CYBERNETICS AND PHYSICS, VOL. 14, NO. 1, 2025, 13–18

OUTLINE OF CYBERNETICAL NEUROSCIENCE

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Article history:
Received 16.06.2025, Accepted 21.06.2025

Abstract

The article discusses a new scientific field — cybernetical neuroscience — which studies mathematical models adopted in computational neuroscience using methods from cybernetics (the science of control and communication in living organisms, machines, and society). It also examines the practical application of results obtained from research on mathematical models. Key tasks, methods, and results in cybernetical neuroscience are outlined. As an example some results in neurointerface control and machine learning methods from the Institute for Problems in Mechanical Engineering, Russian Academy of Sciences (IPME RAS) are presented.

Key words

Cybernetics, neuroscience, neuron models, control, parameter estimation, machine learning, neurointerface.

1 Introduction

In recent years, neuroscience has seen growing interest in research applying methods from cybernetics — defined by its founder Norbert Wiener in 1948 as “the science of control and communication in the animal and the machine” [Wiener, 1948]. Cybernetic methods rely on constructing mathematical models and establishing direct/feedback interactions between a research subject (computer system) and object (e.g. the brain of humans or animals).

The researches on applying cybernetic methods to biological neural systems are forming a new field within computational neuroscience, termed cybernetical neuroscience [Fradkov, 2024]. Below, key tasks, methods, and results in this field are outlined.

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2 Tasks and Methods of Cybernetical Neuroscience.

The current research in cybernetical neuroscience addresses the following tasks:

1. Finding conditions for special regimes in neural ensemble models (e.g., synchronization, desynchronization, spiking, bursting, solitons, chimeras) that correspond to real brain behaviors.
2. Synthesizing external (control) stimuli to induce the above regimes in neural ensembles.
3. Estimating states and parameters of neural ensemble models from input/output measurements.
4. **Classifying brain states and human intents** via adaptation and machine learning.
5. **Designing control algorithms or feedback synthesis** to ensure desired properties in closed-loop systems (interacting controller and plant).

Here, the term "plant"means the nervous system or brain, while the "controller"may be implemented within computer. Apparently physical implementation requires **neurointerfaces** (brain-computer interfaces). However, theoretical work often represents both brain and controller as mathematical models, enabling neuroscientists to explore novel control strategies before real-world deployment.

Methods derive primarily from cybernetics (control theory) and neuroscience:

- *Control-theoretic*: Nonlinear, adaptive, optimal control; observers and filters; Lyapunov functions; sliding mode control; speed gradient and passivity-based methods.
- *Experimental*: invasive (e.g., implanted electrodes) and non-invasive techniques (EEG, MEG, fMRI, etc.).

3 Models in Cybernetical Neuroscience.

Cybernetic models incorporate **inputs** (control stimuli) and **outputs** (measurements). A generalized state-space representation is:

$$dx/dt = F(x, w, t), \quad y = h(x, w, t), \tag{1}$$

where $x(t)$ is n-dimensional state vector, $w(t)$ is m-dimensional input vector, $y(t)$ is l-dimensional output vector.

3.1 Key Models

1. **FitzHugh-Nagumo (FHN) Neuron Model**:

$$\begin{aligned} \dot{u} &= u - \frac{u^3}{3} - v + I_{\text{ext}}, \\ \dot{v} &= \varepsilon(u - a - bv), \end{aligned} \tag{2}$$

where u is membrane potential (measurable output y), v is recovery variable, I_{ext} is external current (input).

2. **FHN Network Model**:

$$\begin{aligned} &\dot{u}_i = u_i - \tfrac{u_i^3}{3} - v_i + I_{i,\text{ext}} \\ &+C_i \textstyle\sum_{j=1}^N G_{ij}\varphi(u_i(t) - u_j(t - \tau_i)), \\ &\dot{v}_i = \varepsilon(u_i - a_i - b_i v_i), \quad i = 1, \ldots, N, \end{aligned} \tag{3}$$

incorporates delays (τ_i), connectivity matrix (G_{ij}), coupling strengths C_i and can model pathologies (e.g., epilepsy). Inputs/outputs may be defined per node or via EEG measurements.

