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Adaptive behavior of autonomous mobile systems with new action selection problem solution

by

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Abstract: The article deals with the issue of controlling the autonomous mobile systems. Considered are the problems focusing around the use of controllers with distributed architecture. Contrary to hierarchical architecture, all layers of distributed controller are operating simultaneously, and have an access to both the receptors and to the effectors of the controlled autonomous mobile system. Simultaneous operation of all layers of the distributed architecture controller entails the emergence of the action selection problem. This problem consists in continuous taking decisions: which one of the layers, or which layers of the controller, should have an influence at given moment on the movement of the controlled mobile system. A proposal for a new solution of this problem is discussed. The results of experiments with the use of real mobile robot are presented.

Keywords: autonomous systems, mobile robots, distributed architecture, action selection problem.

1. Introduction

Mobile robots are mobile autonomous systems. However, every mechatronic system moving in space in controlled manner and equipped with its own source of energy supply, with on board computer (or other equipment that can process data), effectors (e.g. motors of the mobile base and the manipulator) as well as sensors of the state of environment and internal state (receptors), can be called autonomous. The definition of autonomous system can also be extended into the domain of virtual reality and simulation. The mobile system can be autonomous to different extent. The range of autonomy levels ranges from the direct control by man (in this case the mobile system is not autonomous), up to the full autonomy, when human being can only be an observer of the autonomous system actions. The level of autonomy can be variable for a given system, e.g. may depend upon the current mode of operation.

1.1. Typical structures of the controllers of autonomous mobile systems

Hierarchical architecture

The hierarchical architecture is a classical way of structuring of complex control systems. Its basic distinguishing feature is the division of the controller into hierarchical arrangement of layers. Occurring here is an ascending and descending signal propagation. The ascending propagation is leading from the sensors (which supply an information on the environment) through the layer processing this information, up to the top - the most general decisions making - controlling layer. The descending propagation leads from the top layer to the bottom-most layers, and finally to the effectors.

The advantage of the hierarchical structure is in its modular construction (although these modules are depending on each other - they have to be compatible with each other in respect of input and output signals), clear cut structure (easily described cooperation of layers, exact division of tasks). The disadvantages of such structures are: long time of response to the rapid changes of the environment's state (reaction takes place only after the signals pass from the sensors to the topmost layer and vice versa, to the motors of robot; the robot is working in the cycle: testing of environment => processing of information => action), as well as limited flexibility and adaptability.

In order to compensate for the above mentioned disadvantages, various improvements are introduced to the hierarchical structure. In most cases they consist in the adding of additional, independent module used for quick responding and avoiding of obstacles, having its own access to the sensors and motors, or the controller is supplemented with the model of mobile robot environment (this however, requires the knowledge of environment in which robot has to move), Vandrope and Van Brussel (1994).

Distributed architecture

Other solutions are represented by the group of controllers with the architectures similar to biological prototypes. They are generally known as distributed controllers. It was noticed that the lower grade organisms (e.g. insects) are characterized by high efficiency of processing of information from receptors towards proper behaviors or reflexes, Zielińska (1997). The hierarchical arrangement of control layers acting on different levels of generality does not exist there. Usually, all layers have simultaneous access to both the receptors and effectors of the autonomous mobile system (e.g. robot for finding the mines: Fig. 1):

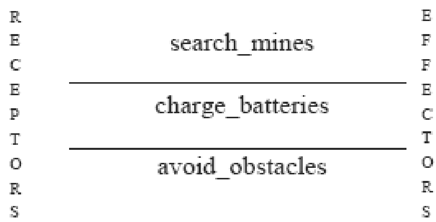


Figure 1. Example of a distributed architecture controller.

In the case of a distributed architecture, the crucial problem is the appropriate organization of cooperation of individual parallel layers. It is the so called "action selection problem". There are various solutions. For example, each layer is acting only then, when it is stimulated to such action by properly filtered data from sensors. The layer is generating control signals only then, when it is necessary, Szynkarczyk (1997). Another solution is to establish constant priorities attributed to individual layers. Also known widely solution of distributed architecture are subsumption architecture, Brooks (1991) and Braintenberg vehicles, Braintenberg (1984). All those solutions do not have adaptation abilities - their structures are constant.

1.2. Embodied artificial intelligence

In an opposition to symbolic representation and processing of knowledge bases in the classical artificial intelligence (AI), a new trend of research on the so called embodied artificial intelligence (Embodied AI, or New AI) came into being. This trend includes, among other things, the research on real autonomous mobile systems of the structure based on sensory-motoric reactions, testing of reactive systems and behavioral systems. The main distinguishing feature of this trend is the belief of the researchers that the classical solutions of artificial intelligence do not turn out to be useful in the controlling of real objects in real world. The claim is (e.g. Pfeifer, Scheier (2000)), that the classical approach to the problem is using the simplified models of world in which artificial agents are operating, or that their interaction with the environment is effected through the agency of man (e.g. in the classical expert systems). Instead of this, proposal is made to understand the phenomenon of intelligence on the way of testing the behavior of real autonomous mobile systems (e.g. mobile robots). Intelligent behavior is not understood here as a result of complex internal structure of controlling systems, but it is regarded as a result of its interaction with the environment. In the embodied artificial intelligence, the distinct shift of attention from making the internal structure of control systems more complex to the improvement of their interaction with environment, takes place.

The example of research within the trend of embodied artificial intelligence can be the so called situated embodied agents. The behavior of such systems is not based on any complex internal representation of the state of environment, models of this environment nor the actions of symbolic nature (e.g. as in expert systems). The main role in the operation of such systems are conditions and connections of sensory-motoric type, however, these are not only the reactive systems. The systems have a real body of specific design, they act in real world. The systems are situated adaptively, they have a certain history. Under identical situations (understood as the states of environment only) they do not have to behave always in the same way. Their behavior depends on their history and their internal states. The architecture of this type is proposed in this work. Synthetic comparison of classical, artificial intelligence and so called embodied artificial intelligence is shown in Table 1.

Table 1. Synthetic comparison of classical artificial intelligence (Classical AI) and embodied artificial intelligence (Embodied AI)

Classical AI	<= ***Features*** =>	**Embodied AI**
computer programs	*Tool of research*	real robots
simulated	*Operating environment*	real world
structure of complex systems using the symbols according to the rules of logic, having data bases of knowledge	*Center of gravity of research*	concentration of research on the interaction of real object with real environment
Complex internal structure of system	*Recipe for intelligence*	simple structure of internal system, the intelligence will result from interaction with the real complex world
resolving of problems, expertise	*Main task of created systems*	survival of mobile robot in the complex real world

The classical artificial intelligence turns out to be useless (in the opinion of supporters of the embodied artificial intelligence) in control of real objects (e.g. mobile robots), since real world is very complex, and in this case it is impossible - like e.g. in the chess game - to define in advance the rules of game and make an analysis of all possible moves. The real world is extremely complex and variable, and the sensors probing its state have limited accuracy.

The trend of embodied artificial intelligence has appeared in the association with the research on animal behavior. The widely known example is the defensive behavior of night butterflies, McFarland and Bösser (1993). Night butterflies (moths) are the hunted objects for bats. In order to survive, the moths have had to develop an appropriate defensive mechanism. They have a kind of two "ears" sensitive to the ultrasounds emitted by bats. They are located under the wings of insect and have links with the nerve cells controlling their movement. In the "ears" there are two kinds of cells - receptors. The first ones, called cells A1, are sensitive to the sounds emitted by bats present already at the distance of about 30m. This distance is too far to detect the presence of prey by bats. On the basis of the fact that the received sound is disturbed by the movement of insect's own wings, it is possible to determine the relative altitude of attacker. The nerve signals from receptors type A1 are emitted with the frequency that is in proportion to the intensity of received ultrasounds - therefore the moth can be aware whether the bat is approaching or flies away. The potential prey takes a position in which intensity of signals from the left and right "ears" is the same, and proceeds in the direction leading away from attacker (this direction is established on the basis of gradient change of the signals from cells A1). In result of the above, it takes a position with its back facing bat, and so becomes a very small area reflecting the signals of the approaching predator. Would it expose its side, then the area of wings would be reflecting quite substantial amount of signal, which would increase the probability of detection. Should this strategy fail to bring an effect, then the receptors of the second kind, known as cells A2 are coming into action. These cell are reacting to ultrasounds from the distance of 2-3m only. The closer is bat, the more intensive becomes their action, which consists in the disturbance of mechanisms controlling the movement of wings. In the last moment, when the attacker is very close, it leads to complete paralyzing of wings, and the moth is falling down inert. It is a sudden maneuver, frequently leading to the escape from the bat.

This is an example of distributed architecture - the two separate tracks of information processing, that is - the left side and the right side cooperating with other layers, e.g. with the mechanism of the wings' movement. It is also an example of "intelligent design" - it consists in the fact, that the whole mechanism is effective, which in result brings complex behavior, and on the other hand it is very simple. It is not claimed hereby that this is a certain form of intelligence, but only that the performing of such maneuvers by control with the use of conventional methods would have required the use of considerably larger number of calculations (e.g. speed and direction of bat's flight, control of wings, etc.), and would require higher consumption of energy.

