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SOME PROBLEMS OF ADVANCED MOBILE ROBOT CONTROL

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Abstract: *At the beginning of a new millenium scientists are closer than ever to the human cognitive model and, as a consequence, to the deeper understanding of life mechanisms. We can speak now, with a sufficient scientific reason, of a new generation of robots whose essential characteristic is the capacity of interaction with the intelligent beings. Communication, algorithm configuration, learning and decision are possible through a two layer organization of the control system.*

Keywords: *mobile robots,cognitive models, perception,intelligent control, autonomous navigation*

1. INTRODUCTION

The integration of advanced environment perception and communication devices into mechatronic structures facilitates the development of strongly associative information systems. Consequently, by the modal fusion at the different presentation and multisensor processing levels, object and event recognition and classification in open environments could ensure the robustness of the perception function. Another important function that can be implemented in these robots is the environment adaptability by means of perception, representation, reasoning and action (Fig. 1).

The recent explosion in computing power has enabled the implementation of highly sophisticated control architectures and algorithms for mobile robots.

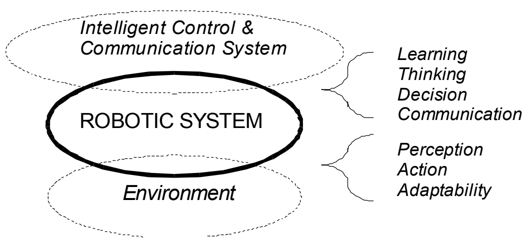


Fig. 1 The organization of adaptation and communication functions in a mobile robot control system

The principles of animal intelligence are extremely important to roboticists. Conceptualizing these different aspects of intelligence by exploring biological and cognitive sciences for insights in intelligence, one intelligent mobile robot could be defined as an artificial system which integrates the main attributes of the intelligence – *perception*, *learning*, *planning*, *reasoning* and *communication*. Under this definition, an intelligent mobile robot can be an agent (Dumitrache, 1996). An agent is self-contained and independent, it has its own "brain" and can interact with the world to make changes or to sense what is happening (Murphy, 2000).

If the learning function is also integrated, one can speak about the *humanoid robot*, capable of communication and efficient adaptation in *a priori* undefined environments. In this context groups of autonomous mini-robots could be defined that can ensure a *collective intelligent behavior* by *communication*.

This type of organization of the adaptation and communication functions in a mobile robot control system assures the fact that the robot is able to:

- communicate in an intelligent way with the environment and with the other robots;
- react in hostile environments and to adapt to a variable evolution context by learning and behavior generation;
- communicate by means of natural language, being flexible in the process of decision making;
- integrate the informatic system with multiple facilities that are specific to the intelligent agents and to communicate in an intelligent way with the mechatronic structure;
- assure the hardware and software reconfiguration capacity, that means a complete fault detection ability.

Under the above description, one can speak about a *cognitive robot*.

Therefore, a new era is opened in the field of intelligent communication systems by the *cooperation between cognitive robots*, as intelligent agents, *and*, respectively, *between robots and human operators*.

The integration of heterogeneous members into an *intelligent behavior* entity with specific *abilities* as *adaptation*, *self-organization*, *cooperation* and *evolution* towards the accomplishment of some global objectives becomes possible as long as *attributes* as *robust perception*, *learning*, *interaction* and *evaluation* could be associated with a new generation of mobile robots, capable of interactions with intelligent beings.

The purpose of this paper is to present state-of-the-art in mobile robot control and to present results of using artificial intelligence techniques like fuzzy logic and artificial neural networks in certain areas of mobile robot control. The validity and performance of such an approach on a real world control problem is demonstrated by examples at hand.

The paper is organized as follows. Section 2 presents state-of-art in the control problem of mobile robots. Section 3 describes recent advances in *neurophysiology*, *ethology* and *cognitive psychology* that raise issues in transferring animal models of behavior to robots, helping to formalize aspects of behavior. The following sections introduces the reader to some real world examples of mobile robot control. Section 6 gives some conclusions and directions of further research.

2. STATE-OF-ART IN MOBILE ROBOT CONTROL

Mobile robotic systems benefits of an impressive repertoire of kinds of learned behavior, navigation and map building. They are interesting not only from the point of view of robotic applications but also for their comparison with similar performance in animals.

Mobile robots are considered situated agents, i.e. mobile devices with tight coupling between perception and action. In real world, perception and action are tightly coupled in the living beings.

