ISSN 0147-6882, Scientific and Technical Information Processing, 2011, Vol. 38, No. 5, pp. 344–354. © Allerton Press, Inc., 2011.
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INTELLIGENT SYSTEMS AND TECHNOLOGIES

Dynamic Planning of Robot Behavior Based on an "Intellectual" Neuron Network

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Abstract—We examine the questions of applying large pyramidal neural (intellectual neuron) networks to solve equipment object control problems. We consider the description of a system for dynamic planning of mobile robot behavior, constructed based on a network of similar elements.

Keywords: robot, neural network, intellectual neuron, dynamic planning
DOI: 10.3103/S0147688211050054

INTRODUCTION

One of the most interesting problems in modern robot engineering remains that of creating autonomous mobile robots capable of being oriented in space, of decision-making in a complex real situation, of solving pattern recognition problems, etc. The range of possible application of similar devices is wide—from the creation of loading robots, patrol robots, and security for robots to robot guides, etc.

The range of problems that such a robot should be able to solve is extremely wide. In this paper we consider one of the components of a similar robot—a dynamic planning system for robot actions in decision-making and processing control actions. As well, an artificial neural network model constructed of so-called intellectual neurons will constitute the basis of the planning system.

As a specific example of a similar type of mobile devices, we consider the problem of creating a robot-guide control system.

1. ROBOT GUIDE

A robot guide (RG) is a mobile device designed to play certain lecture materials. An RG should move along a certain route, which is a marked line. The marks determine the breakpoint and the start for playing the corresponding text. Movement along the route line (zone) is achieved at the hardware level using a special controller, and the robot can determine the accuracy level of positioning on the line. The main requirement for an RG is its *safety*: a robot absolutely must never harm people or exhibits. This means the immediate shutdown of a robot in a worst-case situation, including in the case when an obstacle appears in its path or it loses the route zone. For this, it is equipped with two types of sensors:

level 0 (OS0) sensors that determine an obstacle immediately within the safety zone of the robot and an ultrasound sensors (USS) that reacts to remote obstacles. Reaction to an OS0 signal is unconditional shutdown of the system. Reaction to a US signal is less critical: here the robot has more variety in reacting to it. As well, the distance to the obstacle can be estimated—the degree of potential danger.

A robot is an autonomous device; therefore, it should keep track of the charge level of its onboard batteries. With a decrease in charge lower than critical, the robot should begin the procedure of searching for a power source.

Thus, the robot's main functions are as follows: movement along a certain route/zone; reaction to the presence of obstacles in the robot's working zone; reaction to a decrease in the battery charge level; and determination of breakpoints on the route and playing of the corresponding lecture materials.

2. ROBOT GUIDE STRUCTURE

An RG consists of a drive module, a chassis, a set of primary and secondary sensors, a motor controller, and a controller for operation mechanisms and computer control. Figure 1 shows the basic structure of the RG.

The primary sensors are the obstacle, zone, illumination, etc., sensors. *The secondary sensors* are the acoustic sensors (microphone), video camera, etc. *The motor controller* (MC) is responsible for the robot's movement. It ensures, together with unconditional reflex control, system shutdown in a worst-case situation. *The operation mechanisms controller* controls additional operation mechanisms (head, arms, etc.). The computer control (CC) is the central computer. CC communication with the reflex controller is carried out by a RS232 slow standard interface.

The system is constructed according to a hierarchal principle. At the lowest level of the hierarchy are the sensors, which are responsible for the safety of the sys-

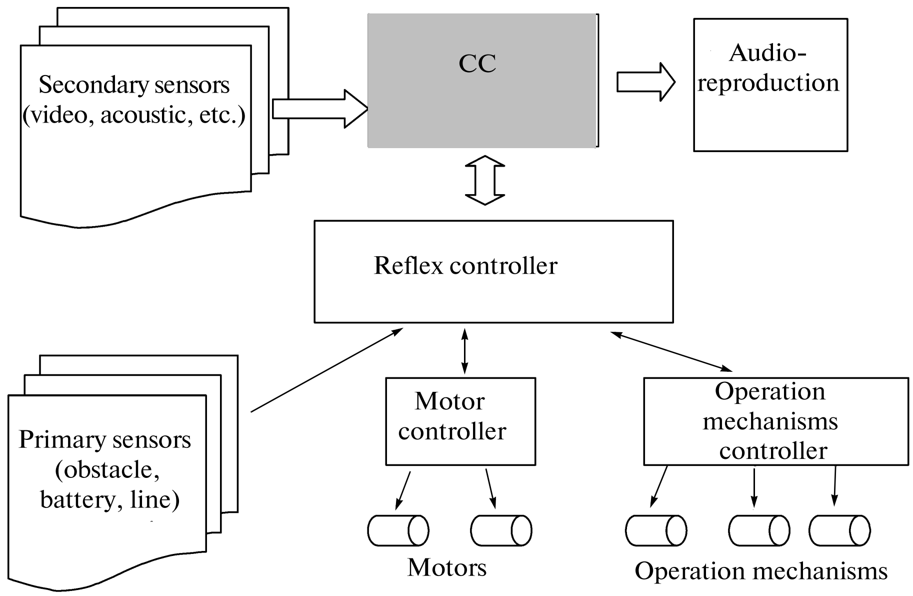

Fig. 1. RG Structure

tem and operation mechanisms. All critical control is carried out via the *reflex controller*. This controller should query the near-action obstacle sensors (safety zone) with sufficient frequency, and when a critical situation arises, it should stop the drive motors in the simplest case (emergency shutdown).

Thus, the robot behavior necessary for solving the posed problem is carried out at the highest level, in the CC, and the rapid reactions necessary to ensure safety, at the lowest level using the reflex controller. Commands processed by the reflex controller are of higher priority, even if they contradict a CC command.