This example illustrates also the proposition, that the controlling system can not be separated from the controlled object - both these components are harmonized with each other, e.g. placement of "ears" of night butterfly under its wings enables the determination of the relative altitude of a bat. It is one of the arguments used by supporters of the embodied artificial intelligence versus the classical approach to the problem. The example that is frequently quoted in this discussion are expert systems, which are completely devoid of the "body", and their contact with environment is effected through the agency of man.

2. Behavior of autonomous mobile systems

The behaviors of autonomous mobile system may assume many different forms. In particular, as far as the application of distributed architecture controllers is concerned, among many features they may show, the most essential seem to be: coherence of behavior, rational behavior, adaptation abilities. Further considerations in this paper are focusing around the analyses and methods ensuring preservation of these features. Quoted hereunder are the selected, and adopted in further considerations, definitions describing these features.

Coherence of behavior: in case of conflict between the execution of decisions made by some layers of controller, the autonomous mobile system shall not behave in an "undecided manner", i.e. it shall not try to execute different goals, depending on insignificantly varying states of environment.

Rational behavior: in every situation the decision on the behavior of autonomous mobile system shall be undertaken with all knowledge contained in controller taken into consideration, and with all goals taken into consideration. In other words: in the case when the autonomous mobile system is in the situation when transferring of control of its effectors to one of its layers will result in achieving of one of the autonomous mobile system goals, then such transfer of control shall take place.

Another definition is given in McFarland and Bösser (1993). According to it, rational behavior consists in the meeting of following requirements:

Compatibility: the autonomous mobile system, due to irrational control shall not try to execute simultaneously two mutually contradicting actions, e.g. the mobile robot can not try simultaneously to travel forward and backward.

Common currency: in the case of the occurrence of conflict between different layers of controller, i.e. when they are trying to execute conflicting actions (which leads to the loss of compatibility), then in order to provide rational selection, there must exist a certain "common currency" for all layers, defining how the execution of given action is important at a given time.

Consistency: the problem of rationality of given autonomous system can also be expressed in the following way: when being twice in the same situation (understood as a state of environment and the internal state of the controller) the autonomous mobile system takes each time a different action, then it can not be regarded as rational.

Transitivity: the action selection is effected on the basis of the currency common for all layers. In the case when the selected action is A, regarded as more important than B (that is: $A > B$), and action B is recognized as more important than C (that is: $B > C$), then in the case of selection between A and C, action A must be selected (that is: $A > B > C$ must take place).

In the further part of the McFarland and Bösser (1993) one can also find the statement that coherent behavior is the necessary condition for the occurrence of rational behavior.

In this article, an analysis was made with the use of both rationality definitions, since they are not contradictory, they are rather mutually complementary.

While studying the behaviors of autonomous mobile systems, the limitations on maintaining of rational behavior should be kept in mind. The limitations are due to:

- limited possibility of data processing (e.g. limited volume of memory, limited speed of computer processing unit, etc.),
- limited possibility of obtaining the data on the state of environment resulting from the finite number of receptors (e.g. distance sensors) with finite accuracies, ranges, etc.,
- limited knowledge about the proper rules of action in a given situation (anticipation of the consequences of one's actions on the basis of finite knowledge base),
- limited possibilities of the execution of control commands - control with zero error is not possible.

In connection with the above it is possible to obtain only "bounded rationality", Simon (1987). The autonomous mobile system can act in a rational way only within the range of certain limitations. From the point of view of an external observer (not bound by all or part of these limitations) the loss of actions' rationality can take place, Russell (1991).

Adaptive behavior: in the case of actions in the unknown and dynamic environment, the autonomous mobile system shall reveal adaptation abilities if it is in a position to change its behavior by adapting itself to the variable states of environment. The additional manifestation of adaptation could be also quicker reactions of the controller to the repeated states of environment.

In the case of the class of controllers discussed in this paper, subject to adaptation can be the control layers, or the manner their cooperation is organized, i.e. the action selection method.

3. Adaptive, distributed controller - a new solution to the action selection problem

3.1. Preliminary assumptions

The distributed architecture controller consists of a set of simultaneously acting layers, jointly controlling the behavior of the mobile autonomous system. The flow of information from different kinds of receptors testing the state of environment as well as the internal state of controller to the effectors takes place simultaneously in each of its layers. The main problem in the proper functioning of distributed controllers is the action selection problem. This problem consists in the continuous taking of the decisions on the questions: the execution of which goal is at given moment the most important, or which layers of the controller have to control jointly the autonomous system. The proposed method[1]

[1]Research performed within the framework of KBN grant No 8T11 A032 14, Piotr Szynkarczyk

of the dynamic assignment of priorities, as well as the use of the elements of artificial neural network unsupervised learning techniques are used to resolve this problem, as shown on the basis of experiments, whose results are quoted in the following part of the article. The method discussed here ensures obtaining of such features of mobile autonomous system behaviors like: coherence, rationality and adaptation.

The general concept of the structure of a new adaptive distributed controller is based on the following assumptions:

1. The controller is distributed, meaning the simultaneous (parallel) operation of all of its layers. In experiments quoted hereunder, such action of the layers is, however, simulated by the computer with serial processing, due to the limitations of available hardware.
2. The data from receptors are initially processed in the modules of preliminary data processing (called as "WPD modules" from now on), which are a kind of task dedicated filters.
3. The data from receptors after their preliminary processing by WPD modules, are then used by the individual layers of the controller in order to generate the appropriate control actions, and also by "decision neurons" used in the process of action selection.
4. The WPD modules are collecting the information on both the state of environment and the internal state of the autonomous system.
5. The element deciding as to the way in which the effectors of the controlled autonomous system shall be made available to the layers of the controller, is called "decision mechanism" (with the structure discussed later in this article). This mechanism enables obtaining of adaptive, rational and coherent behavior.
6. The actions taken by autonomous system are causing changes of the state of environment, making up a kind of feedback loop for the controller, and being thereby the track for the transfer of information between its layers.
7. In certain cases, the WPD modules can exert an influence on each other, e.g. suppression.
8. At every chosen moment it is possible to define the internal state of autonomous system and the state of its environment, as well as the states the individual layers are aiming at. Thanks to the above, it is possible to define the metric describing the distance between the current and desirable states. It is not required that the spaces of states be discrete (they can be continuous). There are no limitations or simplifying assumptions on the sizes and dimensionality of the spaces of states.

These assumptions shall be explained and developed in the following parts of the article. Some of these assumptions are conclusions from the observations of nature, which became the premises for the research on the proposed structure of the controller of autonomous systems.

3.2. Observations of nature as the premises for construction of adaptive distributed controller

Distributed architecture

Separation of control of individual elementary behaviors into separate, isolated layers comes from observation in nature. It was proven that a frog is jumping towards a detected insect using two separate reflexes. One of them allows for making the jump of adequate length, and the second is controlling its direction. The experiments described in Ingram (1996) show that the frog with the damaged part of brain, identified as being responsible for the direction of jump, when hunting, is jumping straight ahead regardless of the fact, at what angle it may see the insect, but it jumps by proper distance. In Ingram (1996) described also tests of behavior of humans with brain damages. In one of the cases, two patient women had problems with the distinguishing and taking objects from the shelf in a shop. However, their problems were completely different. One of them was unable to indicate any difference in the shape of the observed objects. However, she was in a position to grab correctly each of them, so that they were not falling out of her hand. This would have been not possible, should she be unable to match her grip properly to the shape of objects. The second patient was able to describe in a faultless way each of the objects, however she had a serious problem how to grab them properly - in result these objects were falling out of her hands. The complex actions consist, then, of the set of simple and independent behaviors. The parts of the brain that control these behaviors may even not communicate internally with each other. Both of the above cases allow to suppose that the biological control systems, so far the most effective out of those known, have the structure of distributed nature, similarly like the solution suggested in the article.

The role of preliminary data processing

The data processing in the WPD modules is effected in order to carry out strong and specialized reduction of information. Each of the layers, in order to execute the elementary task assigned to it, needs the set of data on the state of environment as well as the internal state of the controlled object. Each of the layers requires synthetic description of the situation of autonomous system as seen from different points of view. Here we have an incidence of analogy to biological systems, in which the sensor information is subjected to strong filtration, Tadeusiewicz (1989). For example, the eyes of a frog are equipped with the movement filters, so that frogs can see small and mobile objects only, Dröscher (1996). Such a simple solution allows for easy distinction of the dead and motionless insects from the living, hence mobile insects. En route of evolution the insects have developed the defensive reflex consisting in lying motionless, defending themselves in this way, since they are invisible to frogs.

Another natural example of filters superimposed on the signals from receptors can be the case of a sleeping squirrel. When the wind is moving the branches, it rains, or other noises arise - squirrel is sleeping firmly. If, however a marten is climbing up the tree trunk, causing the sounds that are more delicate than the rain - the animal reacts immediately, Dröscher (1996).