When an agent acts, it interacts with its environment (Fig. 2) because it is situated in that environment (as an integral part of the environment). By taking action, the agent changes things in the environment or changes the way it perceives the environment (e.g. move to a new viewpoint, etc). Therefore the agent's perception of the world is modified. This new perception is then used for a variety of functions, including both cognitive activities like planning for what to do next as well as reacting.

The evolution of the mobile robot is defined by its behavior in the specified environment, taking into consideration the task it has to fulfill.

An agent is completely defined by a simultaneous description of the agent (mobile robot), of the task and of the environment. One can speak about the the agent - task - environment triangle (Fig. 2).

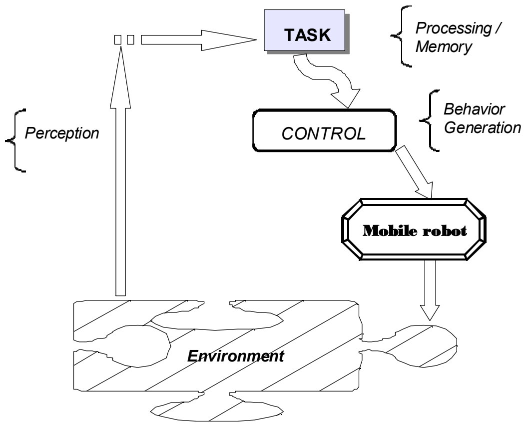


Fig. 2 The mobile robot – task – environment triangle

The "intelligence" is the property of a system that emerges when procedures of *focusing attention*, *combinatorial search* and *generalization* are applied to the input information so as to receive the output results (Dumitrache, 2000).

When referring to mobile robotics, these concepts transforms into mechanisms of *perception*, *processing* and *behavior generation* (see Fig. 2).

Today, autonomous mobile robots are the closest approximation yet of intelligent agents, the age-old dream. For centuries people have been interested in building machines that mimic living beings. From mechanical animals, using clockwork, to the software and physical agents of artificial life – the question regarding a complete definition of life and the understanding of life mechanisms always motivated research.

An *"intelligent" mobile robot* – a *situated agent* – is a mechanical structure that can operate autonomously (Murphy, 2000), i.e. it is able:

a) to move in its environment;

b) to adapt to the changes in the environment;

c) to learn from experience;

d) to modify its behavior (its way of acting);

e) to build internal representations of the surrounding world that may be used for the decision making process (for example, for navigation).

Categories of Mobile Robots

A robot's function, operation and building requirements are defined by the robot's own behavior within a specific environment, taking into account a specific task..

While a mobile robot needs locomotion mechanisms that enable it to move unbounded throughout its environment with a desired degree of autonomy, a large variety of possible ways to move are available today. Among these, in the laboratory there are research robots that can walk, jump, run, slide, skate, swim, fly, and roll.

Taking into consideration that biological systems succeed in moving through a wide variety of harsh environments, most of these mechanical locomotion mechanisms have been inspired by their biological counterparts.

Generally, mobile robots locomote either using wheeled mechanisms (a human technology for vehicles), or using a small number of articulated legs (the simplest of the biological approaches to locomotion).

Wheeled locomotion requires less degrees of freedom and therefore less mechanical complexity than legged locomotion. Mobile robots on wheels concentrate on *traction* and *stability*, *maneuverability*, and *control*. There are different types of wheels that mobile robots can use (Campion, 1996):

- standard wheels, with two degrees of freedom (rotation around the – motorized – wheel axle and the contact point;
- castor wheels, with two degrees of freedom (rotation around an offset steering joint);
- Swedish wheels, with three degrees of freedom (rotation around the – motorized – wheel axle, around the rollers, and around the contact point);
- ball or spherical wheels, with a difficult technical realization.

These wheels differ on their kinematics, therefore the wheel type has a large impact on the overall kinematics of the mobile robot.

The minimum number of wheels required for static stability is two (see Khepera mobile robot as an example). For a complete discussion about wheel arrangements see (Siegwart, 2004).

The *omnidirectional* mobile robots can move at any time in any direction in (x, y) plane regardless of the robot's orientation around its vertical axis. This type of robots usually uses powered Swedish or spherical wheels that can move in more than just one direction. Examples are the robot **Uranus**, from Carnegie Mellon, **Tribolo** designed by EPFL – Swiss Federal Institute of Technology, and **Nomad XR4000** form Nomadic Technologies. Limited maneuverability can be achieved for the mobile robots with standard wheels (Campion, 1996).