Figure 2 schematically depicts the location of the RG's main sensors.

Figure 3 shows an external view of the RG.

3. FORMULATION OF THE PROBLEM

Among the set of various problems of robot behavior control, we consider a simpler one, the model problem. We limit ourselves to considering the situation in which a robot perceives only three input signals—from the obstacle transceiver, from the battery level transceiver, and from the transceiver that determines the accuracy of the robot's positioning in the movement zone. It is necessary to create a robot action planning system as a function of the intensity of these input signals.

The signals from the sensors are analogous, representing intensity level values. It is necessary to develop a control system that, based on signal magnitudes, plans the action of the robot at a certain time segment.

As well, it is assumed that signals have different priorities or significance (a signal from the obstacle transceiver has higher priority, a safety requirement). The plan of action should determine the precisely desired reaction of the system; i.e., it should not directly assign a controlling action, but only determin which problem the robot should solve (reaction to an obstacle, positioning on the line, or launching of the reaction procedure for a decrease in the battery level). Thus, we are talking about dynamic planning of the robot's behavior at a high level. There are many ways of solving similar types of problems—from application of fuzzy logic and knowledge engineering methods to construction of automatic regulators. Here we consider the problem of applicability of artificial neuron networks (ANNs) as grounds for a system for dynamic planning of the behavior of complex systems. As well, the network should not be constructed of known formal neurons, but of so-called *intellectual neurons.*

3.1. Artificial Neuron Network

It is believed that the basis of the neurointellectual direction in AI is the system model proposed in 1943 by W.S. McCulloch and W. Pitts, consisting of threshold neuronlike elements—formal neurons (FNs). Further development of this model let to the creation of the Rosenblatt perceptron (1962), harsh criticism of it, and its subsequent disregard, which let to a certain stagnation in the development of robots in this direction. The situation was rescued by the creation of various multilayer-system models of nonlinear elements by the start of the 1970s.

Initially, there were two main directions in ANN theory. The first, *collectionist*, declared that the basis of the ANN model should consist of simple functional

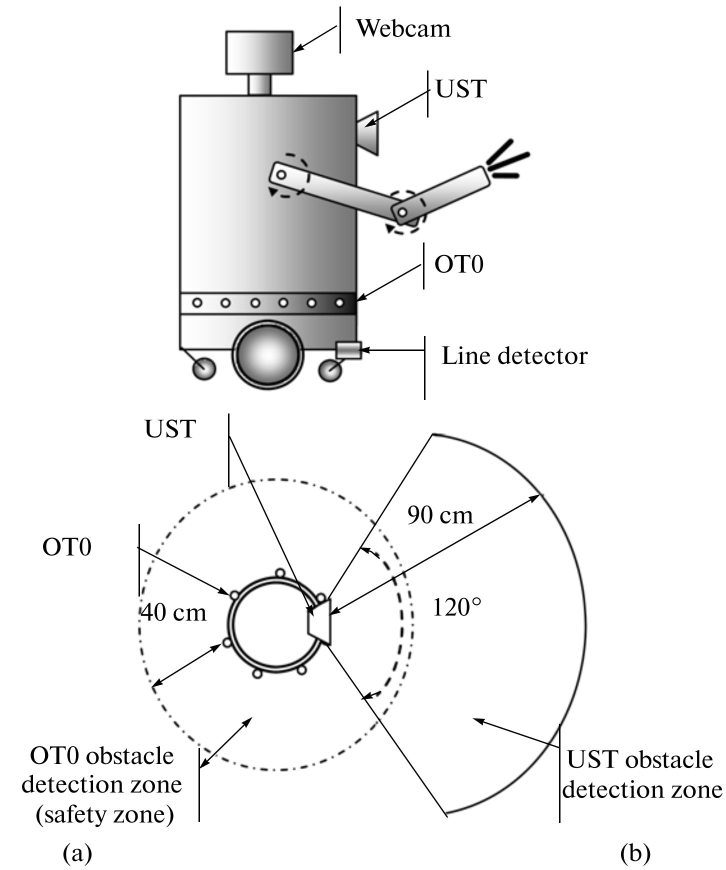

Fig. 2. (a) Location of sensors; (b) obstacle transceiver sensitivity zones.

elements. The entire variety of structures reflecting the device and behavior of real neurons can, according to this approach, result from unification of simple FNs.

Fig. 3. Robot: external view.

The second, *neurobiological*, direction is characterized by the creation of networks consisting of complex neurons approximated to biological models [4].

At present the dominant direction in AI is the connectionist approach. It has primarily resulted from sufficiently well-formalized models. However, the main problem of the connectionist approach is the fundamentally small dimensionality of problems being solved and, as a consequence, its narrow specialization. As soon as we switch from approximation or more multidimensional optimization problems to solving complex, multilevel problems requiring the involvement of semantic levels, it becomes necessary to introduce functional elements that are more complex than formal neurons. Attempts at "growing" a similar type of complex neurons from a network of simple neurons have led to the fact that the number of FNs increases catastrophically, virtually unremovable complexities arise in training such networks, etc. Let's say, to model a detector neuron, something on the order of tens of FNs are necessary, and the memory of a neuron already requires several tens of FNs.

The main difficulties of the neurobiological approach are, first of all, the absence of unambiguous models of biological neurons (different schools describe neurons differently), and second, problems in the formation of a network from complex neurons and the description of connections between them. If the model of an FN network is constructed just on the principle of its self-organization, i.e., the establishment of connections and their weights between elements, then in the neurobiological approach, it is necessary to create both the network itself and its parameters a priori, adjusted to a specific problem. In this sense, it is possible to consider the connectionist approach more universal (in the class of solvable optimization problems).