The same receptors are used for different purposes. In the case of frog the same eyes, which are used for hunting insects, are allowing for the distinguishing the day from the night, seeking partners, avoiding of dangers. Similarly, the WPD modules enable the multiple use of the same sensors by different layers of the controller. Each layer of the controller is receiving an information on the state of environment that is essential only for the correct execution of the task assigned to it.

Phenomenon of adaptation

Under established conditions individual reflexes (or behaviors) are initially ranked according to certain importance. The priorities are making up a certain prototype of typical behaviors, e.g. it is more important to escape from a predator than to have a rest after meal. However, such ranking is changing along the changes within the state of environment - this is the adaptation.

The phenomenon of adaptation to the conditions prevailing in the environment can be manifested by the behavior consisting in a certain kind of "concentration of attention". Such situation can take place, for example, when in the environment of a given living organism there appears a large quantity of food (at a time when it is hungry - it is an internal state of organism, that can be compared to the case of discharged batteries supplying mobile robot with energy). Then it "pays more attention" to reaching food - the reflex of seeking food and reaching it becomes dominant. However, when predators appear in the environment, the reflexes of hiding and escape are activated and begin to be dominant. When comparing two living organisms of different history - the first one, from the environment in which there was large number of predators, and the second, from the environment in which there was a large quantity of food, but no predators at all - then probably in the presence of food the first organism shall be more "careful", that is, it shall react more quickly to the appearance of predators. On the other hand, the second one shall be "more concentrated" on food. This is the manifestation of adaptation - each of these organisms has adapted itself to the conditions of its environment. This phenomenon was found during research on behavior of fish, Jachner (1995). Documented was the dependence of behaviors on the history of given specimens: it was proven that given fish specimens from the species of bleak, coming from the population exposed to the pressure of pikes, are reacting in a stronger way to the presence of an alarm substance than those that have never encountered it. Fish synthesizes the chemical alarm substance, being released to the water environment only in the case of its injury. For other fish it is a warning signal of danger.

It was noticed that in the case of living organisms, the intensity of stimulus has great significance for the promptness of reaction to it. Often the more intensive it is, the quicker the reflex (or behavior) stimulated by it is activated. The dependence of behavior on the intensity of stimuli was described in Dröscher (1996) on the example of birds. Observations were concerning behavior of vultures when eating the carrion. Their group is usually divided into three categories: actually eating, standing directly close to food, but being not admitted to it, and the third category: distant observers. As it turns out, between these groups there occurs incessant rotation, the birds are promoted in turn in the direction of the eating group. The mechanism of this phenomenon is explained as follows Dröscher (1996): in result of waiting the sensation of hunger is increasing among the birds, and at the same time the tendency to attacking. In particular the birds waiting close to food are intensely stimulated by the proximity of this food. At the same time the already eating individuals have satisfied initial hunger and so their tendency to fight is decreasing. From this follows an interesting dependence: in a brawl the winning are not the strongest birds, but those that are currently the most hungry and close to food. Similar example can be found in Jachner (1995), where fish behavior is described. It was found that the delay of reaction in relation to the detection of the signal presence depends on the concentration of alarm substance. At low concentrations this reaction time grows longer.

3.3. Detailed assumptions of the architecture of adaptive distributed controller

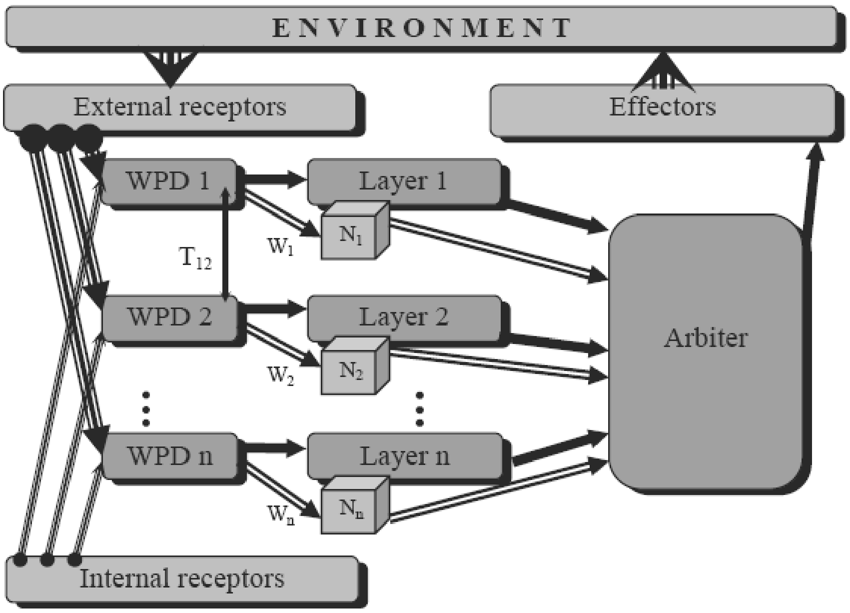
The assumptions and observations quoted above, concerning the character of nature, enable to determine the principles of the structure of the here proposed decision mechanism for action selection in distributed controller. Operation of decision mechanism is the result of cooperation of WPD modules, decision neurons and an arbiter.

The layers executing more complex tasks have generally lower priorities. It is suggested to call this phenomenon "inversion of priorities". Manifestations of this phenomenon can be also observed in the actions of human minds. Usually when somebody gets hungry, or when something is worrying him, he is not in a position to think in a creative and abstractive way. This is a manifestation of existing gradation of the importance of reflexes (or behaviors) in living organisms. The most important is satisfaction of the basic needs (e.g. safety, food). Only then, when they are satisfied - active become the remaining reflexes (or behaviors), e.g. satisfaction of curiosity.

The individual layers of the controller in the proposed solution are by no means internally coupled with each other. The intelligent behavior is not written inside the controller in the form of procedures anticipating all possible situations, but is arising out of it by interaction of actions with the complex external real world. The results of an action, that is, the change of the state of environment and in consequence the change of the internal state of the controller, make up the only information channel between the layers of controller.

It is all different with the WPD modules. The rational behavior of the autonomous system can be initially ensured by the introduction of mutual suppression of the WPD modules. The reason for introduction of such mechanism is the existence of specific circumstances, in which actions of some layers (hence the execution of some actions) are completely needless or illogical. Example: searching for items when container of the robot collecting them is full.

The WPD modules, decision neurons and arbiter are jointly making up the decision mechanism (Fig. 2).



W_n - weights of decision neurons,
T_{nm} - mutual influence of WPD modules with the numbers n and m,
External receptors - receptors collecting data from the autonomous system environment,
Internal receptors - receptors collecting data on internal state of autonomous system,
$\mathrm{WPD}_{1\ldots n}$ - modules of preliminary data processing,
$\mathrm{Layer}_{1\ldots n}$ - layers of controller,
$N_{1\ldots n}$ - decision neurons,
Arbiter - the module making final action selection.

Figure 2. The proposed architecture of the controller

The decision mechanism is to a certain extent behaving like a neural network with the number of decision neurons corresponding to the number of layers in the controller. Each such neuron has one input and one output. The signals at the neuron inputs are the signals coming from WPD modules corresponding to the layers. Signals at neuron outputs are deciding which layer at a given moment shall control the behavior of the autonomous mobile system. The output signals are the result of the product of input signals and the weights corresponding to them. The arbiter selects at a given time instant the control layer with the strongest output signal of the neuron attributed to it. Such signals are from now on called "activations".

Taking decision on the basis of activations calculated in this way is compatible with the "principle of letting through the highest value of behavior tendency" (discoverer of the principle: Nobel prize laureate K. Hartline), Dröscher (1997). This means that, if in the motivation system of any creature (or autonomous system) two contradictory behavior tendencies are aiming at activation, then, contrary to completely nonsensical and inadequate behavior (e.g. continuous hesitation, that is - the loss of coherence), winning is the tendency with the strongest motivation. This principle is ensuring the coherence of behaviors in the autonomous system.

The values of weights are changing incessantly. At a given moment they result mainly from the history of action of the autonomous system, but also to some extent from the current situation. These weights consist of two elements:

1. Constant part - initially attributed to a given layer in accordance with the principle of priority inversion.
2. Adaptive part - result of the incessant process of adaptation of the decision mechanism.

The individual layers of the distributed controller are using - through WPD modules - two different kinds of receptors. These are the state of environment sensors and the autonomous system internal state sensors. The WPD modules make up a certain kind of filters. Their task is strong and specialized reduction of information, so that the control layers could receive synthetic description of the state of environment, or of the internal state. These sensors can be different for each layer, but in some cases different WPD modules can use common sensors.

The WPD modules are preprocessing also the information for the needs of decision mechanism. Also in this case account is made of: state of environment and internal state of autonomous system. Resulting from of such preprocessing are two signals, one of them representing the external situation, and the second representing an the internal situation.