3. **Hindmarsh-Rose (HR) Model**:

$$\begin{aligned} \dot{p} &= q - ap^3 + bp^2 - n + I_{\text{ext}}, \\ \dot{q} &= c - dp^2 - q, \\ \dot{n} &= r(s(p + p_0) - n), \end{aligned} \tag{4}$$

where p = membrane potential (output), q, n model ion dynamics, and I_{ext} = input. Capable of spiking/bursting dynamics and network extensions.

The models above exemplify cybernetical neuroscience's framework for merging control theory with neural dynamics. Further research should include experimental validation and whole brain network modeling inspired by successes of the human connectome studies [Tzourio-Mazoyer et al., 2002; con, 2023].

Neural mass Model The neural mass model [Jansen and Rit, 1995] describes the dynamics of a cortical column modeled by a population of pyramidal cells receiving excitatory and inhibitory feedback from local interneurons. Such a model can be used to model spontaneous EEG and invoked potentials in human brain. The model is described by a set of six differential equations, in which three blocks can be distinguished, describing excitatory and inhibitory postsynaptic membrane potentials (PSPs):

$$\begin{aligned} &\dot{x_1} = x_2, \\ &\dot{x_2} = Aa\sigma(x_3 - x_5) - 2ax_2 - a^2x_1, \\ &\dot{x_3} = x_4, \\ &\dot{x_4} = Aa(u + C_2\sigma(C_1x_1)) - 2ax_4 - a^2x_3, \\ &, \dot{x_5} = x_6, \\ &\dot{x_6} = BbC_4\sigma(C_3x_1) - 2bx_6 - b^2x_5, \end{aligned} \tag{5}$$

where $x = (x_1, \ldots, x_6)^T \in R^6$ is the system state vector, $x_1, x_3, x_5 \in R$ are the outputs of three blocks of postsynaptic potentials, and $y = x_3 - x_5 \in R$ is the output of the entire system. Parameters A and B are proportional to the amplitude of the PSP and are different for the excitatory and inhibitory cases. Parameters a and b are inversely proportional to the duration of the PSP. Parameters C_1, C_2, C_3, C_4 describe the coupling forces during the interaction between pyramidal cells and excitatory and inhibitory interneurons. The function $u = u(t)$ is the external input of the system, representing the spontaneous background activity. The sigmoid function

$$\sigma(v) = \frac{2e_0}{1 + exp(r(v_0 - v))}$$

describes transformation of the average membrane potential of a neuronal population into the average density of action potential pulses.

4 Examples

As an example, consider tasks addressed in the neurointerface-controlled wheelchair system under development at IPMash RAS. The system consists of the following interconnected blocks [Fradkov and Babich, 2025]

- Classification subsystem, incorporating a set of algorithms for recognizing and classifying the subject's intentions based on EEG signals;
- Control subsystem, translating the classifier output into control signals for electric drives that execute wheelchair movements.

Currently, the system recognizes and executes four actions: turn left, turn right, move forward, and stop. We will now detail the classifier algorithms. The system supports standard classification programs from the Scikit-learn library in Python: SVM, KNN, RF, etc. Additionally, the following original classification algorithms are implemented:

$$\eta_i(x) = (-f_i, x) + a_i \geq 0, i \in I. \tag{6}$$

– Modified Yakubovich-Bregman algorithm (YBM). This algorithm is designed to separate two finite sets of points in the space R^n by a hyperplane. The classification problem is preliminarily reduced by a standard transformation (reflection from the origin and increasing the dimension by 1) to the problem of separating a set of points from the origin by a hyperplane, which is equivalent to the problem of finding the intersection point of half-spaces or solving a system of nonhomogeneous linear inequalities:

