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Adaptive Control System for a Mobile Agent in a Physical Environment Based on Functional Systems Theory

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Abstract—We previously developed an adaptive mobile agent control system based on functional systems theory and semantic probabilistic inference (Vityaev, 2008; Demin and Vityaev, 2008). In the present work, we extended the potential of the system by introducing the ability to control a robot in physical environment. On the one hand, this ability shows that the system can operate in the environment that animals function in. On the other hand, it allows testing of the developed algorithm on actual physical environment. We identified two objectives. The first was to extend the capabilities of the system so that it could operate effectively in the physical environment; in particular, it was necessary to add support for continuous sensors and carry out a simulated experiment. The second was to extend the semantic probabilistic inference for the case of continuous sensors. The system was supplemented with abilities to use sensors with continuous real signals and to vary the duration of its actions when selecting a way to achieve the goal. The benefits of the semantic probabilistic inference were preserved. We constructed a robotic platform for experiments in the physical environment. The platform could carry several types of sensors and move according to commands received wirelessly. To show the ability of acting in the physical environment, the system was supposed to learn how to find bricks scattered around the room. The developed algorithm made it possible to solve this task and generate a set of rules for the effective detection of bricks.

Keywords: adaptive control system, mobile agent, machine learning, functional systems theory

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INTRODUCTION

There is a wide range of works dedicated to the study of adaptive control systems. The most important ones are those based on known physiological theories. One of the most developed physiological theories is the functional systems theory of P.K. Anokhin.

There are currently several adaptive control systems developed on the basis of functional systems theory. The closest to this work are the works of K.V. Anokhin et al. (2002), V.G. Red'ko et al. (Red'ko et al., 2007), and A.A. Zhdanov (1999).

In his works, A.A. Zhdanov developed a control system based on his probabilistic model of a neuron (Zhdanov, 1999), which is similar to the probabilistic semantic inference that we developed. On the basis of the control system, several controllers for different purposes were developed (Zhdanov, 1999), and a series of successful experiments on robots (for example, Sytsko, 2005) were carried out. The control system developed by Zhdanov (1999) requires specification of the structure of the control system in advance, which worsens its adaptive properties. This problem is partly solved by the use of evolutionary algorithms (Zemskikh, 2004).

The control system developed by K.V. Anokhin et al. (2002) and V.G. Red'ko et al. (Red'ko et al., 2007) for the formation of actions and outcome prediction uses neural networks. The parameters of neural networks are defined by means of reinforcement learning and the evolutionary algorithm. The main difference from our work is the use of the semantic probabilistic inference instead of neural networks. The potential advantages of this method have been described in the work of E.V. Mikhienko (2003).

The study of various adaptive systems based on biological theories using robots operating in the physical environment is a common practice. A striking example involves the brain-based devices studied in the works of J. Krichmar and G. Edelman (2005), Krichmar et al. (2005), and J. Fleischer and J. Krichmar (2007). The most famous family of brain-based devices is the family of Darwin robots developed at the Neurosciences Institute in La Jolla, California from 1981 to 2007 in the framework of the Nomad project (Krichmar et al., 2005; Fleischer and Krichmar, 2007); the experimental part of our work is based on the use of that experience. The Nomad project also used robotic platforms with sensors, and the control system was presented with tasks that required the implementation of adaptive behavior. The main difference of the Nomad project from our work is that their control systems simulate specific aspects of adaptive behavior, such as orienteering, while we, based on functional systems theory, try to recreate the general principles.

We previously developed a system to control a mobile agent; it was based on functional systems theory and semantic probabilistic inference (Vityaev, 2008; Demin and Vityaev, 2008). It should also be noted that, unlike most other adaptive systems, the structure of which is defined in advance (Zhdanov, 1999; Krichmar et al., 2005), our system can rebuild its structure in accordance with the environmental conditions in which it is located.

The direction of the development of our system, which was selected in this work, is its adaptation to control the mobile agent in the physical environment. This adaptation, on the one hand, demonstrates the system's ability to operate in an environment similar to that in which animals function, while, on the other hand, it allows testing of the developed algorithm on real problems.