The signal for the needs of the decision mechanism, representing the state of the environment, hereinafter called the **external stimulus**, is the distance between the current state of environment, and the state that is intended (or avoided - depending on the kind of task of a given layer). This calculation is made for each layer separately, since due to the use of different data from different sensors, each of them is defined in another space of environment's states. For the control layer of a mobile robot aiming at some point this can be the distance to this point expressed in meters. In this case the space of states is two-dimensional. The space of external states can have any number of dimensions, and this number results from the number of variables, being the data defining the state of environment. For example this can be the number of sensors used for the determination of the distance from the obstacles around the mobile base of robot. In the process of controlling, other values can be taken into consideration than only those measured in meters. This could be an information expressed in other units, like e.g. seconds, Volts, grams, etc.

When building the metric in a given space, it is necessary to prove that to each ordered pair of points (a, b) in the space, the metric $d(a, b)$ is assigns a real non-negative number, and at the same time meets the conditions:

1. $d(a, c) \leq d(a, b) + d(b, c)$,
2. $d(a, b) = d(b, a)$,
3. $d(a, b) = 0 \Longleftrightarrow a = b$.

The signal representing internal situation, hereinafter called **internal imperative**, is the distance between the current internal state, and the state at which a given control layer (using a given WPD module) is aiming, or is trying to avoid (depending on the kind of the task of a given layer). Similarly as in the case of external stimulus, this calculation is made for each layer separately, since due to the use of different data from different sensors, each of them is functioning within another space of internal states. For the layer, whose the task is to take care of charging the batteries, it shall be the difference between their current state, and the state of full charge. In this case the space of internal states is mono-dimensional.

Similarly as in the case of external stimulus, the space of internal states can have any number of dimensions, and this number results from the number of variables making up the data defining the internal state. Also in the case of calculating of internal imperative, it is necessary to use correctly defined metric.

Finally, when the values of external stimulus (symbol: bz) and internal imperative (symbol: $iwew$) are known, the signal x can be calculated (Fig. 2) making up the representation of the data from receptors processed by the WPD module for the needs of decision neurons. This is described by the general formula (1):

$$x = \frac{iwew}{bz} \tag{1}$$

Signal x makes up the input signal for the decision neuron corresponding to the given WPD module. It is easy to see that this signal grows when $iwew$ rises and bz decreases.

The example of using the above assumptions in practice can be the action of WPD modules for the part of reflexes of travel towards a given goal point in the controller executing exemplary task (described in the following pages). The external stimuli bz are defined as the functions determined by formula (2).

$$bz_n = \sqrt{(x_r - x_c)^2 + (y_r - y_c)^2} \tag{2}$$

where: bz_n - external stimulus for layer n ($n = 1, 2, 3, 8$); x_r, y_r - coordinates of the robot; x_c, y_c - coordinates of the goal point.

The internal imperatives for the part of decision reflexes of travel towards the given goal position are determined with the use of the function described by formula (3). With the increase of parameter i, function value asymptotically increases to $iwew_{nmax}$.

$$iwew_n = iwew_{nmax}(1 - e^{-\beta_n i}) \tag{3}$$

where: $iwew_n$ - internal imperative for layer n ($n = 1, 2, 3, 8$); $iwew_{nmax}$ - maximum value of internal imperative for layer n ($n = 1, 2, 3, 8$); β_n - growth rate of signal for layer n, $\beta_n > 0$, $n = (1, 2, 3, 8)$; i - variable of the character of time from the last presence in given goal position.

The output signals from the WPD modules, being the input signals x for the decision neurons are obtained from (1). Every decision neuron has one input and one output. Each input signal x has corresponding weight w. Their product gives the output signal y, called the activation of decision neuron (or more generally: layer activation). The transition function of the decision neurons is an identity function. At a given moment the arbiter selects as the active one the layer with the highest activation. The process of selecting the dominant layer is repeated as quickly as possible (depending on computer hardware parameters), about twice per second in experiments described in this paper.

The weight of each input signal of decision neuron consists of two parts (formula (4)):

$$w = w_{st} + w_a \tag{4}$$

where: w_{st} - constant part of the connection weight; w_a - adaptive part of the connection weight.

In the experimental part, five methods tested were of decision neuron learning (changes of the values of adaptive parts of the decision neurons weights). These methods are described by the formulas given below.

Hebb's classical method:

$$w_i(k) = w_i(k-1) + \eta x_i(k) y_i(k) \tag{5}$$

where: $w_i(k)$ - new weight obtained in the k-th step of learning; k - learning step number k; i - number of decision neuron; $w_i(k-1)$ - previous weight; η - learning coefficient; x - input signal to decision neuron (signal from the WPD module); y - activation of neuron ($y = x * w$).

Hebb's method with forgetting:

$$w_i(k) = w_i(k-1) + \eta x_i(k) y_i(k) - \gamma w_i(k-1) y_i(k) \tag{6}$$

where: γ - coefficient of forgetting .

"Instar" method:

$$w_i(k) = w_i(k-1) + \eta\,(x_i(k) - w_i(k-1)) \tag{7}$$

"Outstar" method:

$$w_i(k) = w_i(k-1) + \eta\,(y_i(k) - w_i(k-1)) \tag{8}$$

Oja's Method:

$$w_i(k) = w_i(k-1) + \eta\, y_i(k)\,[x_i(k) - w_i(k-1)y_i(k)]\,. \tag{9}$$

3.4. The structure and the operation of an adaptive distributed controller executing an exemplary task

The exemplary task

The details of the proposed solution of the structure and operation of the controller shall be discussed on the basis of practical implementation of an exemplary task. The object of control is the mobile robot Nomad 200. In experiments described some operations that are executed by the robot are partly or fully simulated (for example by a time that given operation takes).

The exemplary task consists in the collection of "objects" from the "storeroom" and successive transporting them "home". At the same time the robot has to avoid collisions with the obstacles and take care for an appropriate state of its batteries. Should the batteries be discharged to a certain level, then robot should arrive at the "battery charging station". The robot, as a complex mechatronic system, should also monitor the degree of wear of its more important mechanical parts. Should this degree of wear become adequately large, then the robot should proceed to the "service station", and when being there it should turn off itself in order to enable its overhaul and replacement of parts. In the discussed research all service operations are simulated.

The controller executing exemplary task consists of nine layers (numbered from 0 up to 8):

0. Behaviors connected with avoiding of collisions with obstacles.
1. Reflex of travel towards "storeroom" (or in other words: towards the "goal").
2. Reflex of travel towards "home".
3. Reflex of travel towards "battery charging station" ("station").
4. Behavior of robot when turns up in "storeroom" - grasping the "object" by manipulator.
5. Behavior of robot when turns up at "home" - putting away the "object" from manipulator.
6. Behavior of robot when turns up in "battery charging station" - charging of batteries.

7. Behavior of robot when turns up in "service station" - turning itself off.
8. Reflex of travel towards "service station".

4. Adaptive distributed controller - results of laboratory experiments

4.1. Experimental stand

The photograph of typical arrangement of an experimental track is shown in Fig. 3.

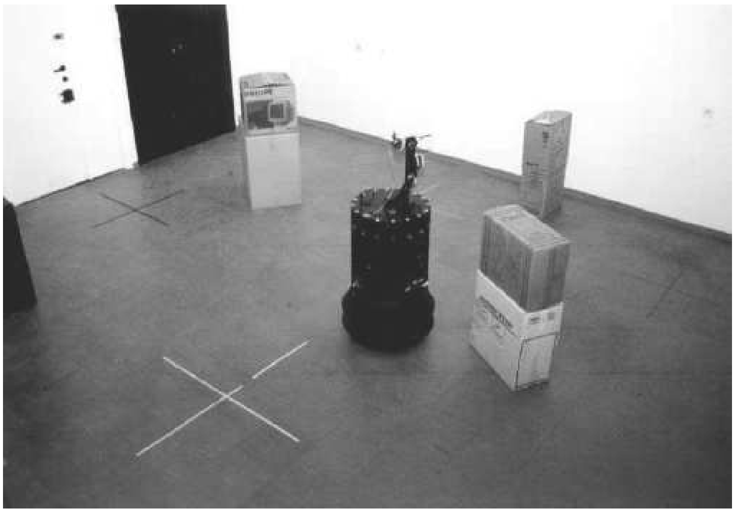


Figure 3. Typical arrangement of experimental track.

Photograph (Fig. 3) shows, marked on laboratory floor, goal points to be reached by the robot within the framework of execution of the exemplary task. The figure shows also cardboard boxes making up the obstacles placed on the path of robot. The research has been carried out on three different routes differing from each other in the arrangement of goal points and obstacles. Goal points marked on the laboratory floor in various experiments with exemplary task were becoming "home", "goal" ("storeroom"), "battery charging station" ("station" for short), "mechanical service point" ("service" for short). The arrangement of obstacles in the case of routes No 1 and 3 was as shown on Fig. 3. In the case of route No 2, arrangement was somewhat different - as shown in Fig. 4. The function of obstacles was performed also by laboratory walls.