$$\eta_i(x) \geq 0, i \in I, \tag{7}$$

where $\eta_i(x) = (-f_i, x) + a_i$. It is assumed that half-spaces of the form $A_i = \{x : (f_i, x) \leq a_i\}$ are given, where $f_i \in H, a_i \in R$, and $R = \bigcap_{i \in I} A_i \neq \emptyset$. Let R contain a point x^* along with some neighborhood, i.e., there exists $\varepsilon_* > 0$ such that $\eta_i(x^*) \geq \varepsilon_* > 0$ for $i = 1, 2, \ldots$. Since $i(n) = i(x_n)$, the index is chosen for which $\min_{i \in I} \eta_i(x_n)$ is achieved. The sequence of points $\{x_n\}$ is designed as follows:

$$\begin{gathered} x_{n+1} = x_n, \text{ if } \eta_{i(n)}(x_n) \geq 0; \\ x_{n+1} = x_n - f_{i(n)} \cdot [\rho_n - \beta_n \cdot \eta_{i(n)}(x_n) \cdot \|f_{i(n)}\|^{-2}], \\ \text{if } \eta_{i(n)}(x_n) < 0, \end{gathered} \tag{8}$$

where $0 < \beta \leq \beta_n \leq 2$, $\rho_n > 0$, $\rho_n \to 0$, $\sum_{k=1}^{\infty} \rho_k = \infty$. For $\beta_n = 1$, the point is projected exactly onto the boundary of the half-space, as in the classical Bregman method. It is shown that algorithm (8) is a finitely convergent algorithm for solving inequalities (7).

– "Implicit Strip" (ISTRIP) algorithm, the idea of which was proposed in [Fradkov, 1990]. This algorithm is also based on reducing the problem of separating finite sets to solving a system of the goal (objective) inequalities. The algorithm for solving inequalities

$$|F_k^T \theta - y_k| < \Delta, \tag{9}$$

where θ is the vector of unknown parameters, includes at each step the preliminary iteration:

$$\begin{gathered} \bar{\theta}_{k+1} = \theta_k - \frac{F_k^T \theta_k - y_k}{(2\gamma_k)^{-1} + ||F_k||^2} F_k, \\ \beta_k(\bar{\theta}_{k+1}) = (F_k^T \bar{\theta}_{k+1} - y_k)^2 (1 + 0.5\gamma_k ||F_k||^2) \end{gathered} \tag{10}$$

and the main iteration:

$$\begin{gathered} \theta_{k+1} = Pr_{\Xi}(\bar{\theta}_{k+1}), \text{ if } \beta_k(\bar{\theta}_{k+1}) > \varepsilon, \\ \theta_{k+1} = \theta_k, \text{ if } \beta_k(\bar{\theta}_{k+1}) < \varepsilon. \end{gathered} \tag{11}$$

– Modified Kozinets algorithm (AKM) for "soft" separation of finite sets. The algorithm seeks a vector θ_* such that

$$\min p_i(\theta_*) = \max_{\theta} \min_{i} (p_i(\theta)), \tag{12}$$

where $p_i(\theta) = y_i(\theta^T F_i)$.

– Fuzzy version of the k nearest neighbors method (fuzzy almost k nearest neighbors, $FAkNN$) [Fradkov and Babich, 2025];

– The implemented classification algorithms also include a novel method based on generating new features from parameter estimates of the FitzHugh-Nagumo (FHN) model for a neural node. During operation, the algorithm builds a sequence of parameter estimates for the FHN model based on EEG signal measurements from a single lead for signals recorded during the intention to turn left and the intention to turn right.

The procedure of signal recording and estimation is repeated $M > 1$ times for each measurement window (frame) of length N for frames corresponding to the intention to turn left, and $M > 1$ times for each measurement window (frame) of length N for frames corresponding to the intention to turn right. The resulting $2M$ points in the parameter estimate space are treated as points of two classes to be separated. For the test set of parameter estimates, one can use either one of the original algorithms (YBM, ISTRIP, AKM or FAkNN) or one of the library algorithms: SVM, KNN, RF, etc.

5 Results of Cybernetical Neuroscience: 1. Model Investigations

5.1 Regulation, Tracking, Synchronization, Chaos Control

Results in the field of cybernetic neuroscience fall into two classes: those concerning control of processes in neuron and neuronal network models, and those concerning control based on real data.

