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LETTER

Learning in a virtual model of the *C. elegans* nematode for locomotion and chemotaxis

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Abstract

In this paper, we propose a learning control system, which models the neural circuits controlling locomotion and chemotaxis of the *Caenorhabditis elegans* nematode. Using the realistic 3D-simulator of the nematode, we have conducted a series of successful experiments in teaching the proposed model. It is shown that the control system can stably learn an effective way of movement forward in 100 working cycles on the average, and identify an optimal chemotaxis strategy in 1000 cycles on the average. At the same time, we observe a considerable visual likeness between the behavior of the model and the behavior of a real nematode and noted the coincidence of the detected chemotaxis strategy with the strategy used by the biological prototype. The results of experiments have shown that the movement function and associated orientation mechanisms of a nematode can be obtained by way of teaching only in interaction with the environment, and the proposed model of control system is quite effective and can be successfully used to control complex objects with many degrees of freedom.

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Introduction

Modeling the behavior of animals is one of the possible ways of enabling to become closer to understanding the essence

of biological processes that control the behavior of living organisms, and is also a good method to experimentally verify our concepts and hypotheses about the mechanisms of the biological control systems operation. For today the *Caenorhabditis elegans* nematode is the most convenient object for studying and modeling of various aspects of the nervous system functioning due to the fact that it is the most studied multicellular organism and the only one for which we know almost all the connectome – a set of

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neurons, interneuron and neuromuscular connections, cells-sensors and other components of the nervous systems. However, although in the first approximation the *C. elegans* connectome has been defined on the basis of experimental data for more than 25 years ago by [White, Southgate, Thomson, and Brenner \(1986\)](#), we still could not to understand the mechanisms of even such a relatively simple nervous systems.

In particular, it remains unknown how the nervous system of nematodes controls the locomotion. In organisms with more complex organization of nervous system were found the so-called «CPG» (central pattern generator) – the central rhythm generators, while in the nematode the similar pattern is absent. In this understanding of how the nervous system of nematode generates and distributes a wave along the body, thereby ensuring the characteristic wave motion is an interesting problem from a theoretical point of view – because such form of locomotion is widely used by different types of living organisms, starting with the simplest nematodes and ending with snakes, and from the practical point of view – in the problems of the control systems development for mobile robots.

Another interesting problem is the study of nematode neural mechanisms of orientation in chemotaxis – the purposeful movement in the direction of increasing the chemical concentration of a substance associated with food. It is known that the nematode perform chemotaxis by evaluating the concentration in only one point in space. Thus, to perform chemotaxis the nematode should be able to evaluate the chemical concentration gradient direction during its motion. Most likely, the nematode “computes” a concentration gradient during the oscillatory motions of the head to the right and to the left by combining those indications, and then it forms an additional impact on the locomotion control circuit, resulting in the rotation in to the right direction. At present, we have been able to identify all neurons responsible for the nematode chemotaxis control. However, as in the case of the locomotion control, it remains unclear how the identified neural circuit works.

Nowadays, there are several theories that explain the work of neural control circuits of nematode locomotion ([Bryden & Cohen, 2004](#); [Mailler, Avery, Graves, & Willy, 2010](#); [Niebur & Erdős, 1991](#)) and of chemotaxis ([Pierce-Shimomura, Morse, & Lockery, 1999](#); [Yuichi & Kazushi, 2009](#)). Also the several computer models have been suggested, they simulate the nematodes movement, neuron circuit operation ([Bryden & Cohen, 2004](#); [Mailler et al., 2010](#)), and the chemotaxis control ([Dunn, Conery, & Lockery, 2003](#); [Ferree & Lockery, 1999](#); [Ferree, Marcotte, & Lockery, 1996](#); [Lockery, Nowlan, & Sejnowski, 1993](#)). But the existing works are largely focused on the parameters selection for the proposed models in order to obtain the most realistic movement, while the possibility of learning and adapting of neuronal circuit have not even considered.