Table 2 and Fig. 5 show coordinates of goal points and their different functions depending on the route.

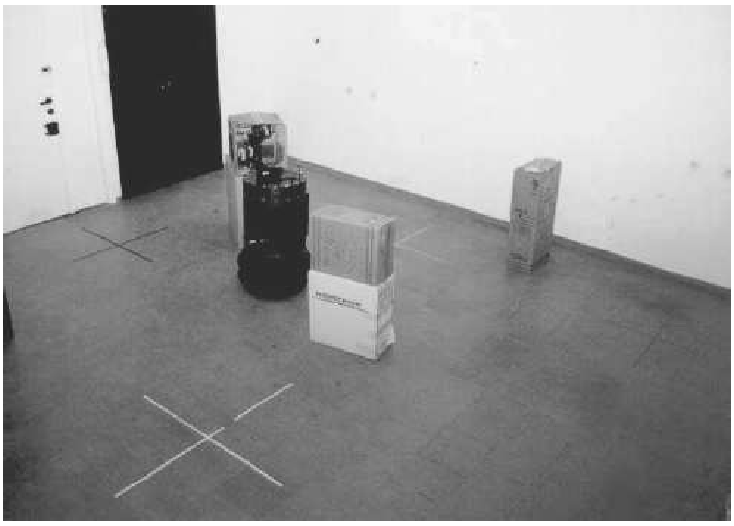


Figure 4. Arrangement of obstacles in the case of route No 2.

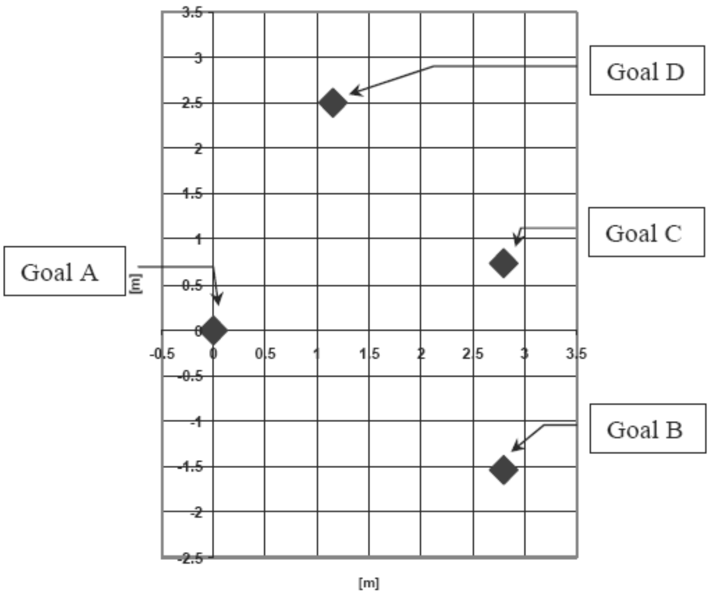


Figure 5. Arrangement of goal points to be reached by robot (scale in [m]).

Table 2. Co-ordinates of goals and their different functions depending on the route.

Goal co-ordinates in [m]	Marking in Fig. 5	Function on route No 1	Function on route No 2	Function on route No 3
(0, 0)	Goal A	"home"	"home"	"home"
(2.8, -1.54)	Goal B	"goal"	"service"	"station"
(2.8, 0.74)	Goal C	"station"	"goal"	"service"
(1.15,2.5)	Goal D	"service"	"station"	"goal"

4.2. Program of research

The principal objective of research was to carry out the experiments, which were meant to demonstrate that the distributed adaptive controller proposed in this article shows such features as: rationality, coherence and adaptation ability. More than 100 experimental real travels of mobile robot Nomad 200 were carried out. The data collected and analyzed from the experiments were obtained within the framework of the following research sub-programs:

1. Due to of theoretical analysis and on the basis of introductory experiments details were selected of controller structure and decision mechanism, as well as the settings of all parameters. These settings were set as the reference for all experimental changes made in the course of further research.
2. A series of experiments was executed on a selected route, with the use of a selected learning method, with the selected settings of the controller. These experiments were all carried out under the same conditions, as a multiple repetition of the same experiment. In this way the repeatability of the experiment results was tested.
3. A group of parameters was sorted in the controller algorithm, which after preliminary analysis appeared to have the significant influence on its operation. The influence of the changes of these parameters on the functioning of the controller was tested for a selected learning method and over different routes.
4. Operation of the controller when using five different learning methods was compared.
5. A series of experiments having to reveal the adaptation features of the proposed solution of the problem of action selection in distributed controllers was carried out.

In the following part of this paper the most important and significant results will be discussed.

4.3. Research sub-program No 1: preliminary experimental selection of controller parameters

The initial settings of all parameters of the distributed controller were selected empirically and analytically. Several series of experiments were executed, and only the results of those that are most important will be shown. Out of the most essential parameters we may mention:

1. $iwew_{nmax}$ for all layers - maximum values of internal imperatives $iwew$ for individual layers (see formula (3)).
2. Values of constant parts of weights for individual layers (see formula (4)).
3. Learning coefficient - η from formulas (5) to (9).

Ad 1) The values of parameters $iwew_{nmax}$ for individual layers were selected so as to reflect the importance of given layers' actions, which in a sense is the equivalent of priorities of these layers. Table 3 shows the initially established values of these parameters for controller executing the exemplary action.

Table 3. Preliminary values of $iwew_{nmax}$ for controller executing the exemplary action.

Layer	Value of $iwew_{nmax}$
Nr 0, avoiding obstacles	15.0
Nr 1, aiming at "storeroom"	6.0
Nr 2, aiming at "home"	7.0
Nr 3, aiming at "station"	8.0
Nr 4, behavior in "storeroom"	20.0
Nr 5, behavior at "home"	20.0
Nr 6, behavior in "station"	20.0
Nr 7, behavior in "service"	20.0
Nr 8, aiming at "service"	9.0

Ad 2) The values of constant parts of weights attributed to given layers, similarly like the values of parameters $iwew_{nmax}$, are reflecting in a sense the priorities of individual layers. The provisionally adopted values of constant weights are shown in Table 4. The influence of these parameters on the operation of controller was examined in the experiments described later.

Table 4. Provisionally adopted values of constant weights.

Layer	Values of constant weight
Nr 0, avoiding obstacles	2.0
Nr 1, aiming at "storeroom"	1.0
Nr 2, aiming at "home"	1.0
Nr 3, aiming at "station"	1.0
Nr 4, behavior in "storeroom"	1.5
Nr 5, behavior at "home"	1.5
Nr 6, behavior in "station"	1.5
Nr 7, behavior in "service"	1.5
Nr 8, aiming at "service"	1.0

Ad 3) The learning coefficient, used in formulas (5) to (9), was provisionally established at the level of 0.1.

4.4. Research sub-program No 2: repeatability of results

Within the framework of the second research sub-program, 16 experiments were carried out on route No 1, using the "instar" learning method (formula (7)), for the controller settings selected in the first research sub-program. These experiments were carried out under the same laboratory conditions, at the few day intervals, as a multiple repetition of the same experiment.

For the purpose of analysis of the repeatability of results, the following phenomena taking place in the experimental series were tested:

1. Order of reaching the goals and number of achieved goals.
2. The course of layers' activity.
3. The course of layers' activations.
4. Duration of experiment.
5. Number of interventions made by the obstacle avoiding layer.
6. Total length of route covered during a given experiment.

Statistical analysis of the experiments carried out within the framework of the second research sub-program leads to the conclusion that the experiments carried out under the laboratory ensured repeatable conditions, are in fact repeatable. This proves the fact that a relatively small number of experiments can make up the basis for generalization and analysis of the observed phenomena.

4.5. Research sub-program No 3: the influence of parameters on the operation of controller

Within the framework of this research sub-program, the group of parameters within the algorithm of controller was sorted out, which after preliminary analysis and experiments within the first research sub-program seemed to have the significant influence on its operation. The influence of these parameter changes on the operation of the controller was tested for the selected learning method ("instar", formula (7)) and different routes.

Within the framework of this research sub-program a few dozen of experiments were carried out. Only the most interesting results shall be presented herein. Within one of the series of experiments, the operation of controller was intentionally brought to serious disturbances. In effect of blocking of the external stimulus signals bz, the movement of robot was decided almost exclusively by internal imperative only (see formula (1)). Consequently, the robot was few times nearby the subsequent goals, but instead of reaching them and executing local tasks corresponding to them (e.g. charging batteries), robot was passing them by and traveling to other goals. Fig. 6 shows the route it has covered. There was no loss of coherence, but in this case one can hardly talk about rational behavior.