We first enumerate results on controlling neuron and neuronal network models. These results have theoretical significance, demonstrating the fundamental possibility of controlling neuronal processes under the assumptions that the models adequately describe real processes, output variables are measurable, and input variables are adjustable. The control problem, besides the model of the plant, includes the description of the control objective. Objectives may include typical cybernetic requirements such as driving the process toward a given state or trajectory (regulation or tracking). Tasks may also include synchronizing processes in different parts of systems, inducing oscillations, their chaotization, etc. The first results on controlling neuron and neuronal network models were obtained in the 1990s and pertained to chaos control and synchronization. The work [Carroll, 1995] proposed an impulse control algorithm for synchronizing two FHN models based on simulation and analogies between neuronal and electrical processes. In the work [Dragoi and Grosu, 1998] an algorithm for controlling a chain of FHN neurons with the goal of bringing (synchronizing) the oscillations of each neuron closer to those of a "reference" neuron is proposed.

Stability of the synchronization process was established in a region of initial conditions based on linear approximation. In the work [Plotnikov et al., 2016b] synchronization algorithms for a heterogeneous network of diffusively coupled FHN neuron models with hierarchical architecture, based on the speed gradient method are proposed. Synchronization conditions were obtained based on the Lyapunov function method. Similar results were obtained for adaptive control algorithms that do not require exact knowledge of neuron model parameters [Plotnikov et al., 2016a], for networks of arbitrary structure [Plotnikov and Fradkov, 2019b] and networks with delays in connections, as well as for the desynchronization problem [Plotnikov and Fradkov, 2019a], which is important for treating a number of mental diseases such as Parkinson's disease, tremor, etc.

The Lyapunov function method and the speed gradient method were also successfully applied to the design and analysis of control algorithms for synchronization and chaos control in Hindmarsh-Rose models and their networks [Plotnikov, 2021; Semenov et al., 2022] and , for controlling oscillations in neural mass models, and for adaptive control of Landau-Stuart oscillator networks [Selivanov et al., 2012; Lehnert et al., 2014].

5.2 State and Parameter Estimation of Models

The problem of estimating the state and parameters of neural ensemble models is important for ensemble control based on measurable data. Moreover, knowledge of network parameters and state is essential for better understanding its behavior and properties. There are quite a few works on estimating parameters of a single neuron model, with the majority employing stochastic approaches [Jensen et al., 2012; Che et al., 2012; Doruk and Aboshar, 2019]. There are works [Dong and Wang, 2015; Rudi et al., 2022] that use artificial neural networks for estimating FHN model parameters. The work [Rybalko and Fradkov, 2023] proposed and justified an algorithm for estimating the state and parameters of a pair of FHN neurons based on the speed gradient method and filtering. The speed gradient method was also applied to estimating parameters of the Hindmarsh-Rose neuron model [Fradkov et al., 2022; Kovalchukov and Fradkov, 2022] and a neural mass model [Plotnikov, 2024]. Other approaches to estimating neuron model parameters are presented in [Postoyan et al., 2012; Zhao et al., 2016; Dong et al., 2019; Wang et al., 2019].

6 Results of Cybernetic Neurobiology: 2. Real Data Investigations

6.1 Brain State Classification and Diagnosis

Classification of states of neural ensembles, including whole-brain states, is an important application area for cybernetic methods. Here, pattern recognition methods and machine learning methods, often attributed to the field of artificial intelligence, are used. The classification task is as follows. Given measurement results of the state of a finite set of N neurobiological objects, each belonging to one of M classes, it is required to construct a set of decision rules that, based on measured data, determine the class of a new object to be classified. Such tasks are typical for medical diagnostics, where cybernetic pattern recognition methods have long been applied. In neurophysiology and psychiatry, recognition and machine learning methods are actively used, see [Mueller et al., 2010; Lebedev et al., 2014; Boyko et al., 2022; Zubrikhina et al., 2022; Yoon et al., 2022; Shanarova et al., 2023]. Both well-known statistical methods (discriminant analysis, principal component analysis (PCA), independent component analysis (ICA), random forests) and deterministic machine learning methods are employed. Works are emerging that apply approaches new to neuroscience, for example, the method of targeted inequalities [Lipkovich, 2022].