This paper considers one of the neurobiological models of constructing an ANN. V.B. Val'tsev, the creator of this model, calls it the brainputer [1, 7]. Its basis consists of the model of a real nerve cell—the neuron.

4. THE CONCEPT OF INTELLECTUAL NEURONS

The microstructure of the functional unit of the brain is the neural module, consisting of a population of nerve cells having a common effector output. A large pyramidal neuron (LPN) and the group of neurons connected to it that use the LPN effector output represent such a module. The LPN has the largest branching of dendrites responsible for perception of information, which allows it to collect information from neurons of all layers of the brain cortex. The LPN has the maximum set of functional blocks [2, 3]. The LPN's dominance in intellectual mechanisms is confirmed by the fact that the LPN predominates in associative zones. It is believed that the evolution of the brain was accompanied primarily by growth in LPNs; ontogenetic maturation of the human brain coincides with the largest increase in the number and sizes of precisely LPNs.

According to the brainputer approach, development of intellect is characterized not by simple growth in flows of perceived and analyzed information, but by adaptative *targeted* activity of an organism. The purposefulness (motivation) of behavior is determined by an *actual requirement* being satisfied—removal of influences causing the requirement. As a consequence, the purposefulness principle is a common one for the psyche, the brain, and an LPN [3, 5]. An LPN is considered basic microstructural link of the brain's intellectual mechnism.

5. CONSTRUCTION OF AN INTELLECTUAL NEURON

Figure 4 shows the external view and construction of intellectual neuron cell inputs:

The main functional elements of the cell are its body, in which accumulation of the potential from inputs occurs, and the axon hillock, which, when the cell potential exceeds a certain threshold value, generates nerve impulses from the cell's output.

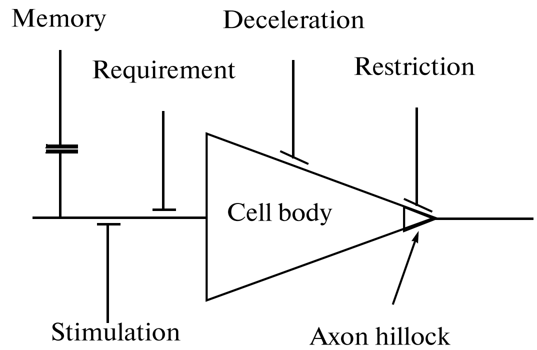

Fig. 4. Structure of intellectual neuron.

The nerve cell *restriction input* acts as a brake for the axon hillock. Owing to it, impulse transfer from the cell can be terminated, and its internal potential will not be changed.

Braking input. As neural impulses are fed to it, the internal potential of the cell decreases, reducing its activity.

Requirement input (regulation). When impulses are fed to the requirement input, the nerve cell potential grows; however, if there are only impulses at this input, it cannot exceed its threshold value necessary for the onset of output impulse generation.

Stimulation input. When there are impulses only at this input, the nerve cell potential cannot exceed a value equal to about 30% of the threshold value.

Memory input. The most complex, trainable input. When impulses are fed to the most-trained memory input, the nerve cell potential cannot rise above a value of 70% of the threshold value. In a state of zero trainability, impulses to the memory input do not increase a nerve cell's potential. Memory training occurs when there certain combinations of impulses are present at the *regulation, memory, and stimulation inputs*. As well, the memory input is *trained*: the potential introduced by this input into the nerve cell increases by 20%. In the absence of impulses at the memory inut, a neuron unlearns over time.

Potentials introduced by all inputs except for the restriction input, are added to the overall nerve cell potential, which when this cell's threshold value is exceeded induces its reaction at the output.

We will not dwell extensively on the mathematical model of a neuron, noting only that a nerve cell adds up the input potentials:

$$\varphi = \varphi_0 + \sum_{n=1}^{4} \varphi_n$$

here, φ_0 is the initial potential, and φ_n ($n = 1.4$) represents the memory, regulation, stimulation, braking, and restriction inputs, respectively.