In this paper, we propose a learning control model of nematode locomotion and chemotaxis. While developing this model, we did not aim to maintain full biological compliance of the model with real neural circuits. Instead, we set the task of developing a generalized model capable of self-education by experience of interaction with the environment which, however, is based on the basic principles of nematodes neural circuits. For a number

of reasons the development of such a model seems to us to be more interesting and promising task. First, experiments with such a model will help us to answer the question if it is generally possible to teach the complex behaviors exhibited by living beings to an artificial controlling system, while just being based on the experience of system interaction with the environment. Second, due to its generality, this model can be further expanded and used for modeling the other, more complex behaviors. Third, a learning model is rather interesting and promising from a practical point of view, because it allows to develop adaptive control systems, for example, to control the robots.

C. elegans nematode

C. elegans – is a free-living soil nematode, a small worm a length of about a millimeter. Its biological characteristics are unique in many respects. The short life cycle and the maturation period, counted a few days, has made it an extremely convenient for research in the field of genetics. In 1998 the genome of *C. elegans* was sequenced. Also the deserved attention on it drew the neuroscientists. The beginning of a large-scale study of the *C. elegans* nervous system presented in the work [Altun and Hall \(2009\)](#), where in the first approximation was studied and described the structure of the entire nervous system, and was received the connectome. As it turned out, the nervous system of all individuals of the same sex is identical: 302 neurons, about seven thousand interneuron connections (~5 thousand connections between itself and ~2000 – between the neurons and muscles), 95 muscle cells, several tens of different sensory cells and about 86 connections between the neurons and the sensory cells ([Altun & Hall, 2009](#)).

Another one significant advantage of this organism in terms of modeling is the transparency in the optical range. The more complex organisms have a tendency to securely protect its central nervous system – the brain in all vertebrates is hidden inside the skull, and the insects and crustaceans have got a strong external skeleton. None of those allows us to observe their brains without the additional shifts, especially under the microscope, directly in the living organism and, under certain conditions it is possible for the *C. elegans*. There are hundreds of photomicrographs for the separate neurons, their ramifications, muscle cells and other illustrations of the organism internal structure at high resolution.

At a relatively simple nervous system the organism has a broad spectrum of behavioral reactions. Until 1990 no one seriously examined the ability of *C. elegans* to the plasticity of behavior and did not use the experience to teach, but later as a result of a number of works the opinion of scientists on this matter has changed considerably. It was found that the nematode can learn: to approach, or, conversely, to avoid the sources of taste, smell, or temperature changes, to predict the presence or absence of food. The worm also manifests the associative forms of learning, such as the development of classical and differential conditioned reflex, and has the ability to the short-term and the long-term memory ([Rankin, 2004](#)). These properties, which are fundamental to any more or less developed nervous system, are of

particular interest for the study, and goes far beyond the nematode.

Simulator

To conduct experiments with the proposed model we have used an interactive 3D-simulator of nematode with a graphical interface developed and grant to us by Palyanov and Dibert (2009) and Palyanov, Khayrulin, Larson, and Dibert (2012). This 3D-simulator designed for combining the existing and future data on the worm systems (sensory, neurological, muscular, etc.).

The core of the simulator is a physical engine that allows to construct the complex objects from a set of the following primitives: the mass points, the springs (which are connecting a pair of mass points), the muscle cells (active springs, which can be reduced in proportion to the intensity of the signal from the motor neuron), and two other types – the neuron and the connection between two neurons or between a neuron and a muscle. Any configuration of the above objects can be created in the virtual environment, in this case – the worm body model and its muscular system. The relationships between its objects are described by the system of linear differential equations, as also taking into account the external forces – the gravity, the reaction of the support (from the surface and obstacles), the friction force of static/slip and the energy dissipation as a result of the springs operation. They are numerically integrated with a time step $dt \sim 8 \cdot 10^{-3}$ s. Each object belongs to one of the above classes is visualized in a 3D scene.