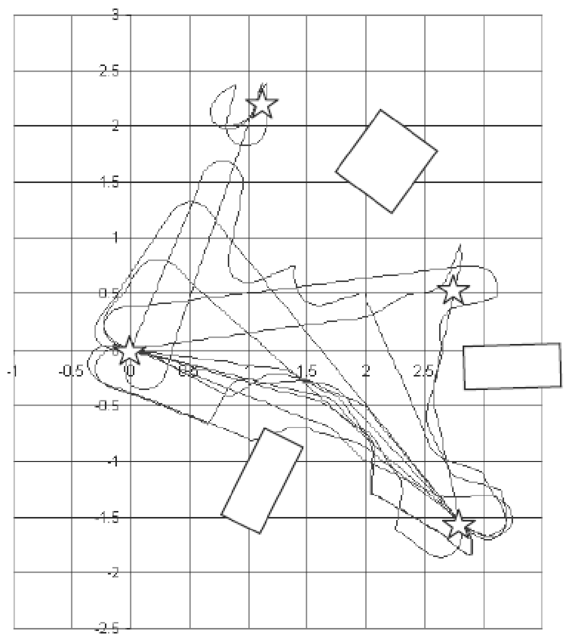


Figure 6. The route covered by robot (scale in [m]).

In another experiment, the mutual influence of the WPD modules of travel to "storeroom" and "home" was turned off. The robot has reached the "storeroom", and from this moment on it has remained in this area - every time upon leaving the "storeroom" it was turning back after a while. Also in this case the coherence was retained, but behavior was not rational. Fig. 7 shows the route of the robot.

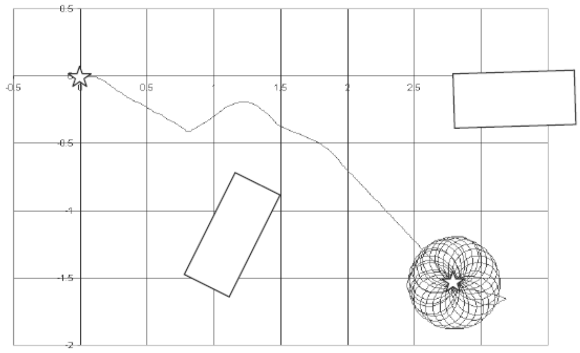


Figure 7. Route of robot (scale in [m]).

Another series of experiments have been carried out with the purpose of testing the influence of $iwew_{nmax}$ parameters (see formula (3)) on the behavior of robot. With regard to the values established in first research sub-program $iwew_{nmax}$ was changed to the values ten times bigger, ten times smaller, and all of them remaining the very same, as well as replaced by random values. The only noticed difference in robot behavior with regard to experiments from the first or second research sub-programs were the changes in frequencies of reaching individual goals. The conclusion resulting from the above is that it has no importance whether values of $iwew_{nmax}$ are large or small, important are only their mutual proportions.

Similar series of experiments has been carried out with the purpose of testing the influence of all constant parts of weights of the decision taking mechanism on the behavior of robot (see formula (4)). With regard to the values established in first research sub-program the constant parts of weights were changed to the values ten times bigger, ten times smaller, all remaining the same (equal 1.0 and 0.0), as well as for random. The courses of these experiments were not distinguished by any significant feature, with only one exception. It was noticed that the values of constant parts of weights have an influence on the promptness of controller reaction to the internal and external stimuli. This occurs in particular in the case when at the moment of action of a given stimulus, the current activation of the layer reacting to it was low.

Another group of experiments were the ones, whose purpose it was to test the influence of the learning coefficient (formulas (5)-(9)) on the operation of the controller. Behavior of the robot on various routes and for different values of the learning coefficient (from 0.1 up to 0.999) was tested. Fig. 8 shows an example of the way covered by the robot on route No 2, at $\eta = 0.1$. Fig. 9 shows the robot's path on route No 3, at $\eta = 0.1$.

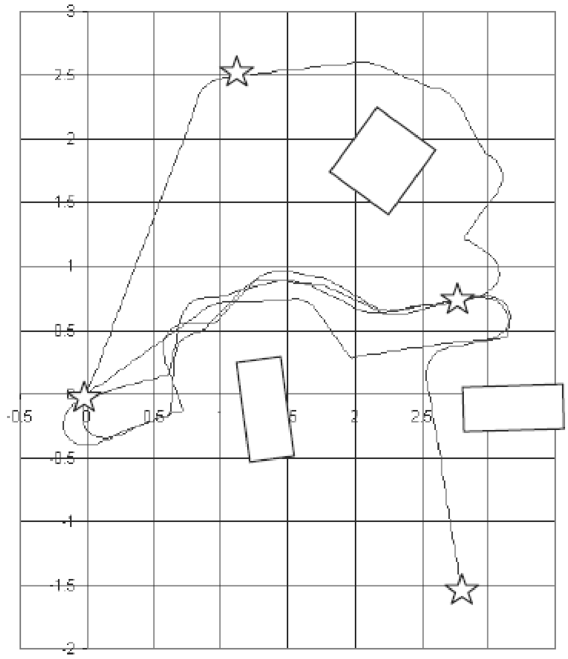


Figure 8. Robot's path on route No 2, at η=0.1 (scale in [m]).

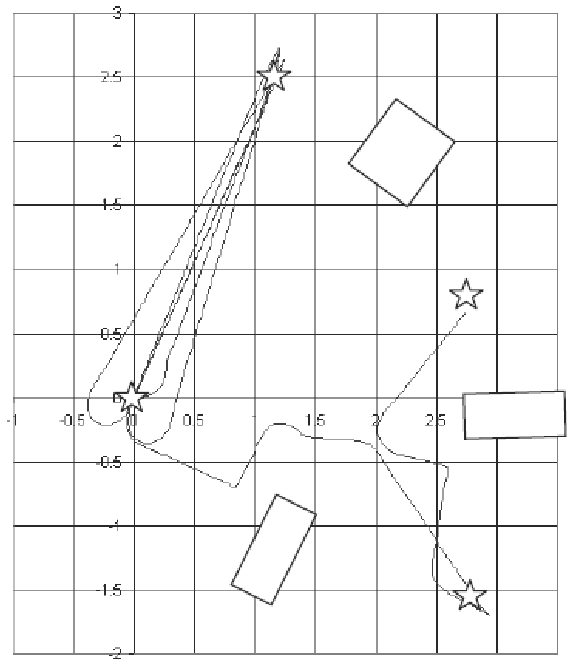


Figure 9. Robot's path on route No 3, at η=0.1 (scale in [m]).

At higher values of the learning coefficient η an intensification of the phenomenon of the loss of coherence was observed. The value of $\eta = 0.1$ turned out to be universal for all routes in the here tested exemplary task. Decrease of the value of learning coefficient η (formula (7)) causes that the adaptation parts of weights are reacting somewhat slower to the changes in situation, introducing a certain kind of inertia and eliminating the occurrence of temporary losses of coherence. Then, further decrease of the value of η results in the disappearance of adaptation features.

4.6. Research sub-program No 4: comparison of learning methods

In the fourth research sub-program the actions of controller were compared for the use of five various learning methods, according to formulas (5) to (9).

Conclusion from the fourth research sub-program: only the "instar" type learning method (formula (7)) allows for obtaining of the correct operation of the decision taking mechanism.

4.7. Research sub-program No 5: adaptive features of controller

Within the framework of the fifth research sub-program a series of experiments having to document the occurrence of adaptation features in the proposed solution of the problem of action selection in distributed controllers was carried out. The experiments were carried out on route No 1, with the use of the "instar" learning method (formula (7)), for the controller setting selected in the preceding research sub-programs.

The experiments in this research sub-program consisted in:

1. interruption of experiments at certain moments, then manual guiding of the robot into various points of the test track and again transfer of the control of the robot movement to its distributed controller,
2. interruption of experiments at certain moments, then holding of robot in place and releasing it after certain time,
3. forcing the robot to remain within a certain area of the test track with the appropriate use of the mobile obstacles,
4. rearranging of obstacles on the way to goals,
5. putting the robot in motion on three different routes (routes No 1, No 2, No 3) without any modification of parameters of the distributed controller,
6. various combinations of the above interventions.

The adaptation phenomenon has manifested itself in two ways within this series of experiments:

1. Short term adaptation: controller was immediately adapting itself to the suddenly changed state of the environment (e.g. new position of the robot, forced by the operator) and was changing its current priorities. Depending on the new, external and internal stimuli, as well as its history, the robot was modifying accordingly its current goals. For example, if the state of

discharging the batteries was adequately significant, and the distance to the "station" in a manually forced new position of the robot was adequately small, it was reaching the "station" in spite of fact that before the operator's intervention it was traveling to the "storeroom". If, however, at a small distance from the "station" the state of batteries was satisfactory, the robot was continuing its travel towards the "storeroom" from a new manually forced position.

2. Long term adaptation: controller was modifying its general behavior in the consequence of operator's interference, or the route changes (switching between routes No 1, 2, 3). For example, if normally during the movement along a given route after a given time it was reaching the "station", then in a new situation (after operator's interruption) it was not doing this after the same time and covering the same route. The controller was executing new plan. The robot was behaving in a rational and coherent way, but under completely new conditions caused by the interference of the operator. An observer could say that the robot was adapting its route plan on up-to-date basis with new situation.