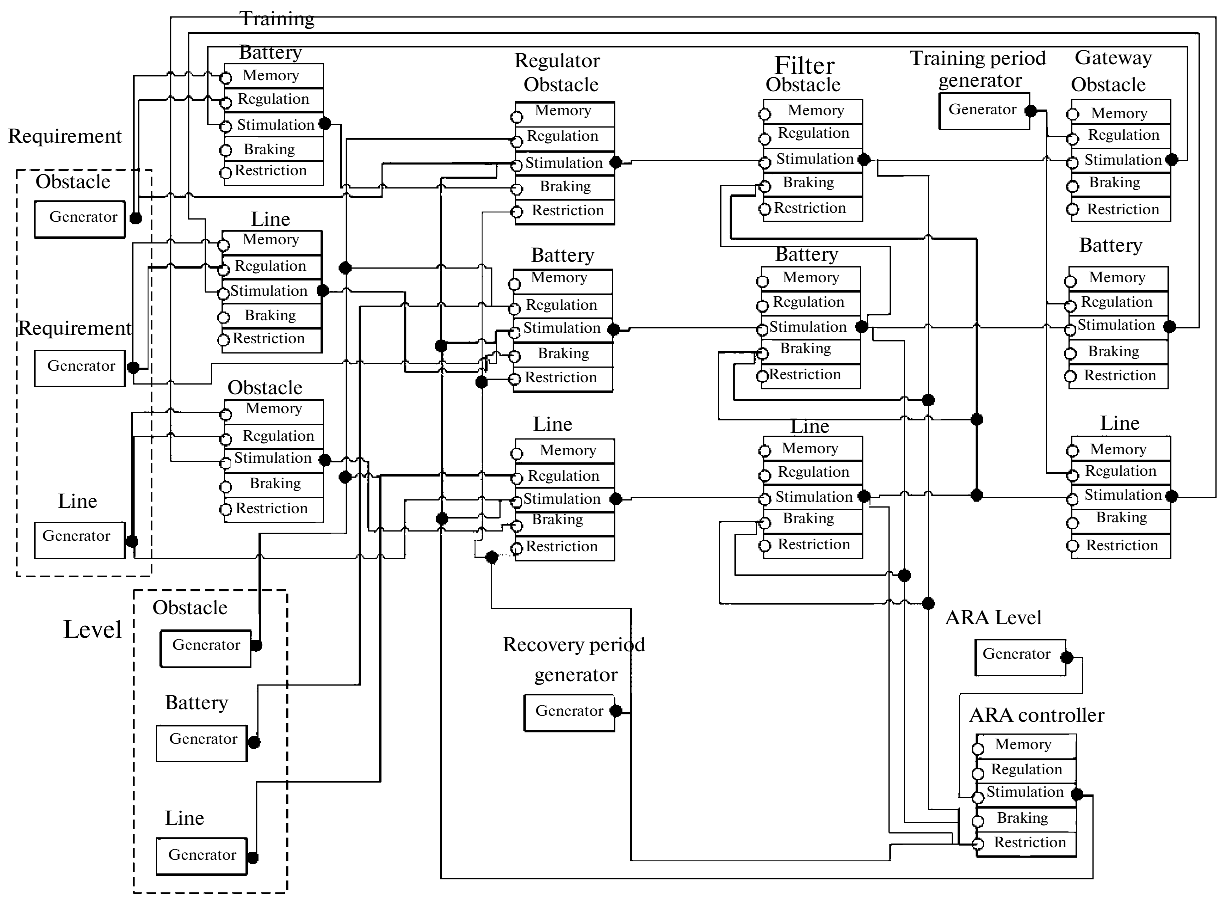

Fig. 5. ANN of the RG control system.

When the potential exceeds the threshold level and the potential at the restriction input does not exceed a certain threshold level, a neuron generates impulses directly proportional to the amount by which the potential exceeds the threshold:

$$\omega = \Omega\Delta\varphi + \Omega_0$$

where $\Delta\varphi = \varphi - \psi$; ψ is the neuron's threshold; Ω is the coefficient of the generation rate from the above-threshold potential.

6. DESCRIPTION OF NEURAL NETWORK FUNCTIONING

As has already been mentioned, one of the main concepts of the functioning of a neural network is the *requirement*. The purposefulness of the network's behavior is determined precisely by the transition to such a state during which the influences caused by these requirements are removed (satisfaction of *actual requirements*). Requirements were chosen from the following types:

1. Battery. The requirement of the availability of a certain battery charge level for the robot.

2. Line. The requirement to follow a designated route line.

3. Obstacle. The requirement not to run into any obstacles, i.e., reaction to an obstacle.

On this basis, the network should be constructed in such a way that behavior satisfying (removing) these requirements is ensured. For instance, with decreasing battery charge level, a robot should send a certain warning signal; if the line is lost, the robot should strive to return to the movement zone; when there is an obstacle, the robot should shut down, avoid, or give a warning depending on the distance to the obstacle (i.e., on the intensity of the arising requirement). As well, precisely the intensities of robot reactions depending on the magnitude of the arising requirement are of course of the most interest.

A control neural network is shown in Fig. 5. The network consists of standard building blocks—training, regulation, filters, etc.

Impulse generators (Obstacle, Battery, and Line) generate at the neuron-stimulation inputs of the Regulator block impulses proportional to be intensity of input signals. An impulse raises the level of the potential at these neurons to a certain prethreshold value.

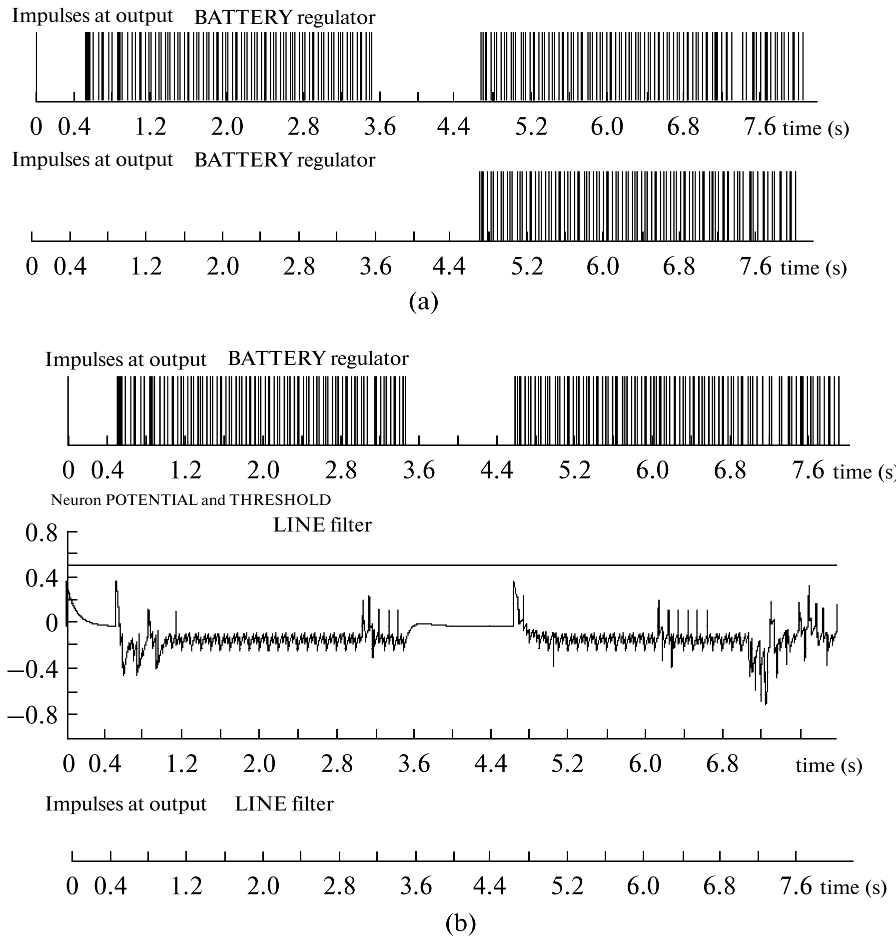

Fig. 6. Filter action.