The body of an adult *C. elegans* has a spindle shape, a length of about 1 mm and a diameter of $60 \dots 80 \mu\text{m}$ in the central part. The elastic outer shell is filled with a fluid under pressure that on the one hand, maintains the body shape and on the other hand – provides its flexibility. The model of the worm's body is presented as a complex periodic structure formed from the mass points and the spring connections, some of which corresponds to the outer shell, and another one mimic the "internal pressure" (Fig. 1) that supports the body shape of nematode. The proposed construction provides an adequate flexibility of the system, allowing you to receive the specific nematode's body position.

The worm's body model includes the 26 body segments similar to each other by the structure, as well as the head and tail segments. The objects that model the muscle cells, related to the worm body model in accordance with the scheme given in Altun and Hall (2009), provides a

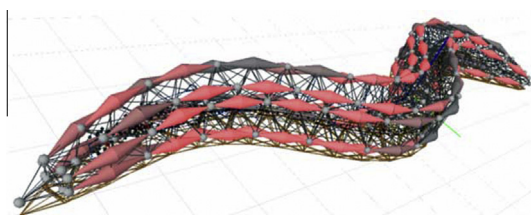


Fig. 1 "Screenshot" of a 3D-simulator of the *C. elegans* nematode.

sufficiently accurate approximation of the real skeletal system for the adult individual.

Locomotion control system

One of the feasible theories on the work of neural circuit that ensures a wave movement of nematodes is based on the assumption of the existence of the so-called stretch receptor, which is sensitive to the body bending (Niebur & Erdős, 1991). In works Niebur and Erdős (1991) and Bryden and Cohen (2004) was shown that the complex wave movement of nematode, if we assume the existence of stretch receptor, can be obtained even with a very simple neural network model.

Following the works Niebur and Erdős (1991) and Bryden and Cohen (2004), we also rely on the assumption about the existence of stretch receptor in the model. In accordance with this assumption, the head segment of nematode acts as an oscillation source, based only on the feedback from the stretch receptor. Further the signal is distributed over the nematode body with some time delay, thereby providing the wave movement.

In this paper we chose the neural circuit consisting of 12 neurons (Fig. 2). Each neuron N_i , $i = 1, \dots, 12$ controls 8 muscle cells – two coupled cells from each group of muscles: DR_{2i-1} , DR_{2i} , DL_{2i-1} , DL_{2i} , VR_{2i-1} , VR_{2i} , VL_{2i-1} , VL_{2i} , where DR and DL – right and left dorsal group of muscles, and VR and VL – right and left ventral group of muscles. The exception is the last neuron N_{12} that controls only 7 muscle cells, as a VL group, unlike the other groups contains 23, instead of 24 cells.

The head neuron N_1 receives the input information from the stretch receptor, located in the brain segment, and modeled as the bending angle between the head and the subsequent segment. Also, via feedbacks, neuron receives a signal from its own output with a time delay Δt . Other neurons N_i , $i = 2, \dots, 12$ receive on its input only the signal from the output of the previous neuron N_{i-1} with a time delay Δt .

Neurons functioning are determined by the set of logical regularities (Demin & Vityaev, 2008; Vityaev, 2013) with the estimates that have the following form:

$$\underbrace{Input_1, \dots, Input_n}_{\text{Input of neuron}}, \underbrace{Output}_{\text{Output of neuron}} \rightarrow \underbrace{reward}_{\text{reward}}, \quad (1)$$

where $Input_1, \dots, Input_n$ – is the set of predicates that describe the neuron input signals, $Output$ – is the predicate

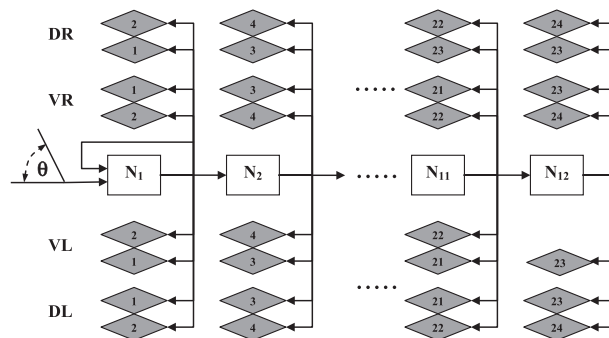


Fig. 2 Scheme of the neural control circuit for locomotion.