The trajectories along which robot was moving were not revealing any irrational behaviors, e.g. repeated return to one of the goals, colliding with obstacles or making circles around without reaching none of the goals. There was no single case of the loss of coherence.

As an example let us consider one of the experiments. It was consisting in that when the robot was for the first time on its way to the "storeroom", it was interrupted and directed manually to the point located close to the "service" (point A on Fig. 10). However, due to the fact that internal imperative for the layer of aiming at "service" was very small at the moment (that is, the simulated degree of the wear of robot's mechanical parts was small), in spite of the proximity of this goal - the robot has renewed its drive towards the "storeroom".

After unaided reaching of "storeroom" and back "home", the robot was again directed in the vicinity of "service" (point B on Fig. 10). Also this time it has not traveled to this goal, but upon the return from the originally planned "storeroom", robot was heading towards the "station". In addition, during one of the subsequent travels "home" it was forced again (by the proper shaping of the obstacle) to travel along a longer way - avoiding of the obstacle on its left side (point C on Fig. 10).

Fig. 11 shows the dynamics of activations of decision neurons during the experiment illustrated also in Fig. 10. The arbiter selects at a given moment the layer with the highest activation as the active one.

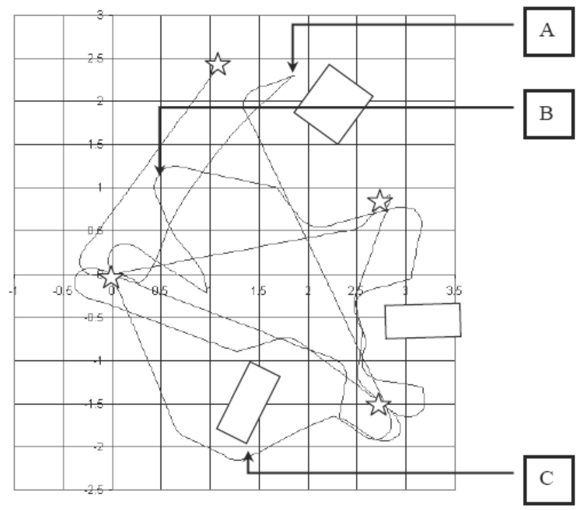


Figure 10. The route covered by robot (route No 1, scale in meters).

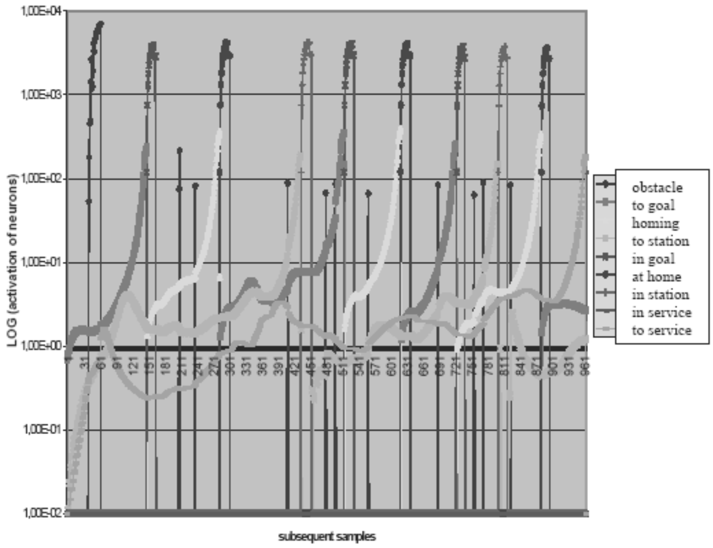


Figure 11. LOG [activation of decision neurons] 2 samples ≈ 1 second. At a given moment the layer of the highest activation is selected.

4.8. Problem of action selection

In the following part of this paper the analysis of behavior of robot controlled by adaptive distributed controller will be presented basing on the results of experimental research and on the definitions adopted earlier in this paper.

The coherence

The coherence of the controller proposed here equipped with the decision mechanism, has been demonstrated on the basis of a series of the experiments. The coherence can be tested directly with the use of the layers' activity graphs. Such graphs (as in Fig. 12) show the activity of layers, that is the numbers of layers selected by the arbiter at given moments. In the case when during a short time one can see many changes of numbers of currently active layers, one can suppose loss of coherence.

Fig. 12 presents the course of experiment, in which the loss of coherence has not taken place, and Fig. 13 - the case in which due to an intentional experimental actions the loss of coherence took place (vicinity of points A, B and C).

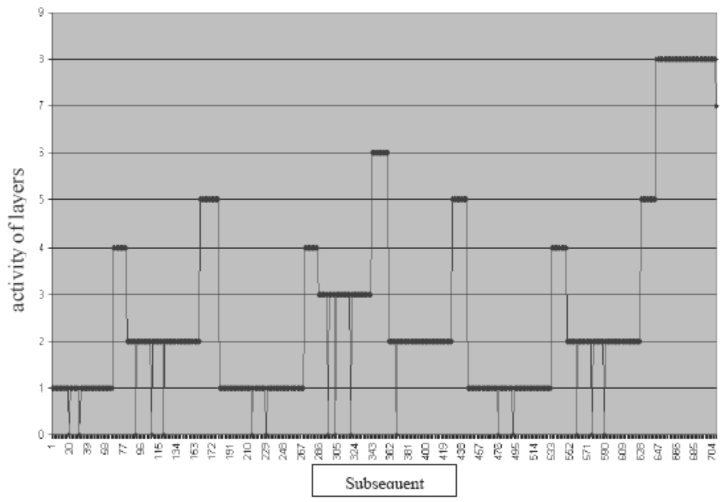


Figure 12. Coherent activity of layers (2 samples ≈ 1 second).

All the discussed experiments, not counting those in which the disturbances of the decision mechanism's functioning were intentionally introduced by changing of some of its parameters or learning method, show that the established method of action selection by means of decision mechanism allows for the achieving of coherent behavior. The coherent behavior was achieved regardless of the

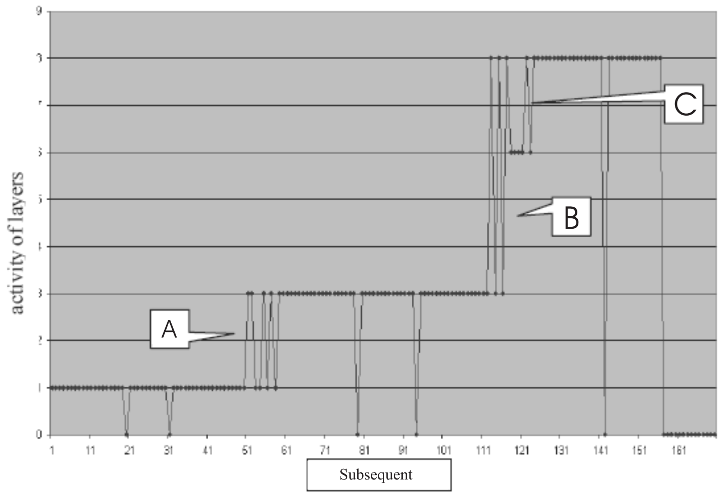


Figure 13. The loss of coherence: points A, B and C (2 samples $\approx$ 1 second).

used experimental track (routes No 1,2,3), of some parameters of the controller (experimental sub-programs No 2 and 3) and of rapid changes of the environment state (experimental sub-program No 5).

The rationality

The rational behavior of the controller is ensured provisionally by the very method of its operation - by the appropriate design of the WPD modules. By their appropriate design, it was provisionally established in advance which layer of controller is to be activated at the occurrence of a given state of the environment and a given internal state. There exists a certain kind of information filtration, described in the paragraphs pertaining to the premises based on nature.

Selection of individual layers as the controlling layers, is not only decided by the WPD modules since they can activate to operation many layers at the same time. The action selection results mainly from the operation of the decision mechanism. In taking of decision as to which layer shall at a given moment be controlling the behavior of autonomous mobile system, account is taken of the external circumstances (the state of environment), the internal ones (internal state) as well as the history of actions (adaptation parts of weights). The behavior of a system is not based on any complex internal representation of the state of environment, models of this environment, nor the actions of symbolic nature (as e.g. in expert systems). The main role in the operation of a system is played by conditions and connections of sensory-motoric type, though this is not only simple reactive system. This system have real body of specific design, it acts in the real world. The system is situated adaptively, it has a certain history. Under identical situations (understood as the states of environment only) it do not have to behave always in the same way. Its behavior depends also on the their history and their internal states.

When carrying out the analysis of the rationality of autonomous mobile systems it is necessary to keep in mind the phenomenon of bounded rationality, Simon (1987). An example of the occurrence of this phenomenon can be the situation, in which the robot is avoiding the obstacle by making an excessive number of maneuvers. One can imagine the case in which e.g. the last few observed maneuvers were not already necessary - should the robot travel straight on to the goal point, it would not have collided with the obstacle. The parameters of the algorithm of avoiding the obstacles are the result of an arbitrary, and often supported by a number of experiments, decision of human system designer. From the point of view of a human observer, behavior of the robot is irrational. However, there is no irrational behavior from the point of view of the controller executing correctly its program and utilizing in full the data from the sensors. Even human behaviors - those being analyzed later on, in particular with better knowledge on the given event - may seem to be irrational.