As well, signals of the Obstacle generator reach the Regulator Obstacle, Regulator Battery, and Regulator Line neuron regulation inputs. It can be interpreted that the reaction to the obstacle has a requirement for each of the listed types of regulators. Signals of the Line and Battery generators only reach the regulation inputs of corresponding neurons, i.e., reaction to loss of the line and battery discharge experience no other requirements.

Regulator block. These three neurons represent the *robot's requirements*, which are reflected in the level of the output impulse of corresponding neurons. Further, this impulse is fed to the neuron-stimulation inputs of the dominant filter block.

Filter. The output of each of the three neurons of the neuron filter is connected to the braking input of the two remaining neurons. The impulse values from the filter and neuron outputs will be *network output values*. The task of the filter is to allow a neuron with the highest output impulse intensity to brake neighboring neurons. This is the so-called *dominant filter*. Thus, in removing the information from three filter neurons, it is possible to unambiguously determine the neural network output that was activated. Correspondingly, an intense impulse at one of the dominant filter outpus indicates the recommendation of the neural network toward deriving a requirement corresponding to the neuron name.

The role of the dominant filter is illustrated in Fig. 6.

In the graphs we can seen that despite the intense impulse of regulator neurons, the corresponding filters produce a partial or full cutoff of the output impulse. Figure 6b shows the graph of a filter neuron potential that is close to the threshold, but it cannot exceed it. Apparently, in this situation we are dealing with explicit dominance of the Obstacle regulator signal.

In the design of the neural network, along with the main blocks, service blocks are provided for—automatic regulation of amplification, back training, and restoration.

Automatic regulation of amplification block (ARA). The task of this block is to increase the neuron sensitivity of the Regulator block to the smallest influences. The fact of the matter is that a weak impulse of generators responsible for giving measurable parameters can

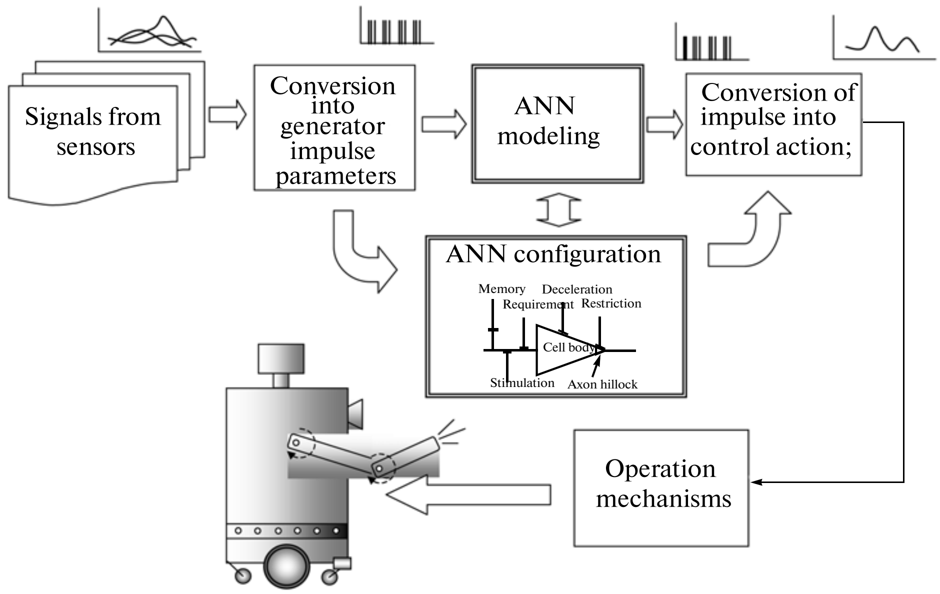

Fig. 7. Principle of planning system operation.

lead to the absence of any reaction at a neural network output.

Training block. The neural network is trained in time periods determined by the training period generator. For this, in the necessary periods, the generator delivers an intense uniform impulse lasting over the course of the training period. Output from this generator reaches the neuron regulation inputs of the Gateway block, and outputs from the dominant filter neurons are fed to the stimulation inputs of these neurons.

A uniform stimulating impulse from the Battery, Line, and Obstacle generators reaches the memory inputs of the aforementioned neurons. Neurons are trained with a certain combination of impulse packets at memory and stimulation inputs. The neuron outputs of the Training block reach the neuron braking inputs of the Regulator block. Thus, trained neurons will brake regulator neurons, in so doing removing their relevance. This is necessary when there are long-term unchanging generator parameters in order to satisfy as many parametric categories as possible and not concentrate only on one; i.e., the network will always reflect several requirements and not be limited to only one.

The Recovery block is designed to prepare the system for making a new decision. Its essence is reduced to elimination of a remnant dying impulse.

Here we should point out one important moment. The considered diagram is almost an exact copy of a neural network diagram that was proposed at one time for problem solving in a completely different area. It concerned the problem of distribution of resources under competitive conditions—distribution of television air time. It turned out that, despite their dissimilarity, these problems can be successfully solved based on one neural network structure. Apparently, we are talking about the possible availability of certain neural network invariants.

7. MODELING

Since the program is an upper level control system, its task is decision making and not immediate processing of control signals to the robot's operation units.

Figure 7 depicts the design of planning system operation.