that describes the neuron output signal, *reward* – is an award, the maximization of which is a task of the entire neural circuit. These regularities predict that if in the neuron input will receive the signals described by the predicates $Input_1, \dots, Input_n$, and the a neuron will submit at its output the signal described by the predicate *Output*, the mathematical expectation of reward will be equal to a certain value r .

A set of input and output predicates for the neurons is obtained by the quantization the range of possible values of the neuron inputs and outputs. The award for the entire neural control circuit for locomotion is determined depending on the speed that the nematode will develop over the time interval Δt : the higher speed – the greater reward.

The neuron functioning occurs as follows. Let us assume that at some time on the neuron input a set of input signals enters. In the process of decision-making the neuron selects among a set of regularities, defining its operation, those regularities which predicates $Input_1, \dots, Input_n$ in the condition of the rules are performed on the current set of input signals. Then, among all selected regularities we choose one regularity R_{best} that has the maximum value of the mathematical expectation of reward r . Then, on the neuron output we send the output signal *Output*, specified in the condition of regularity R_{best} .

In the initial stage of the neuron functioning, where a lot of regularities describing the operation of a neuron are still empty, or when there are no rules applicable to the current set of input signals, the output of a neuron is determined randomly. The learning of a neuron consists in finding the plenty of regularities of the form (1) that define its work. For learning regularities the semantic probabilistic inference algorithm, described in Demin and Vityaev (2008)

and Vityaev (2013), is used that analyzes the statistics data of the neuron operation (input-output of a neuron and the received award) and extracts all the statistically significant regularities of the form (1). As shown in Vityaev (2013), the semantic probabilistic inference provides a formal model of neuron that satisfies the Hebbian rule and at the same time provides the consistency of predictions and solution of the problem of statistical ambiguity. Theoretical and practical advantages of this inference presented in Kovalerchuk and Vityaev (2000), Vityaev and Kovalerchuk (2004), and Vityaev (2006).

As the neurons N_2, \dots, N_{12} have the same structure of the input and output connections, we decided to combine their experience to increase the learning speed for these neurons. That is, in learning each particular neuron from this group, we, in addition to its own statistics, have also used the statistics of all other neurons of the group. Of course, combining the experience of these neurons we restrict in some ways the possible ways of locomotion, which can be found during the learning, but in return we get a significant increase in the speed of learning.

Teaching of locomotion

Using the interactive 3D-simulator of nematode, we have conducted a series of successful experiments on learning of the proposed control system model for locomotion. Results of experiments show that the control system can stably be trained the effective method of undulating forward movement in the average per 100 cycles of the neural circuit operation. Noteworthy that during the visual comparison the movement way, found by the model, with the biological prototype movement, we can observe their