We identified two problems. The first was to extend the capabilities of the system so that it could operate effectively in the physical environment; in particular, it was necessary to add support for continuous sensors and carry out a simulated experiment. The second was to extend the semantic probabilistic inference for the case of continuous sensors.

The control systems implemented in previous works (Demin and Vityaev, 2006; Mukhortov et al., 2012) used binary sensors and operated in step mode, that is, all actions of the agent had the same duration. However, most sensors used in robotics, as well as receptors of living organisms, produce a continuous output signal. Moreover, various actions in the real world have a different length of time, which must be considered when deciding how to achieve the goal. The system was supplemented by the ability to use sensors with continuous real signals, as well as the ability to vary the length of its actions when deciding how to achieve the goal. At the same time, the ability to use the semantic probabilistic inference was preserved.

The simulation of the real world mechanics is a difficult computational problem, which, however, does not need to be carried out if the used agent is a robot. Therefore, to carry out experiments in the physical environment, a robotic platform was constructed. It can carry several kinds of sensors and move according to commands received wirelessly.

As an experiment in the physical environment, the robotic platform, without having any information on the purpose of its sensors and the consequences of its actions, had to learn how to find bricks scattered around the room. Our algorithm made it possible to solve this problem and to develop a set of rules for effective search of bricks.

MATHEMATICAL MODEL OF THE CONTROL SYSTEM

A mathematical model of the developed system is based on our previous works (Demin and Vityaev, 2006; Demin and Vityaev, 2008; Mukhortov et al., 2012). Some changes were introduced into the model so that the control system could operate with continuous real sensor signals and take into account the duration of actions of the agent. The changes mainly affected the process of formation of the control system, while the basic principles of its work were preserved.

Basic Operation Principles

Let us briefly consider the basic operation principles of the control system. We assume that the system functions in discrete time $t = 0, 1...$.

The agent has a set of sensors $S_1, ..., S_n$ that characterize the state of both the agent and the environment. The indications of each sensor S_i are real variables that can take values in some interval $VS_i = (v_i^{\min}, v_i^{\max})$, where $v_i^{\min}$, $v_i^{\max}$ are the minimum and maximum readings of sensor S_i, respectively.

The agent has a set of actions $A_i, ..., A_m$. Agent actions can be performed with different duration Δt. Any agent action started at time t_i and performed with duration Δt can lead at times $t_i + 1, t_i + 2, ..., t_i + \Delta t$ to some change in the environment and, as a consequence, a change in sensor readings. For every action, a maximum possible execution time $\Delta t_{\max}$ is defined.

Because the agent receives information about the environment only through sensors, then, in its view, the state of the system at time t can be represented by a vector of sensor readings $v(t) = (v_i, ..., v_n)$, where $v_i \in VS_i$ are readings of the ith sensor at time t. The set of all possible states of the agent is denoted as $SS = (VS_1 \times VS_2 \times ... \times VS_n)$.

Because the sensors have physical limitations and their potential is not always sufficient to characterize the current state of the environment unambiguously, the same action performed under same sensor readings can transfer the system into several different states. Thus, the agent action A_i can be represented as a mapping that transitions the agent–external environment system from one state to another with a certain probability:

$$A_i(\Delta t) : (SS_i) \to (SS \times P),$$

where SS_i is a subset of the system states in which action A_i is possible; Δt is the duration of action A_i; $SS \times P$ is a set of pairs of the form (ss, p), where $ss \in SS$ is the final state; $p \in [0,1]$ is the probability of transition into one of the set of states from the initial state $ss \in SS_i$ while performing action A_i with duration Δt.