For wheeled mobile robots with conventional standard wheels, the limitation of the contact forces between the wheel and the ground translates to kinematic constraints.

Legged locomotion is characterized by a series of point contacts between the robot and the ground. They could be easily used in rough terrain because their facile adaptability and maneuverability. The main disadvantage of legged locomotion refers to the power and mechanical complexity. High maneuverability will only be achieved if the legs have sufficient number of freedom to impart forces in a number of different directions.

In the case of legged mobile robots, a minimum of two degrees of freedom is generally required to move a leg forward by lifting the leg and swinging it forward. Three degrees of freedom are sufficient for more complex movements. The most complex leg configuration can be found in the case of the human leg, with more than seven major degrees of freedom, combined with further actuation at the toes.

Mobile robots with legged locomotion can have *one leg* (the **Raibert** hopper, by LegLab, the **2D single bow leg** hopper, by Carnegie Mellon University), *two legs – biped mobile robots* (the **Sony Dream Robot SDR-4X II**, by Sony Corporation, the **P2** humanoid robot, from Honda Motor Corporation, the **WABIAN-RIII** humanoid robot, at Waseda University, **ASIMO** from Honda), *four legs – quadruped* (the artificial dog **AIBO**, from Sony, the **Titan VIII**, from Tokyo Institute of Technology), *six legs – hexapod* (**Lauron II**, from University of Karlsruhe).

In general, supplementary degrees of freedom for a robot leg has an impact over the design complexity, as well as for the maneuverability and the controllability of the implementation.

Sensing Abilities of Mobile Robots

Robot, task and environment are tightly linked. The overall behavior of a robot is the result of the interaction of these three components. Therefore mobile robotics would benefit from a large range of sensors in order to detect environment characteristics.

All sensors are designed to sense or to measure a particular physical property, which usually has a meaningful relationship with a property of the environment. Mobile robotics needs to (Everett, 1995):

- *detect physical contact with an object*. Tactile sensors that can be used are microswitches (bumper sensors), and strain gauges or piezoelectric transducers;
- *detect obstacles*. Non-contact sensors that can detect obstacles are the infrared sensors (IR) that operate by emitting an infrared light, and detecting any reflections off surfaces in front of the robot;
- *measure distance*. A sonar range finder measures the time it takes for a sonar pulse to be heard again by a receiver placed next to the transmitter. Using the time for the pulse to travel to the object in front of the sensor and back, given the speed of sound, the distance to the object can be computed;
- *measure the distance, velocity and acceleration of perceived object*. Laser range finders measure distance by emitting a short pulse of light;
- *measure direction*. Compass sensors are very important for navigation applications and they measure the horizontal component of earth's natural magnetic field;
- *measure rotation*. Shaft encoders are used to measure rotation, for example the rotation of the rotor's axles to perform path integration.

Path integration or dead reckoning is the simples form of odometry, and, with the required corrections, can be used to measure the movement of the motor's sensors, therefore the movement of the robot on a certain trajectory;

- *interpret the environment through images*. Vision sensors or CCD cameras use Charge Coupled Devices to generate matrices of numbers that correspond to the grey-level distribution in an image. CCD cameras are available for grey-level and color image acquisition, with a range of image resolution and frame rates.

Because mobile robotics can benefit from a large range of sensors with different characteristics, different strengths and different weaknesses, some form of sensor fusion is needed.

Applications Families for Mobile Robots

The available applications of mobile robots are influenced by their ability to move around autonomously in their environment. Specific task for mobile robotic applications include transportation, exploration, surveillance, guidance, inspection, etc.

Particular applications of mobile robots ate those applications dedicated for environments that are inaccessible or hostile to human beings. Underwater robots (i.e. *UUV – Unmanned Undersea Vehicles*), planetary rovers (i.e. *UGV – Unmanned Ground Vehicles*) or robots operating in contaminated environments or at high altitudes (i.e. *UAV – Unmanned Aerial Vehicles*) are such examples.

As already mentioned before, a *collective intelligent behavior* can be obtained in groups of autonomous mini-robots, the so-called *multi-agent systems*. Today, multi agent teams are organized as test-beds that describes artificial societies in which societal rules can be analyzed. Example of tasks in multi-agent teams are *robot foraging*, *robotic soccer*, and *robot formation*.