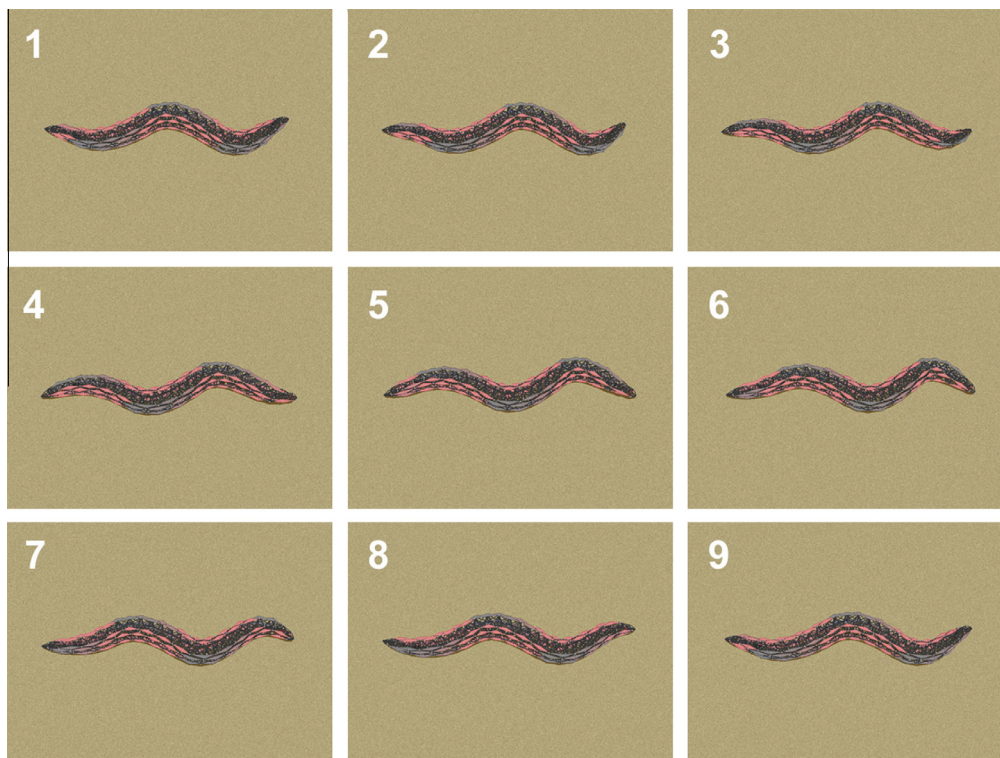


Fig. 3 Sequence of movements while moving forward.

coincidence. Fig. 3 shows the found by the system during the teaching the optimal movement sequences when moving forward.

Thus, the results obtained show that the neural control circuit for locomotion can be learned a complex undulating form of the nematode's movement based solely on the experience of the system interaction with the environment.

Chemotaxis control system

The live worms' observations showed that during chemotaxis the nematodes use the long "runs" alternating with the "pirouette" – the sharp turns. During the "runs" the nematodes carry the wave motion forward, which is displaceable in the direction of the concentration increasing. During the "pirouette" the nematodes make the sharp turns, radically changing the direction of their movement, and then continue to "run" in a new direction.

More detailed studies and experiments with live worms gave us the following information (Ferree & Lockery, 1999; Pierce-Shimomura et al., 1999; Yuichi & Kazushi, 2009):

- The nematode chemotaxis does not depend on the absolute concentration value.
- The chemotaxis does not depend on the second derivative of chemical concentration. I.e. the direction of the first derivative of chemical concentration is only used to control the chemotaxis.
- If the movement is carried out up the chemical concentration gradient, it is likely to provide a "run".
- If, over a certain time the movement down the gradient of the chemical concentration, it significantly increases the probability of a "pirouette".

Taking into account the information presented above for the chemotaxis modeling we decided to add to the above neural control circuit of locomotion that was previously taught and fixed, one more neuron circuit, consisting of one neuron N_0 (Fig. 4). Outputs of this neuron are connected to a group of muscles, controlled by a head neuron N_1 , resulting in its possibility to supply at this muscle an additional stimulating effect. At its input, this neuron re-

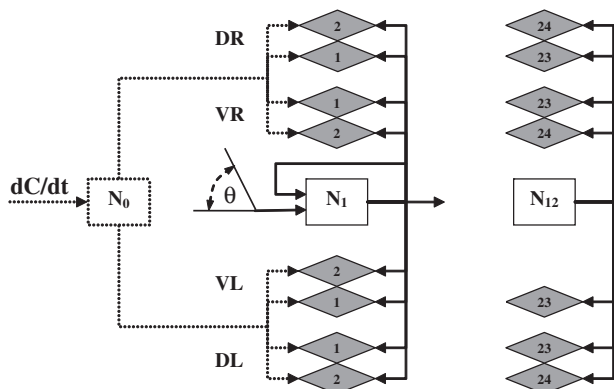


Fig. 4 Scheme of a neural control circuit for locomotion and chemotaxis.