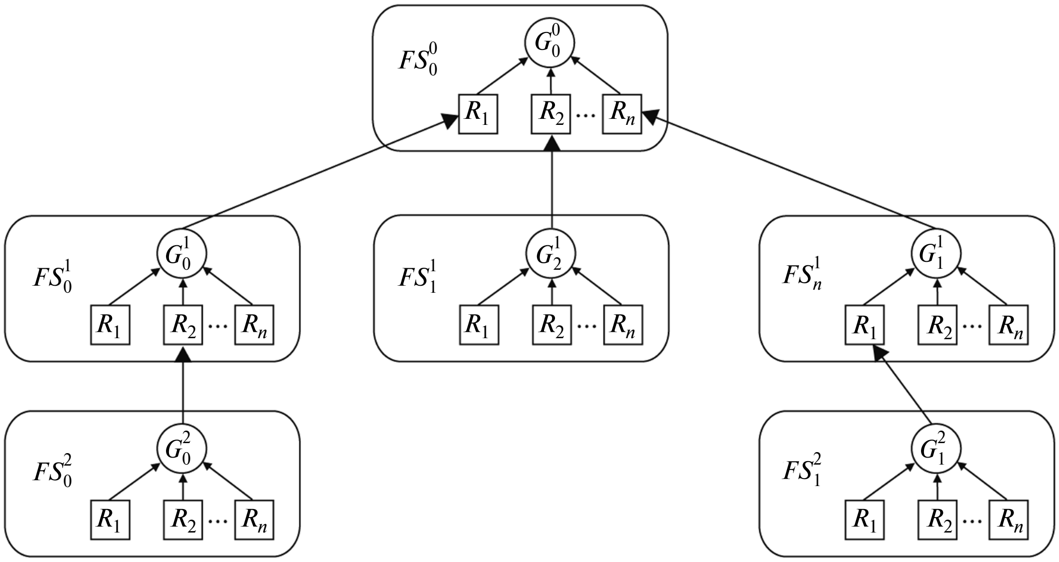

Fig. 1. Hierarchy of functional systems.

Let us divide the intervals of readings of each sensor VS_i into smaller intervals (vs_{i1}, ..., v_{ik_i}). Then vector $ST = (vs_1, ..., vs_n)$ can represent a set of states $V = (v_1, ..., v_n)$ such that $v_1 \in vs_1$, ..., $vn \in vs_n$.

The objective of the agent is to achieve a certain goal. Let us define the purpose through the vector of intervals of readings of sensors:

$$G = (vs_1, ..., vs_n).$$

The agent achieves the goal by means of functional systems. The functional system FS^{rank} can be represented by the following set:

$$FS^{\text{rank}} = (G^{\text{rank}}, R_1, \dots, R_v, FS_1^{\text{rank}+1}, \dots, FS_d^{\text{rank}+1}),$$

where G^{rank} is the goal the achievement of which is the main task of FS^{rank}; R_1, ..., R_v are rules; $FS_1^{\text{rank}+1}$ are subordinate functional systems that correspond to certain rules from R_1, ..., R_v.

Rule R is a transformation $ST_0 \xrightarrow[\hat{p}]{A(\Delta t)} ST_e$, where ST_0 is the set of initial system states, which is specified by intervals (vs_1^0, ..., v_n^0); ST_e is the set of final states, which is specified by intervals (vs_1^e, ..., v_n^e). If the rule belongs to FS^{rank}, then $ST_e = G^{\text{rank}}$; A is the action of the agent; Δt is the duration of executing this action; $\hat{p}$ is the estimate of the probability with which action A performed with duration Δt takes the system from the initial to the final state.

The estimate of probability $\hat{p}$ of rule R is calculated as follows: if a is a number of cases when the agent in state ST_0 performed some action, and b is a number of cases when action $A(\Delta t)$ transferred the agent from state ST_0 to state ST_e, then $\hat{p} = \frac{b}{a}$. Pair (a, b) will be called the statistics rule.

The functional system FS^{rank} can generate subordinate systems $FS^{\text{rank}+1}$, the task of which is to achieve subgoals included in the initial state of one of the rules of FS^{rank}. An example of hierarchy is shown in Fig. 1.

Estimate w_i^{rank} of the possibility of achieving the goal G^{rank} by transferring the control to the subordinate system $FS_1^{\text{rank}+1}$ is calculated by the fact that goal $G_i^{\text{rank}+1}$ is the initial state of some rule of the superior system $R_i^{\text{rank}} = G^{\text{rank}+1} \xrightarrow[\hat{p}_i]{A(\Delta t)} G^{\text{rank}}$. This means that, when the system $FS_1^{\text{rank}+1}$ reaches its goal $G_i^{\text{rank}+1}$, goal G^{rank} of system FS^{rank} can be achieved with the estimate of the probability $\hat{p}_i$. To calculate w_i, we need to consider both $\hat{p}_i$, and estimate $w_i^{\text{rank}+1}$ of the possibility to achieve goal $G_1^{\text{rank}+1}$ by system $FS_1^{\text{rank}+1}$.