Signals from the sensors (line, obstacle, battery) are converted into impulses—the parameters of the corresponding generators of signal levels. The established generator parameters are an integral part of the neural network configuration. Further, operation of the ANN is modeled, during which signals are taken from *dominant filter* neurons. To receive the impulse of output neurons represents a time scan of the intensities of corresponding *requirements*, i.e., the robot's plan of action. Further, this impulse is converted into a frequency-time characteristic and can be scanned into the robot's plan of action (reaction). In accordance with this plan, a complex of controlling actions to the robot's operation mechanisms is generated (Fig. 8).

Thus, in assigning the impulse intensity of the Level block generators, the current activity of neural network signals is determined. The readout of output neuron impulses of the Filter block makes it possible to obtain a time scan of the relevance of corresponding network reactions, i.e., a time scan of the system reaction (action) plan.

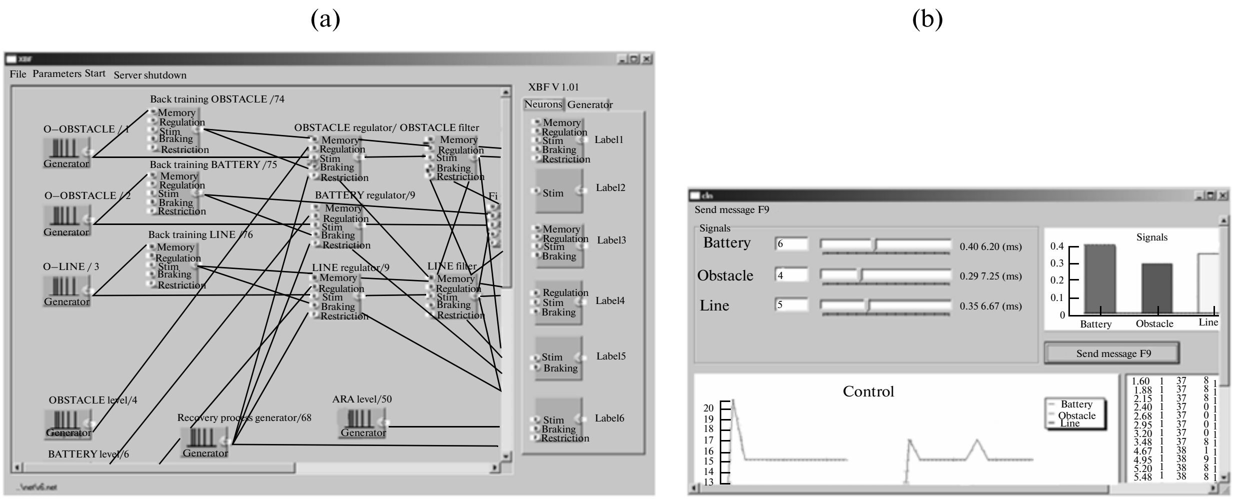

Fig. 8. Details of program interfaces. (a) Modeling program; (b) control program.

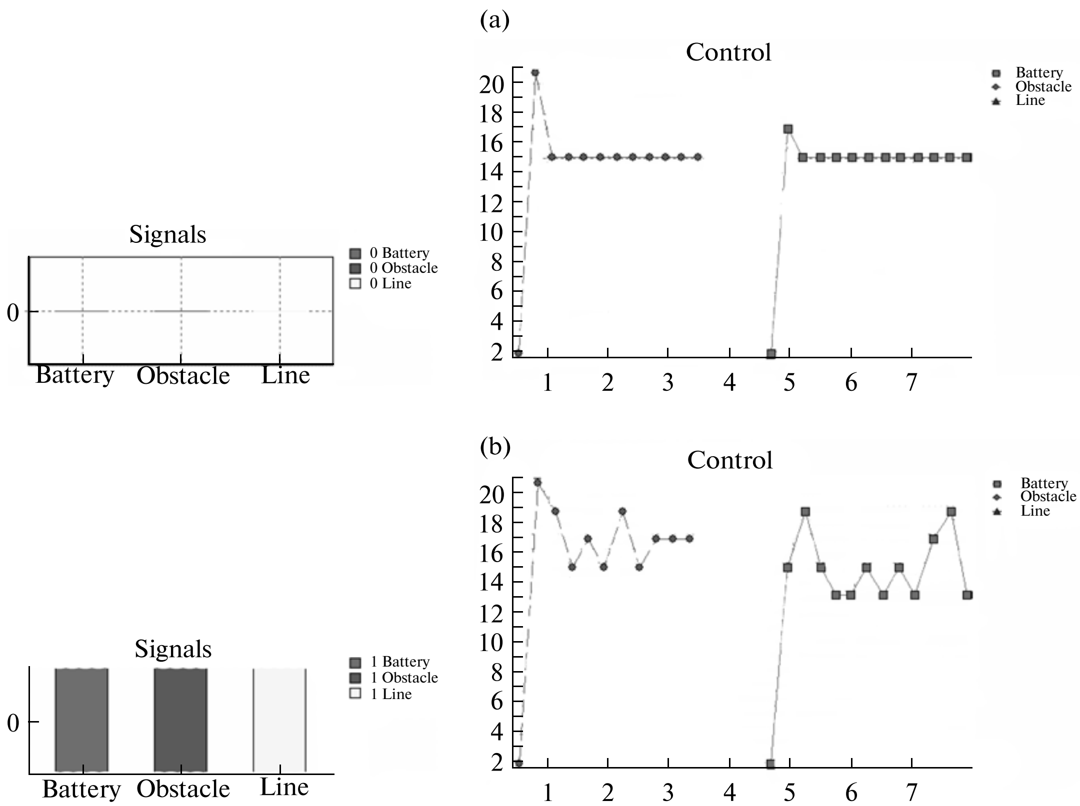

Fig. 9. System reaction to identical input actions.

