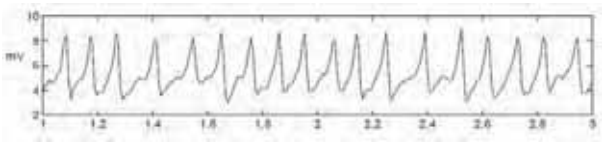

Fig. 5. Exemplary results of the EEG simulation, $V_e(t)$ for Alfa rhythm, P=180 pps, c_{ee}=750, c_{ie}=c_{ei}=1200
Rys. 5. Przykładowe wyniki symulacji EEG, $V_e(t)$ dla rytmu Alfa: P=180 pps, c_{ee}=750, c_{ie}=c_{ei}=1200

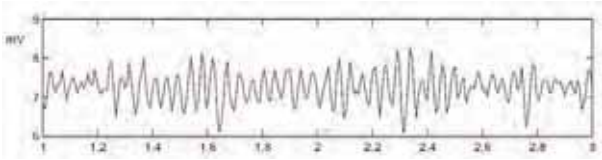

Fig. 6. Exemplary results of the EEG simulation, $V_e(t)$ for Beta rhythm P=250 pps, c_{ee}=450, c_{ie}=c_{ei}=1000
Rys. 6. Przykładowe wyniki symulacji EEG, $V_e(t)$ dla rytmu Beta: P=250 pps, c_{ee}=450, c_{ie}=c_{ei}=1000

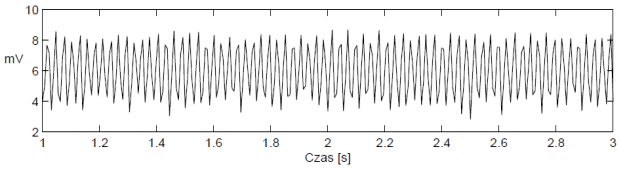

Fig. 7. Exemplary results of the EEG simulation, $V_e(t)$ for Gamma rhythm: P=500 pps, c_{ee}=300, c_{ie}=c_{ei}=1500
Rys. 7. Przykładowe wyniki symulacji EEG, $V_e(t)$ dla rytmu Gamma: P=500 pps, c_{ee}=300, c_{ie}=c_{ei}=1500

The largest values of amplitude are reached in gamma rhythm, but the range of frequency is relatively small. The broadest band and the smallest values of amplitude are observed for Beta rhythms.

As a result of these experiments it was possible to verify the model. The process of controlling a mobile robot on the basis of the model was conducted by an appropriate classification of the EEG signal [3].

5. Conclusion

The aim of the research presented in this article is to compare individual neuron models and population models of neuron webs to implement an own optimized solution. The suggested population model is used in the process of controlling the mobile robot by generating appropriate frequencies of the electroencephalographic signal. As a result of these activities, it was possible to control the motor vehicle in laboratory conditions without the measurement of the EEG signal on a specific person [4]. These types of solutions definitely facilitate scientific research because of the relatively proper EEG signal. This signal can be used a few times in the process of controlling. There is no fear for its reduction when the stimulus which is an impulse for the movement of the robot is repeated. Unfortunately, in case of research on a human as a person who controls the robot, the next repetitions of a particular action reduce radically the quality of the signal which is gained for the controlling.

References

1. Zmarzły D., *Pomiary elektrycznych wielkości medycznych*, Oficyna Wydawnicza Politechniki Opolskiej, Opole 2004.
2. Ibrahimi T., Vesin J.M., Garcia G., *Brain-Computer Interface in Multimedia Communication*, "IEEE Signal Processing Magazine", Vol. 20, No. 1, 2003.
3. Siegwart R., Nourbakhsh I.R., *Introduction to autonomous mobile robots*, The MIT Press, 2004.
4. Dudek Z.T., *Interfejs BCI – próba przełamania bariery pomiędzy człowiekiem a komputerem*, „Przegląd Telekomunikacyjny i Wiadomości Telekomunikacyjne", 7/2003, 377–382.
5. Wolański N., *Rozwój biologiczny człowieka. Podstawy auksologii, gerontologii i promocji zdrowia*, Wydawnictwo Naukowe PWN, Warszawa 2005, p. 374.
6. Tortella F., Rose J., Robles L., Moreton J., Hughes J., Hunter J., *EEG Spectra Analysis of the Neroprotective Kappa Opioids Enadoline*, Maryland 1997.

Modelowanie populacyjne frakcji komórek neuronalnych z przeznaczeniem do sterowania robotem mobilnym

Streszczenie: W artykule przedstawiono modelowanie populacyjne frakcji komórek neuronalnych z przeznaczeniem do sterowania robotem mobilnym. Porównano istniejące modele komórek neuronalnych w celu opisania problemu. Porównano również modele populacyjne reprezentujące frakcje (komórki piramidalne i interneurony). W wyniku przeprowadzonej analizy dokonano wyboru podejścia populacyjnego dla sterowania robotem mobilnym. W warunkach laboratoryjnych, proces modelowania frakcji komórek zdecydowanie wspomaga proces sterowania w przypadku implementacji koncepcji interfejsu mózg-komputer.

Słowa kluczowe: modelowanie, komórki neuronalne, robot mobilny

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