Calculation of $w_i^{\text{rank}+1}$ is carried out by the subordinate system $FS_1^{\text{rank}+1}$. To do this, similar to FS^{rank}, it estimates the possibility of achieving the goal $G_i^{\text{rank}+1}$ for the available ways of achieving the goal (the use of its own rule or transfer of control). Estimate $w_i^{\text{rank}+1}$ is assumed to be the maximum of the estimates of these ways. Calculation is carried out recursively. Recursion ends on the functional systems of the lowest level, which have no subordinate systems, so they must

Results of experiments in a physical environment

Type of control system	Time		
	average	minimum	maximum
Randomized system	>10 min	>10 min	>10 min
With original way of estimation (Demin and Vityaev, 2006; Demin and Vityaev, 2008)	6 min	4 min 40 s	>10 min
With alternative estimation method proposed above	3 min 40 s	3 min 10 s	5 min

either select the rule and return its estimate or return nil, indicating thereby that they do not have a suitable rule. After calculating $w_i^{\text{rank}+1}$ and $\hat{p}_i$, estimate w_i is calculated as $w_i^{\text{rank}} = \gamma\min(\hat{p}_i, w_i^{\text{rank}+1})$, where γ is the given discount rate lying in the range from 0 to 1. The rate γ is required to be such that a shorter plan with the same probability estimate had the advantage: the quicker the goal is achieved, the better. A typical value of γ from computer experiments was 0.95.

As explained above, calculation of the estimate w^0 can involve various functional systems of different levels of hierarchy transferring control to each other. Each estimate w^0 of achieving the goal G^0 by the upper hierarchy level system FS^0 is associated, in addition, with a certain sequence of subordinate to each other functional systems FS^0, FS^1, ..., FS^k and a sequence of rules R^0, R^1, ..., R^k selected in these functional systems to achieve their goals. The decision is made by selecting such a sequence of functional systems calling each other and corresponding rules that has the highest estimate w^0. Thus, system FS^0 selects one of many sequences of rules R^0, R^1, ..., R^k, which are then executed in the order from k to 0 by the corresponding functional systems.

If in order to achieve its goal, some functional system used rule R and the goal of this functional system was achieved. This rule is reinforced and its statistics is supplemented with positive experience; otherwise, the rule is penalized and its statistics is supplemented with negative experience. If some goal of the functional system is not reached, then the whole system of the called functional systems is rebuilt.

Formation of Functional Systems

The creation of a separate functional system and its rules, as well as the allocation of subgoals and the creation of the hierarchy, is implemented through the mechanism of the formation of functional systems.

A functional system FS^{rank} is created in three stages:

1. Allocation of goal G^{rank};

2. Construction of rules R_1, ..., R_n to achieve G^{rank}.

3. Allocation of subgoals $G^{\text{rank}+1}$ and formation of subordinate systems $F^{\text{rank}+1}$.

This process continues until reaching a predetermined subordination level $\text{rank}_{\max}$ or until the allocation of subgoals will become impossible. Goal G^0 of the upper level functional system is defined from the outside. Goals G^{rank} for rank > 0 are allocated through the mechanism of generation of subgoals. This process is restarted from time to time to update the control system structure.

The allocation of subgoals and construction of rules are carried out using statistical hypercubes. For a certain set of states ST_e and action A, statistical cube GS^{A, ST_e} is a multidimensional table of dimension $n + 1$. The first n of its measurements correspond to each of n sensors of the agent. The number of intervals for each of these dimensions equals to the number of partitions of the interval of the corresponding sensor readings. The number of these partitions is set from the outside. Dimension $n + 1$ is used to indicate the duration of the action. The number of cells of this dimension is equal to the maximum possible duration of action $\Delta t_{\max}$.

Each cell of hypercube GS^{A, ST_e} corresponds to a specific vector of intervals of readings of sensors ST – $(vx_1, ..., vs_n)$ and a certain execution time of action Δt. The cell contains statistics (b, a) for rule $R = ST \xrightarrow[\hat{p}]{A(\Delta t)} ST_e$. The cells are filled based on the history of events.