8. EXPERIMENTS

The network was adjusted in such a way that the dominant requirement was Obstacle. This means that at equal input generator signal levels, the system primarily plans a reaction just to obviate an obstacle (safety requirement).

Below we give the results of certain experiments at characteristic input signal values. Figure 9a shows the reaction of the system at zero transceiver signal values. In this situation, in the first half of the period, the system plans to process tracking of obstacles (despite the fact that the obstacles are not yet visible) and further plans to analyze the battery charge state.

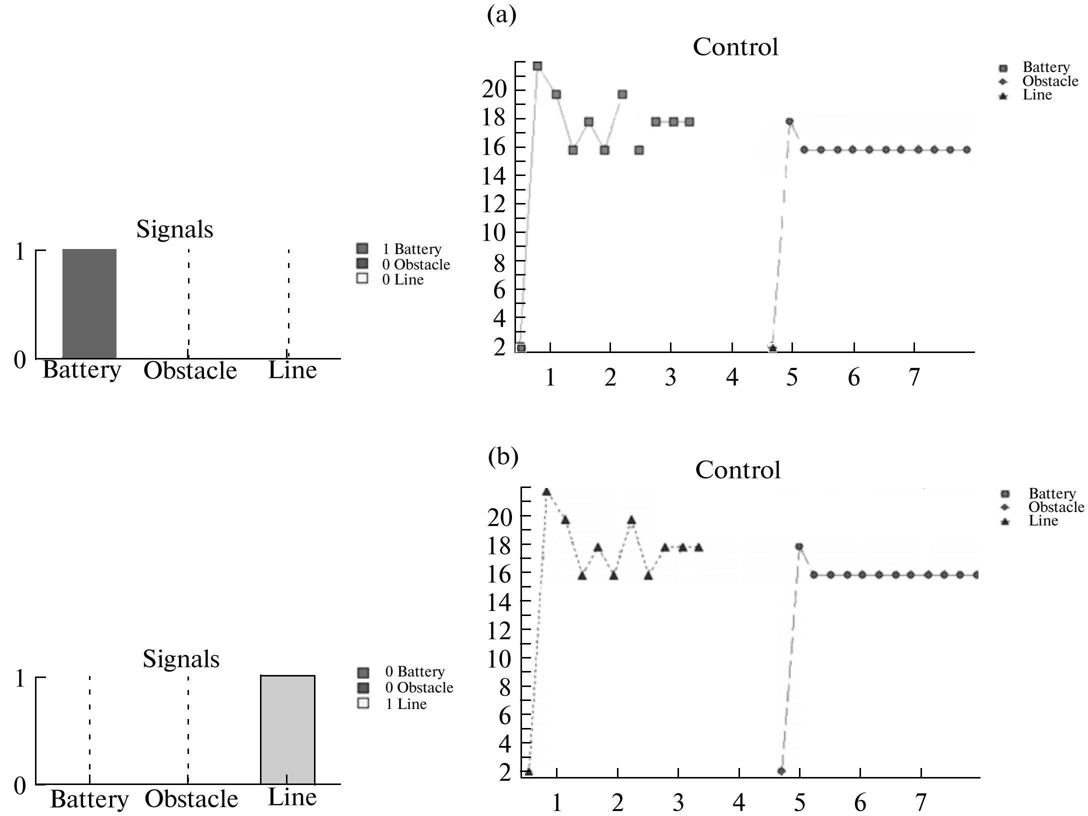

Fig. 10. Reaction to dominant signal.

It is interesting that nearly the same plan of action is also generated at the most intense input signal values; i.e., in the situation when obstacles are detected, the battery charge is almost dead, and the robot has lost the line (Fig. 9b).

The system's reaction to one implicitly dominant signal is also trivial: the system determines the reaction just to it. Here, only one thing can be of interest: planning the reaction to a stimulus at the beginning of the period, the system still determines the reaction to the obstacle in the second half of the period (Fig. 10).

The fact that the system primarily plans to process the Obstacle signal is clear from Fig. 11.

Only when the level of other secondary stimuli is implicitly exceeded does the system either plan a reaction to the obstacle in the second period (Fig. 12a) or plan no reaction to it (Fig. 12b).

CONCLUSIONS

The conducted experiments have shown the fundamental possibility of using intellectual neural networks in solving problems of controlling complex technical objects. In addition, we obtained confirmation of the pieces that they are apparently should exist certain invariants of ANN structures that can be applied for a wide circle of the most various problems—from the aforementioned problem of distributing resources to the considered problem of dynamic planning in controlling of am equipment object. This is especially important because the design process for a similar type of networks, determination of connections, nomenclature, and parameters of the network elements is extremely labor-intensive (in contrast to formal neural networks with their self-organization mechanisms based on training).

Furthermore, of undoubted interest are such system properties as frequent nontriviality (reasonableness) of suggested solutions. This concerns, for instance, how a system plans its behavior in the case when there are no explicit stimuli.

In addition, the system possesses peculiar flexibility in the sense of simplicity and naturalness of changing its behavior—it suffices to change the generator parameters of the requirement block so that the network alters the priority of its aims.