In the experimental research the irrational behavior of robot was encountered. The irrationality of behavior was expressed by: omitting the execution of tasks to be performed when being at a given goal point, lack of coherence of behaviors (it is impossible to talk about rational behavior without coherence), avoiding of non-existing obstacles, colliding with obstacles, making circles around only one goal point, execution of selected part of tasks only with full omission of the remaining ones, the behavior resulting from internal states only - without taking into consideration the state of environment. None of these phenomena does occur in the case of controller with the mechanism taught by the "instar" method, with properly selected parameters. Correct operation of such controller has been documented in particular in the second and fifth research sub-programs.

In section on "Behavior of autonomous mobile systems", the following was written about the rational behavior: "in every situation the decision on behavior of autonomous mobile system shall be undertaken with all knowledge contained in controller taken into consideration, and with all goals taken into consideration. In other words: in the case when the autonomous mobile system is in the situation when the transfer of control of its effectors to one of its layers will result in achieving of one of the autonomous mobile system goals, then such transfer of control shall take place". According to this definition, the proposed solution of the problem of action selection ensures the rational behavior of autonomous system. It is a direct consequence of the structure of distributed controller described in the article. The structure and operation of the controller are the direct realization of the idea expressed by the above definition.

The rationality of the here described adaptive distributed controller can be also considered according to the definitions from McFarland and Bösser (1993):

1. Compatibility: In connection with the fact that behavior of the autonomous mobile system is the result of selection of one of control layers as currently controlling its movements, there is no possibility of occurrence of a conflict in the form of attempt of executing simultaneously two contradictory operations, like e.g. simultaneous travel forward and backward. Such conflicts also do not arise within the confines of individual layers. Consequently, the compatibility is always retained.
2. Common currency: The common currency is constituted by the levels of activation of the controller layers, that are then compared by an arbiter. These signals are defined uniquely, and consequently this postulate is met.
3. Consequence: The consequence of controller actions is always retained. This follows directly from the fact that all behaviors of the autonomous mobile system are the result of control resulting from internal states (including history-defined factors) as well as the states of this system's environment. No other factors have the influence on the course of control. Consequently, always in the case of the same states of environment and internal states of the controller, behavior of autonomous mobile system is the same.
4. Transitivity: The activations of the controller layers are expressed numerically. Each such value can be compared with another, in accordance with the basic rules of mathematics. In this way the postulate of transitivity is met by definition.

Since coherence also has been proven, the autonomous mobile system with proposed distributed adaptive controller architecture is rational.

The adaptability

In connection with the existence of the decision mechanism, whose operation is based mainly on the dynamic assignment of decision parts of weights to the layers, the described controller shows the adaptation features. The results of research carried out within the fifth research sub-program can serve as a proof of the above. These results show that the controller is adapting itself to the variable states of the environment and is in a position - without any adjustments by man - to control the movements of the robot in various environments (routes No 1, 2, 3).

5. Concluding remarks

5.1. Conclusions

The article presents the problems connected with the issue of action selection in the distributed controllers of autonomous mobile systems. The adaptive distributed controller described in the article, equipped with action selection mechanism constitutes a solution that is ensuring for the autonomous mobile system the coherent and rational behavior with simultaneous demonstration of adaptation properties. This is evidenced by the results of experimental research carried out during the realization of exemplary task.

The exemplary task is one out of many possible cases of using the proposed methods of action selection. It has been formulated only for the needs of carrying out of the experimental research on a real object - the mobile robot Nomad 200. The usefulness of the proposed solution is growing along with the complexity of the distributed controller, since it is resolving in an unambiguous way the problem of action selection. If it is possible to meet the required assumptions (see point 3.1), then the tasks assigned for distributed adaptive controller can be more complex.

One of the more interesting conclusions from this work is the observation that when building more and more complex control systems, the boundary (seemingly distinct) between the hierarchic architecture and distributed (parallel) architecture is fading away. The problem of action selection in the adopted solution is partly resolved by the WPD modules (preliminary data processing). The results of decisions made by control layers are transferred to effectors, which in turn have controllers of low level ensuring e.g. the maintenance of the required rotational speed of motors. Therefore, there exists a point of view, from which each of the controller layers (consisting among other things of: sensors, WPD module, control layer, low level controllers of effectors, effectors) is a hierarchical structure. In the final effect one can look at it as at hybrid structure - distributed system consisting of sub-systems of hierarchical character.

The very important factor influencing the behavior of autonomous mobile system, turned out to be constituted by the phenomenon of bounded rationality. The influence of this phenomenon can be seen in practice in all the discussed cases of the autonomous mobile systems controllers.

5.2. Further research

Further work may proceed in several directions. The features, that were not tested in full in the work described are: the problem of scaling ability and the problems with the implementation, Pfeifer, Scheier (2000). The research in this area should consist in verification whether during the expansion of the controller by addition of new layers, its correct functioning is not disturbed. On the basis of principles of decision mechanism construction, and the tests and analyses carried out we can expect that this should happen. Then, the following advantage of solution proposed in this work would appear.

Another direction of research can be constituted by the attempts of application of genetic algorithms. In particular, this technique could be applied in the selection of controller parameters. At the present state of research work, these parameters were selected by means of the methodology as described and used in the first and third research sub-programs.

The next interesting question could be the differentiation of the value of the learning coefficient η (formula (7)). Currently all layers have the same value of the learning coefficient. Selection of these parameters, separately for each layer, can be carried out with the use of genetic algorithms.

It appears interesting to test the application of a tree-like structure. In that situation the groups of layers of e.g. simple reflexes contributing to complex behaviors, could be equipped with their own separate decision mechanisms. On the second, higher level of organization - the complex behaviors could compete with each other, also by means of the described decision mechanism. In addition, it would be possible to introduce independent actions of layers in the cases when they are controlling mutually independent degrees of freedom while executing common global goals.

The most important step that can be made in further work may consist in the testing of the proposed action selection mechanism implemented on computers with parallel processing. In the research discussed, the parallel operation of the controller was simulated only.

References

Braintenberg, V. (1984) *Experiments in Synthetic Psychology.* Cambridge MA, The MIT Press, Bradford Books.

Brooks, R.A. (1991) Intelligence Without Reason. *Proceedings of IJCAI-91*, 139-159.

Dröscher, V.B. (1996) *Reguła przetrwania* (*Rule of Survival*). Wyd. II (second edition). Warszawa, PIW.

Dröscher, V.B. (1997) *Białe lwy muszą umrzeć* (*White Lions Have to Die*). Wyd. I (first edition). Warszawa, PIW.

Ingram, J. (1996) *Płonący dom* (*House on Fire*). Warszawa, Prószyński i S-ka.

Jachner, A. (1995) Komunikacja chemiczna u ryb słodkowodnych (Chemical Communication of Fresh Water Fish). *Wiadomości Ekologiczne* **XLI** 3, Dziekanów Leśny, 153-175.

Mcfarland, D. and Bösser, Th. (1993) *Intelligent Behavior in Animals and Robots.* Cambridge, Massachusetts, The MIT Press, London, Bradford Book.

Pfeifer, R. and Scheier, Ch. (2000) *Understanding Intelligence.* Cambridge, Massachusetts, The MIT Press, London, Bradford Book.

Russell, S.J. (1991) An Architecture for Bounded Rationality. *SIGART Bulletin* **2** (4), 146-150.

Simon, H.A. (1987) Bounded rationality. In: J. Eatwell, M. Millgate and P. Newman, eds., *The New Palgrave: A Dictionary of Economics.* London and Basingstoke, Macmillan.

SZYNKARCZYK, P. (1997) Inteligentne zachowanie sterownika robota mobilnego jako wynik współpracy równoległych i niezależnych odruchów (Intelligent Behavior of a Mobile Robot Controller as the Result of Co-operation of the Parallel and Independent Reflexes). *Materiały konferencyjne AUTOMATION '97 Automatyka - Nowości i Perspektywy*, PIAP, Warszawa, 577-584.

TADEUSIEWICZ, R. (1989) *W stronę uśmiechniętych maszyn* (*Towards Smiling Machines*). Wyd. I (first edition), Warszawa, Wydawnictwa ALFA.

VANDROPE, J. and VAN BRUSSEL, H.(1994) Navigation Algorithm for an Autonomous Mobile Robot. *Proc. of Int. Conf. on Multisensor Fusion and Integration for Intelligent Systems, MFI'94*, Las Vegas, 251-259.

ZIELIŃSKA, T. (1997) Architektury systemów sterujących robotami mobilnymi (Architectures of Mobile Robots Controlling Systems). *Materiały konferencyjne WMR'97 (Warsztaty Robotów Mobilnych)*, Zakopane, 7-14.