6.2 Control Based on Neurofeedback

Neurofeedback (NFB) (or biofeedback (BFB)) is the most effective approach for interaction between the human brain and an external control device and one of the most promising cybernetic approach in neurobiology and neurophysiology. NFB is based on the idea of conditioned reflexes and reinforcement of spontaneous behavior deemed desirable. This reflects brain plasticity — the brain's ability to change under the influence of learning. During a BFB experiment, the subject is presented with information about the state and desired changes in certain physiological parameters. The basic principle of cybernetics — feedback (reflecting information about activity outcomes) — serves as a "mirror"in which otherwise consciously inaccessible physiological parameters can be seen, allowing regulation of parameters of the brain's electrical activity. NFB implementation requires a neurointerface — a device enabling real-time information exchange between the brain and a computer. Typically, a noninvasive neurointerface uses electroencephalography (EEG) data, reflecting changes in the electric field potential on the surface of the subject's head (scalp). Some current EEG parameters (or their combination) [Kropotov, 2009] are presented to the subject in the form of, for example, a visual stimulus (bar height on a screen, screen brightness) with the task of changing these parameters in a desired direction. In this paradigm, the subject, focusing on the NFB signal, tries to memorize the connection between the parameter and their state. The EEG parameters and electrode locations forming the NFB protocol are chosen depending on the task [Kamiya, 1968]. The problem of forming the neurofeedback signal is very complex, as there are currently no clear rules for stimulus presentation that must be followed to help the subject cope with the task most efficiently (e.g., in terms of time spent). In most cases, the NFB signal is generated proportionally to the deviation of the subject's EEG parameters from normative values. The measured deviation is translated into the NFB signal based on experimentally derived rules [Holten, 2009; Kropotov, 2009] that work "on average"for most subjects. It seems advisable to develop adaptive methods for calculating the feedback signal that adjust rule parameters for a specific subject. The rules for calculating quantitative EEG parameters, which are then used to form the NFB signal, depend on a large number of parameters, such as the length of the data processing time window or the delay in presenting the control action. Individual selection of these parameter values can also enhance the efficiency of NFB training [Kropotov, 2009]. One promising direction for NFB development is the use of adaptive mathematical models of brain activity, proposed in [Ovod et al., 2012; Plotnikov et al., 2019].

7 Conclusion

The application of cybernetics and control theory methods to problems in neurobiology and neurophysiology holds great promise, and the number of publications in this direction is rapidly growing. Summarizing publications and reviews have appeared [Wilson and Moehlis, 2022; Howlett and Paulus, 2024]. This work attempts to structure and systematize this field and presents some ongoing research at IPME RAS.

References

(2023). Human connectome projects. https://www.humanconnectome.org/.

Boyko, M., Abramova, O., Yarkin, V., Sharaev, M., et al. (2022). Machine learning approaches to mild cognitive impairment detection based on structural MRI data and morphometric features. *Cognitive Systems Research*, **78**, pp. 1–10.

Carroll, T. (1995). Synchronization and complex dynamics in pulse-coupled circuit models of neurons. *Biological Cybernetics*, **73**, pp. 553–559.

Che, Y., Geng, L., Han, C., Cui, S., and Wang, J. (2012). Parameter estimation of the FitzHugh–Nagumo model using noisy measurements for membrane potential. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, **22** (2), pp. 023139.

Dong, X., Si, W., and Wang, C. (2019). Global identification of FitzHugh–Nagumo equation via deterministic learning. *IEEE Access*, **7**, pp. 107334–107345.

Dong, X. and Wang, C. (2015). Identification of the FitzHugh–Nagumo model dynamics via deterministic learning. *International Journal of Bifurcation and Chaos*, **25** (11), pp. 1550159.