Event $E = (V_0, V_e, A, \Delta t)$ is an isolated fact of the transition of the system from the state of sensor readings V_0 into the state of readings V_e when performing action A of time Δt. The agent logs the events and adds them to the history, a time-ordered list of events. When considering event E in the statistical hypercube cell $GS^{A, G}$, which corresponds to readings V_0 and action duration Δt, positive statistics are added if $V_e \in G$; otherwise, negative statistics are added.

Let us consider the process of allocation of subgoals for system FS^{rank}. For each rule R_i of system FS^{rank}, we analyze its initial condition ST_0. If ST_0 satisfies the following criteria of the subgoal formation, a subordinate functional system $FS^{\text{rank}+1}$, the target state of which is ST_0, is created for system FS^{rank}. The criterion for subgoal formation consists of the presence of such a cell

(b, a) in the statistics of hypercube $GS^{A,\,ST_0}$ for one of actions A of the agent that:

$$\frac{b}{a} > x \wedge a > y,$$

where x is the threshold value of the probability estimate, and y is the minimum number of observed events. In the course of different experiments, the following values were chosen: $x = 0.4$, $y = 5$. These values depend on the process of learning and its duration. These values were selected based on computer experiments.

To build rules of system FS^{rank} with goal G^{rank}, we use statistical hypercubes $GS^{A_i,\,G^{\text{rank}}}$ for each available action A_i of the agent. The rule formation is as follows:

1. For each action A_i we fix an interval of readings of sensors ST, which corresponds to some cell $GS^{A_i,\,G^{\text{rank}}}$, and for all the possible durations of action A_i we calculate the probability estimates $p = \frac{b}{a}$, using the statistics. Then we select such an action A and its duration Δt such that the probability estimate value was the largest. Thus, for all intervals of readings of sensors ST we formulate rules of the form $R = ST \xrightarrow[\hat{p}]{A(\Delta t)} G^{\text{rank}}$.

2. Sensor readings intervals for which there is no or an insufficient amount of collected statistics are generalized. The hypothesis that a small change in sensor readings has little effect on the result of the action is proposed. The generalization is carried out as follows: the goal achievement statistics are extracted from the neighboring cells and summarized; then, based on the resulting values, the estimate of the probability of the generalized rule $R = ST_0 \xrightarrow[\hat{p}_i]{A(\Delta t)} G^{\text{rank}}$ is calculated, where ST_0 is a vector of the combined intervals of sensor readings, which corresponds to the considered cells.

3. The resulting rules are generalized with the semantic probabilistic inference algorithm described in the work of Demin and Vityaev (2008). The algorithm makes it possible to get rid of insignificant sensors and thus improve the quality of rules.

EXPERIMENTS

Experiments in virtual and real environments were implemented to test the efficiency of the proposed control system.

The virtual world (Fig. 2) was a limited area with randomly located "food." The main purpose of the agent was to "eat" it. The "food" and the agent were represented by circles with a fixed radius. The "food" was considered "eaten" if the circle of the agent at the end of any of its actions was crossing the circle of "food."

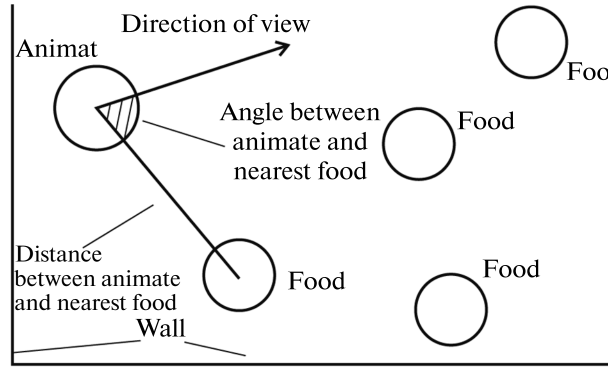

Fig. 2. Experiment in virtual environment.

The agent had two continuous sensors: the first reported on the distance to the nearest "edible" object and the second estimated the angle between the line of sight of the agent and this object.

The agent could perform three actions: move in the direction of view and turn to the left or right. Turns and forward motion were executed at a predetermined speed. The execution time was regulated by the control system under the proposed model.