Of course, a whole series of problems exist related to using the suggested method. These are the purely technical complexities connected with the necessity of rapid simulation (ideally, parallel computations would be the most suitable), the labor intensity of creating and adjusting the network, and what is called the *weak controllability* of the decision-making process. The latter case concerns the fact that, in contrast to the

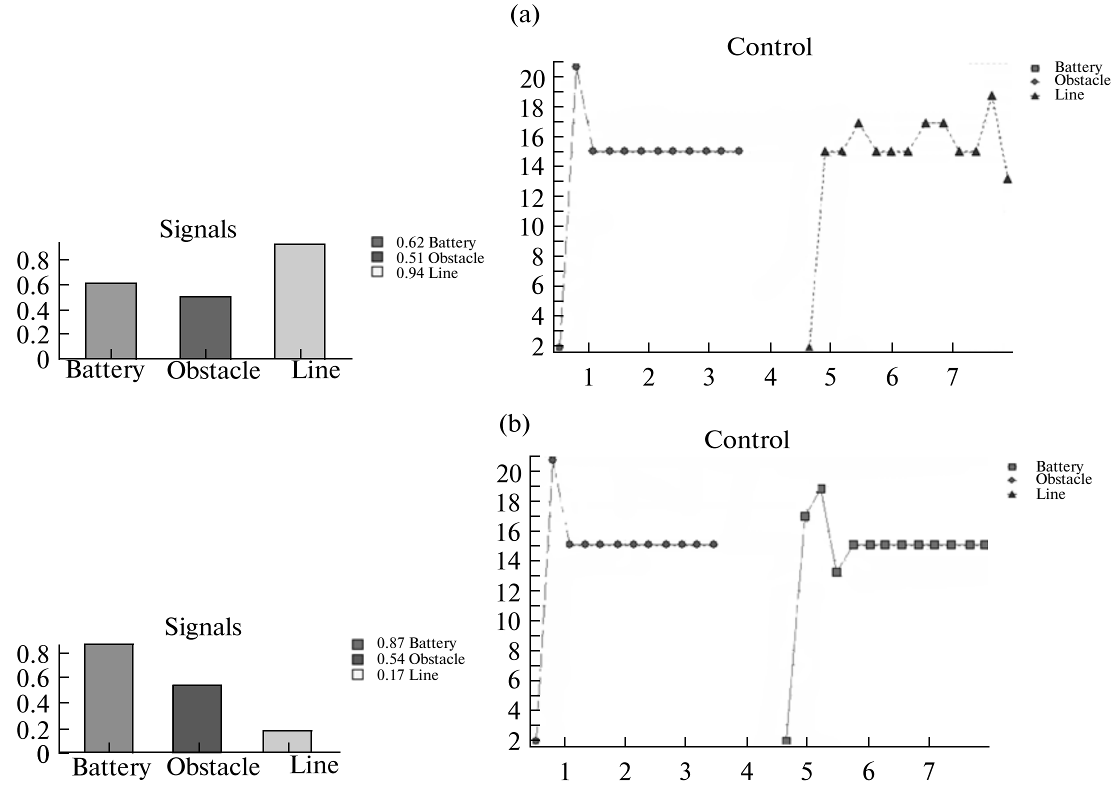

Fig. 11.

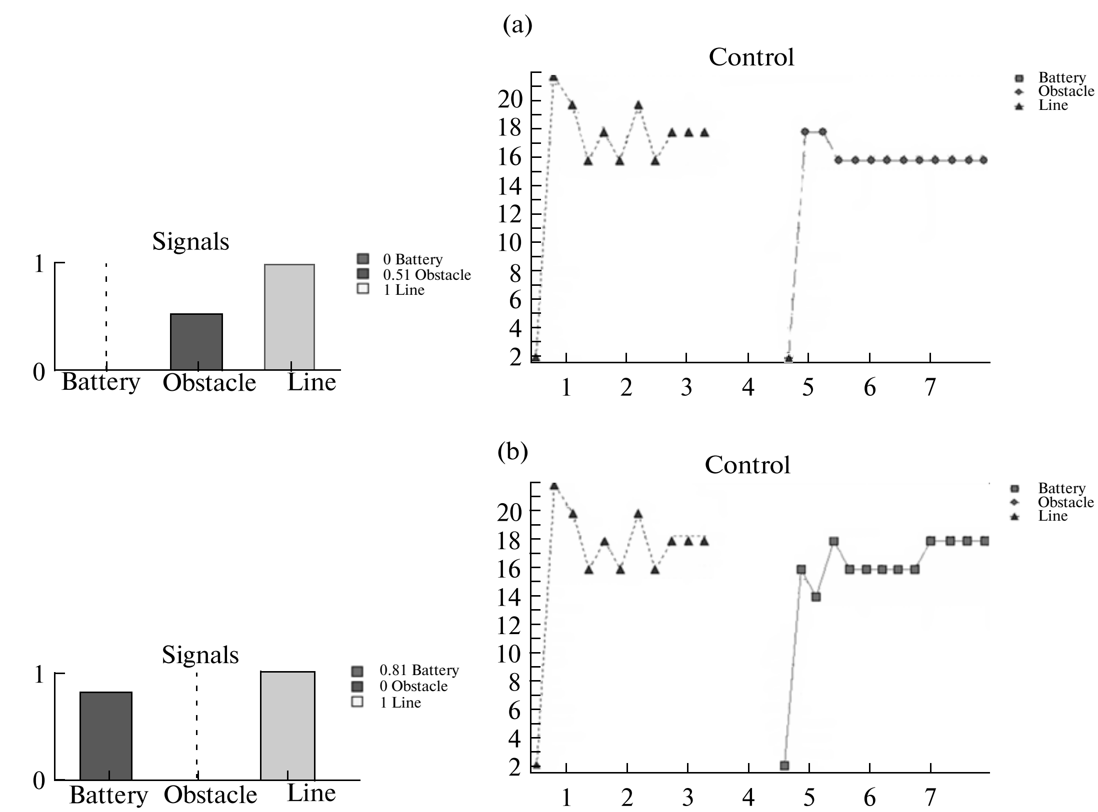

Fig. 12. Explicit dominance of secondary signal levels.

majority of formal systems, it is impossible to obtain an explanation as to why a system has developed precisely such a plan of action. By the way, this is peculiar to all neural-like structures [6].

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