Doruk, R. O. and Aboshar, L. (2019). Estimating the parameters of FitzHugh–Nagumo neurons from neural spiking data. *Brain Sciences*, **9** (12), pp. 364.

Dragoi, V. and Grosu, I. (1998). Synchronization of locally coupled neural oscillators. *Neural Processing Letters*, **7**, pp. 199–210.

Fradkov, A. (2024). Definition of cybernetical neuroscience. *arXiv preprint arXiv:2409.16314*.

Fradkov, A. and Babich, N. (2025). Three-position vehicle control based on neural interface using machine learning. *Informatics and Automation*, **24** (1), pp. 5–29.

Fradkov, A. L. (1990). *Adaptive Control of Complex Systems*. Nauka, Moscow.

Fradkov, A. L., Kovalchukov, A., and B.R., A. (2022). Parameter estimation for Hindmarsh–Rose neurons. *Electronics*, **11** (6), pp. 885.

Holten, V. (2009). Bio and neurofeedback applications in stress regulation. *Neuroscience & Cognition, Track Behavioural Neuroscience*.

Howlett, J. R. and Paulus, M. P. (2024). Out of control: Computational dynamic control dysfunction in stress and anxiety-related disorders. *Discover Mental Health*, **4**, pp. 5.

Jansen, B. H. and Rit, V. G. (1995). Electroencephalogram and visual evoked potential generation in a mathematical model of coupled cortical columns. *Biological cybernetics*, **73** (4), pp. 357–366.

Jensen, A. C., Ditlevsen, S., Kessler, M., and Papaspiliopoulos, O. (2012). Markov chain Monte Carlo approach to parameter estimation in the FitzHugh–Nagumo model. *Physical Review E*, **86** (4), pp. 041114.

Kamiya, J. (1968). Conscious control of brain waves. *Psychology Today*, **1**, pp. 56–60.

Kovalchukov, A. A. and Fradkov, A. L. (2022). Speed-gradient approach to Hindmarsh–Rose model identification based on membrane potential measurements. *2022 6th Scientific School Dynamics of Complex Networks and their Applications (DCNA)*.

Kropotov, Y. D. (2009). *Quantitative EEG, Event-Related Potentials and Neurotherapy*. Elsevier.

Lebedev, A., Westman, E., Van Westen, G., Kramberger, M., Lundervold, A., Aarsland, D., Soininen, H., Kłoszewska, I., Mecocci, P., Tsolaki, M., et al. (2014). Random forest ensembles for detection and prediction of Alzheimer's disease with a good between-cohort robustness. *NeuroImage: Clinical*, **6**, pp. 115–125.

Lehnert, J., Hövel, P., Selivanov, A. A., Fradkov, A. L., and Schöll, E. (2014). Controlling cluster synchronization by adapting the topology. *Physical Review E*, **90** (4), pp. 042914.

Lipkovich, M. (2022). Yakubovich's method of recursive objective inequalities in machine learning. *IFAC-PapersOnLine*, **55** (12), pp. 138–143.

Mueller, A., Candrian, G., Kropotov, J. D., Ponomarev, V. A., and Baschera, G. M. (2010). Classification of ADHD patients on the basis of independent ERP components using a machine learning system. *Nonlinear Biomedical Physics*, **4** (Suppl 1), pp. S1.

Ovod, I. V., Ossadtchi, A. E., Pupyshev, A. A., and Fradkov, A. L. (2012). Design of neurofeedback based on adaptive model of human brain activity. *Neurocomputers*, **2**, pp. 36–41.

Plotnikov, S. (2021). Synchronization conditions in networks of Hindmarsh–Rose systems. *Cybernetics and Physics*, **10**, pp. 254–259.

Plotnikov, S. A. (2024). Identification of neural mass network parameters using eeg evoked potential data. *Cybernetics and Physics*, **13** (4), pp. 296–301.

Plotnikov, S. A. and Fradkov, A. L. (2019a). Desynchronization control of FitzHugh–Nagumo networks with random topology. *IFAC-PapersOnLine*, **52** (16), pp. 640–645.