At the beginning of the experiment, the agent knew nothing about the destination of its sensors or the possible outcome of actions. By trial and error, the agent learned to effectively collect "food." Implementation of the proposed model of the control system within 50–100 actions contributed to generation of an ideal behavior: as the first action, the agent turned to the closest object, and the agent then approached this object and "ate" it within the second action.

We invented a simple but significant experiment to demonstrate the ability of the control system to operate in the physical environment. The purpose of the agent in this experiment was also to collect "food."

A room contained bricks that represented "food." In the same room, we placed the robotic platform controlled by our proposed system. The goal of the control system was to collect "food." The example of allocation of bricks and the platform is shown in Fig. 3.

The robotic platform had a number of sensors that provided the control system with partial information about the location of bricks (Fig. 3). When a brick lying within the sight of the robot was close enough, a special sensor triggered and the brick was considered as been "collected." The control systems had three available actions: turn right, turn left, and move forward. Actions were carried out at a fixed speed. Execution times were regulated by the control system.

At the beginning of each experiment, the control system knew nothing about the arrangement of the bricks or the purpose of the sensors or the possible outcome of its actions. In the experiment the system had to learn on its own to detect bricks effectively.

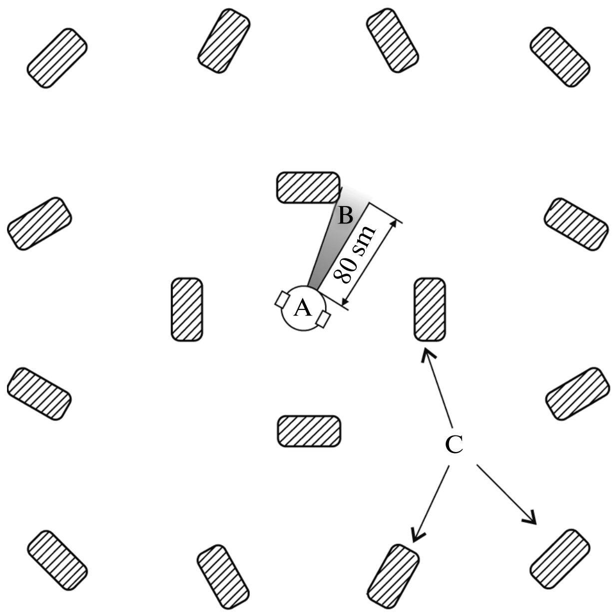

Fig. 3. Scheme of experiment in physical environment.
A, robotic platform; B, visual field of the platform. Sensors allow the robot to "see" within 80 cm. A brick is considered to be eaten if it appears in the visual field closer than 10 cm to the robot; C, "food" bricks.

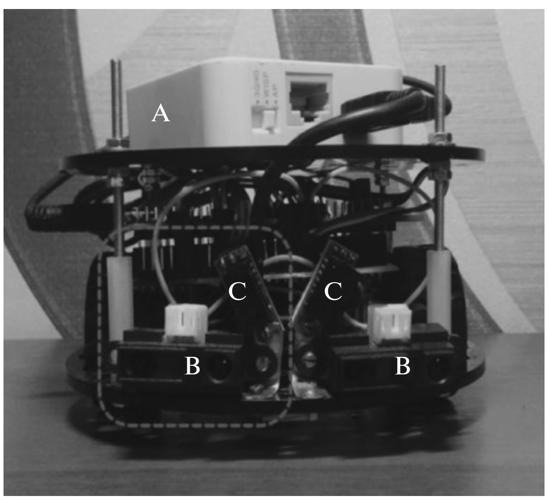

Fig. 4. Robotic platform.
A, Wi-Fi module; B, infrared proximity sensors; C, binary proximity sensors.

The experiment was carried out in two stages: learning and control. At the stage of learning, the agent for a fixed time was exploring the environment, its sensors, the actions, and their results. During the learning stage, the bricks and the agent were arranged arbitrarily. After "collecting" the brick, the robot was automatically rolling back at a distance unknown to the control system and turning by some random angle. The distance at which the robot rolled away was increasing during the learning process.