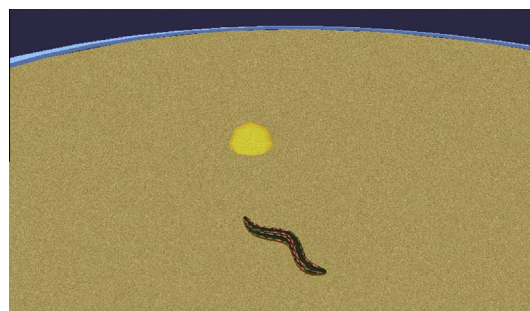


Fig. 5 A simulator "Screenshot" of chemotaxis learning.

ceives the information from a chemoreceptor in the form of duration of income positive or negative sign of change in chemical concentration.

For learning of neuron N_0 as a reward we have used amount of change in the chemical concentration per one clock cycle work of the neuronal circuit.

Teaching of chemotaxis

Using the 3D-simulator of the nematode we have conducted a series of experiments on the learning chemotaxis. The concentration function in the experiments was given by the following formula:

$$C(x, y) = e^{-a((x-x_0)^2+(y-y_0)^2)},$$

where (x_0, y_0) – is a concentration peak. To ensure a continuity of learning every time when the nematode was approaching the concentration peak close enough, the concentration peak randomly was displaced to a new point. Fig. 5 shows a screenshot of the simulator learning of chemotaxis, the bright hemisphere in the simulator represents the concentration peak.

The experimental results have showed that the control system successfully learn a chemotaxis strategy that coincides with the strategy used by the biological prototype, including "runs" and "pirouettes", what allows us to conclude that this strategy in terms of the set task is optimal.

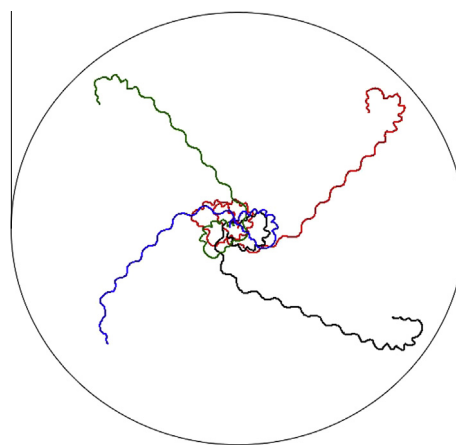


Fig. 6 The nematode movement trajectories examples obtained in the experiments. Concentration peak is in the center of the circle.

Fig. 6 shows the examples of the learned nematode movement trajectories. The average time to achieve the optimal behavior by the system in the experiments was 1000 clock cycles of the neuronal circuit work.

Conclusion

In this paper we proposed a learning controlling system that simulates the work of neural circuits which control locomotion and chemotaxis of *C. elegans* nematode. Experiments showed that the motor function and the associated mechanisms of nematode orientation can be obtained by learning from experience of interaction with the environment.

Of course, the structure of neural circuits proposed in this paper does not meet the biological prototypes. So naturally the further development of this work is to attempt to train the model with such a neural network, that it would coincide with the neural network of a real nematode.

It should also be noted that in this paper were not examined the issues of interaction between various forms of behavior that will inevitably arise, while attempting to model organisms with a higher level of the behavior organization, including the hierarchy of needs. A possible solution in this case may be the integration of the control system model which is proposed in this paper with the concepts of the theory of functional systems by Anokhin (1973).

From a practical point of view, the experiments results show that the control system model proposed in this work is quite efficient and can be used to control the complex objects with multiple degrees of freedom. In particular, one of the possible extensions of this work is to use the proposed model for the management of other worm-like model organisms and robots that use similar principles of locomotion, for example, snakes, salamanders, etc.

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