In multi-agent systems the concurrent but independent actions of each robot leads to an *emergent social behavior*. The group behavior can be different from the individual behavior, emulating a certain *group dynamics*.

Different applications of multi-agent systems can be found today. With a strong biological basis, foraging robots (see section 5) may find potential use in mining operations, explosive ordnance disposal and waste of specimen collection in hazardous environments (for example, the **Mars Pathfinder rover**).

Robotic soccer (see section 5) is a particular good task for multi-agent research because it includes cooperation between teammates, competition versus an opponent and unpredictable dynamic play (Balch, 1998).

Where sensor assets are limited, formation habits (i.e. the combination of sensing abilities of animals in groups in order to maximize the chance of detecting predators or to more efficiently forage for food) are important in mobile multi-agent applications. Formation allow individual team members to concentrate their sensors across a portion of the environment, while their partners cover the rest.

3. MOBILE ROBOTICS IN CONNECTION WITH BIOLOGICAL SYSTEMS

Recent results imposed by *neurophysiology*, *ethology* and *cognitive psychology* displayed new methodologies to transfer animal behavior models towards intelligent robots, therefore helping to formalize certain aspects of biologic behavior.

By analyzing the way in which living creatures fulfill specific actions (analyzing the "inputs" and the "outputs" of their behavior) modalities of organizing intelligence can be defined.

Perception, *action*, *adaptivity*, *learning* as well as *decision making* are possible by integrating specific intelligent control techniques like artificial neural networks, fuzzy logic, genetic algorithms or synergetic combinations of them. Today AI roboticists often turn to biological sciences being that animals can provide existence proofs of different aspects of intelligence.

By focusing on the way living creatures "do" something roboticists can gain insights into how to organize "intelligence".

By now no artificial control systems have been designed that works as flexibly and robustly as a biological control system.

In particular, neuroscience has benefited from techniques for imaging the brain (via monitoring of blood flow or metabolic processes) during performance of cognitive, perceptual or motor tasks. Brain imaging methods (Simion, 2002) include computerized tomography (CT or CAT), and functional magnetic resonance imaging (MRI or fMRI) and positron emission tomography (PET).

As was recently suggested (Levine, 2000), the cerebellum and basal ganglia are both involved in different aspects of motor control and it was traditionally believed that their functions were limited only to motor control. But for voluntary, adaptive movements, other centers are necessary, including cerebellum, basal ganglia and motor cortex. Growing evidence suggests that they are involved in non-motor, cognitive functions, too.

Thus, a new theory was postulated that the cerebellum, the basal ganglia and the cerebral cortex have evolved to implement different kinds of learning algorithms: the cerebellum for supervised learning, the basal ganglia for reinforcement learning, and the cerebral cortex for unsupervised learning (Doya, 1999), (Doya, 2000).

These recent results in neurophysiology should be correlated with the strong evidence that exist in biology that animals build internal representations of their environments while performing navigational tasks.

The agent space in biological systems is not an absolute universe in which both the agent and its environment are described. The agent space in biology seems to consist of two parts: one to represent places, and the other to represent head directions. These two representations are established on the basis of some inborn neuronal learning mechanisms and adapted with the experience of an agent in navigation.

At present, specific results exist about the existence of a biological place mapping system and of a biological head direction system. The locations in a brain where a place mapping representation is formal are believed to be in the hippocampus (O'Keefe, 1978) and its neighboring regions. Abundant evidence that supports this belief can be found in neurophysiological studies. By using functional neuroimaging of brain activity while human subjects were performing navigational tasks in a complex virtual reality, activation of the right hippocampus was found to be strongly correlated with knowing accurately were places were located and with navigating accurately between them (Maguire, 1998).

It was also found that the right hippocampus is involved in storing, over a long or short time course, the large scale topographical layout of a spatially extending environment.

Closely related to the place coding in the hippocampus is the head direction system (Taube, 1990) in postsubiculum, anterior thalamic nucleus and some other brain regions, which was found to be responsible for spatial orientation function (Chen, 1994). Similar to place cells in hippocampus, both path integration and landmarks in the environment affect the firing properties of the head direction cells, regardless of the location in the environment and the position of the head relative to the body (Blair, 1995).

Mobile robotic systems benefits of an extremely range of biologically - inspired techniques, including artificial neural networks. Often, artificial neural networks can be used to generalize representation of landmarks. Among these are neural networks of the multilayer perceptron type, especially used as a pattern associator, and also of the self-organizing feature map (SOFM) due to Kohonen. There are also applications of the Adaptive Resonance Theory Networks (ART) associated with the pioneer of neuromodelling, Stephen Grossberg.