At the control stage, the bricks and the learned agent were arranged in a way shown in Fig. 3. When the robot was "collecting" the brick, the experiment was suspended to remove the brick from the field. Control was considered complete when the robot collected all the bricks or if it could not complete the collection within ten minutes. The efficiency of the behavior of the agent was estimated by the time spent on the collection of bricks.

Robotic Platform

Based on the circuit STM32VLDISCOVERY, we developed for the experiment a special, two-wheeled robotic platform equipped with two sets of sensors and a Wi-Fi module for wireless communication with the control system running on a PC.

Two sensor types for orientation in space were used. The first of those was an infrared-range finder capable of measuring the distance to the object in the range from 10 to 80 cm. The second type was a binary sensor responsive to the approach to the object closer than 10 cm. Two sensors of each type were used. The sensors were fixed so as to provide the robot with the field of view shown in Fig. 3. Sensors of different types were mounted one above the other and grouped in pairs. The appearance of the platform is shown in Fig. 4.

Results of the Experiment in the Physical Environment

During the experiments, the control system was supplemented with an alternative method of estimating the possibility of achieving the goal when transferring the control to the subordinate functional system.

In previous works (Demin and Vityaev, 2006; Demin and Vityaev, 2008), the possibility of achieving the goal G^{rank} by system FS^{rank} by transferring the control to the subordinate system $FS_1^{\mathrm{rank}+1}$ was estimated as follows: let $w_i^{\mathrm{rank}+1}$ is the estimate of the possibility to achieve goal $G_i^{\mathrm{rank}+1}$ by the subordinate functional system $FS_1^{\mathrm{rank}+1}$; $\hat{p}$ is the estimate of the probability of rule R^{rank} of system FS^{rank}, the condition of which is the goal of system $FS_1^{\mathrm{rank}+1}$; then the final estimate of the possibility of reaching the goal when transferring the control to system $FS_1^{\mathrm{rank}+1}$ was calculated as $w_i = w_i^{\mathrm{rank}+1}\hat{p}$. The product of several probabilities was small. This method of estimation proved to be ineffective in the physical environment. Because of the noise in the sensors, false positives, and robot design flaws, the upper level control system generated ineffective rules. For example, the proximity sensor could respond without response of the range finder, and the following rule was reinforced: move forward with a weak range-finder signal. Although it was very rare, the

Fig. 5. The robot during the experiment.

estimate of such a rule was often greater than the recursive estimate of the possibility of achieving the goal when transferring the control to the subordinate system with more effective rules. The control system for a long time could use such a rule before its estimate was lowered to the level of preference for subordinate systems. This seriously slowed the learning process.

In this paper we introduced an alternative estimation method. The final estimate is calculated as $w_i^{\mathrm{rank}} = \gamma \min(p_j,\ w_i^{\mathrm{rank}+1})$, where γ is the given discount rate in the range from 0 to 1. This method allows the control system to use subordinate systems with a good estimate of achieving the goal instead of the rules of systems of the upper hierarchy level with bad estimates. The discount rate allows preference of good upper-level rules to the transfer of control to subordinate systems.

The experiments were carried out for different versions of the control system: a randomized control system that selects random actions and their duration; a control system that uses an original means of estimating the possibility of goal achievement (Demin and Vityaev, 2006; Demin and Vityaev, 2008), and a control system with the alternative estimation method given above. For each system, a series of ten experiments was carried out. Before each series of experiments, the agent received a special learning period limited to 30 minutes. The duration of the control stage of the experiment was limited to ten minutes. The efficiency of the agent was estimated by the time spent on collecting all the bricks of "food." The results were summarized in the table; the robot during the experiment is depicted in Fig. 5.

The table shows that the control system is able to effectively collect the bricks; in addition, the introduction of a new method of forecasting improves its performance.

CONCLUSION

The mobile-agent control system based on functional systems theory was adapted for operation in a physical environment. The system was supplemented with the ability to use real and continuous signals from sensors, as well as the opportunity to consider and vary the action execution time. A new method for predicting goal achievement was introduced; it improves operation in the physical environment.

The control system was tested in a virtual experiment and an experiment in the physical environment. A robotic platform was developed for the experiment in the physical environment. The system showed good results in both experiments. During the experiments with the robot, we detected and corrected some shortcomings of the algorithm and demonstrated its ability to solve problems in a physical environment.

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