Plotnikov, S. A. and Fradkov, A. L. (2019b). On synchronization in heterogeneous FitzHugh–Nagumo networks. *Chaos, Solitons & Fractals*, **121**, pp. 85–91.

Plotnikov, S. A., Lehnert, J., Fradkov, A. L., and Schöll, E. (2016a). Adaptive control of synchronization in delay-coupled heterogeneous networks of FitzHugh–Nagumo nodes. *International Journal of Bifurcation and Chaos*, **26** (4), pp. 1650058.

Plotnikov, S. A., Lehnert, J., Fradkov, A. L., and Schöll, E. (2016b). Synchronization in heterogeneous FitzHugh–Nagumo networks with hierarchical architecture. *Physical Review E*, **94** (1), pp. 012203.

Plotnikov, S. A., Semenov, D. M., Lipkovich, M., and Fradkov, A. L. (2019). Artificial intelligence based neurofeedback. *Cybernetics and Physics*, **8** (4), pp. 287–291.

Postoyan, R., Chong, M., Nešić, D., and Kuhlmann, L. (2012). Parameter and state estimation for a class of neural mass models. *Proc. 51st IEEE Conference on Decision and Control (CDC)*, pp. 2322–2327.

Rudi, J., Bessac, J., and Lenzi, A. (2022). Parameter estimation with dense and convolutional neural networks applied to the FitzHugh–Nagumo ODE. *Mathematical and Scientific Machine Learning (PMLR)*, pp. 781–808.

Rybalko, A. and Fradkov, A. (2023). Identification of two-neuron FitzHugh–Nagumo model based on the speed-gradient and filtering. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, **33** (8), pp. 083126.

Selivanov, A. A., Lehnert, J., Dahms, T., Hövel, P., Fradkov, A. L., and Schöll, E. (2012). Adaptive synchronization in delay-coupled networks of Stuart–Landau oscillators. *Physical Review E*, **85** (1), pp. 016201.

Semenov, D. M., Plotnikov, S. A., and Fradkov, A. L. (2022). Controlled synchronization in regular delay-coupled networks of Hindmarsh–Rose neurons. *2022 6th Scientific School Dynamics of Complex Networks and their Applications (DCNA)*.

Shanarova, N., Pronina, M., Lipkovich, M., Müller, A., and Kropotov, J. (2023). Application of machine learning to diagnostics of schizophrenia patients based on event-related potentials. *Diagnostics*, **13** (3), pp. 509.

Tzourio-Mazoyer, N., Landeau, B., Papathanassiou, D., Crivello, F., Etard, O., Delcroix, N., Mazoyer, B., and Joliot, M. (2002). Automated anatomical labeling of activations in SPM using a macroscopic anatomical parcellation of the MNI MRI single-subject brain. *NeuroImage*, **15**, pp. 273–289.

Wang, L., Yang, G., and Yeung, L. (2019). Identification of Hindmarsh–Rose neuron networks using GEO metaheuristic. *Proceedings of the Second International Conference on Advances in Swarm Intelligence*, **Part I**, pp. 455–463.

Wiener, N. (1948). *Cybernetics: Or, Control and Communication in the Animal and the Machine*. MIT Press.

Wilson, D. and Moehlis, J. (2022). Recent advances in the analysis and control of large populations of neural oscillators. *Annual Reviews in Control*, **54**, pp. 327–351.

Yoon, J., Kang, C., Kim, S., and Han, J. (2022). D-vlog: Multimodal vlog dataset for depression detection. *Proc. AAAI Conference on Artificial Intelligence*, **36**, pp. 12226–12234.

Zhao, J., Aziz-Alaoui, M. A., Bertelle, C., and Corson, N. (2016). Sinusoidal disturbance induced topology identification of Hindmarsh–Rose neural networks. *Science China Information Sciences*, **59**, pp. 112205.

Zubrikhina, M., Masnyi, D., Sharaev, M., et al. (2022). Autoencoders with deformable convolutions for latent representation of EEG spectrograms in classification tasks. *Proc. SPIE*, **12701**.