The results provided by cellular neurophysiology and cognitive neuroscience (Gazzaniga, 1995) formed the foundations of transferring natural intelligence into machines. While the *behavior* is considered to be the building block of natural intelligence, it was used as a concept integrated in a special type of organization of the control system of the mobile robot.

Therefore, a second broad area of applications of mobile robotics is in the fields of artificial intelligence, cognitive science and psychology. Autonomous mobile robots offer an excellent means of testing hypothesis about intelligent behavior, perception and cognition.

Control Paradigms for Mobile Robots

Intelligent control techniques with biological insights, as artificial neural networks, fuzzy control, genetic algorithms or synergetic combination of them can be used successfully in building control systems for autonomous operation of mobile robots.

Therefore, following the biological traces, inside the control system of a mobile robot intelligence can be organized in a *deliberative*, *reactive* or hybrid *deliberative / reactive* way:

- *the deliberative paradigm* refers to a control strategy with global planning based on a world model. This strategy intends to implement the ability of reasoning and planning of every movement of the robot. This kind of navigation structure should build elaborate world models and to make decisions in order to fulfill the tasks. As a general strategy, it implies four steps: perception of the surrounding world, building an internal world model, planning actions according to the associated tasks and the execution of these tasks using the control module. Therefore, the control architecture for autonomous navigation is organized in functional tasks (*perception*, *world model*, *planning* and *execution*). It was also called the "geometric world approach" (Li, 1999) because the environment is seen like a geometric layout of static objects and the aim is to build the internal representation of the agent space as a replica of this layout. This approach with pure planning based on a world model is very sophisticated and it was difficult to be implemented on real systems;
- *in the reactive control paradigm*, the control system is build based on a set of independent modules operating in parallel. Each module is responsible for a *behavior*, that is a pair sensorial information - system answer. Each *behavior* is responsible for a certain task like "follow the line of the wall", "avoid the obstacle on the left side", and so on. Each module of this type has the ability to process its own senzorial information and to generate the corresponding commands. Examples of reactive implementations are the subsumption architecture (Brooks, 1986) and the potential field architectures based on motor schemas (Arbib, 1981). Because they are commonly built with behaviors, the reactive control architectures are called *behavior-based systems*;
- *in the in combined deliberative / reactive paradigm*, the control strategy intends to integrate together the two control strategies above mentioned in order to improve the overall performance of the system. Basically, a combined control system should be able to support a supervizory module for the reactive level. This high level planning implemented in the supervision module should be able to allow a much more complex navigation ability. At this level it is also possible to define a clear sequence of the behaviors (tasks) that should be fulfilled for navigation. These behaviors may be activated or deactivated in order to fulfill global objectives with a high degree of abstractization. Examples of hybrid architectures are the managerial architectures (**AuRA** – Autonomous Robot Architecture, **SFX** – Sensor Fusion Effects), the state-hierarchy architectures (**3T** – 3 Tiered), and the model-oriented architectures (**Saphira**, **TCA** – task Control Architecture).

4. BEHAVIOR-BASED SYSTEMS FOR MOBILE ROBOT CONTROL

Both fuzzy logic and artificial neural networks could be integrated in one way or another into a general behavior-based organization of the execution layer.

While fuzzy logic can be suitable for the implementation of collision avoidance behaviors, artificial neural networks may be used for sensory information categorisation and classification (for collision avoidance or localization), or stimulus - response mapping (for reactive behavior), as further depicted.

Another immediate use of neural network techniques are in the field of adaptive control of mobile robots (Constantin, 1999), (Dragoicea, 2000), (Dumitrache, 2001).

Generally speaking, a behavior may not just consist of a stimulus - response pair (i.e. situation – action), see Fig. 3.

Typically, the sensory situations to which a behavior can react are limited. Only a portion of the information supplied by all sensors triggers a behavior, and all the behaviors that are triggered may react differently. The reactions of all behaviors together contribute to the action finally executed in the actuators.

A mechanism is needed to mediate all reactions suggested by behaviors that respond to the current sensory input and to formulate one action to the actuators. Distributed execution of behaviors leads to fast decisions making, so the agent can react to sensory input quickly. Each behavior fully implements a control policy for one specific sub-task, like following a path, avoiding sensed obstacles, or crossing a door.

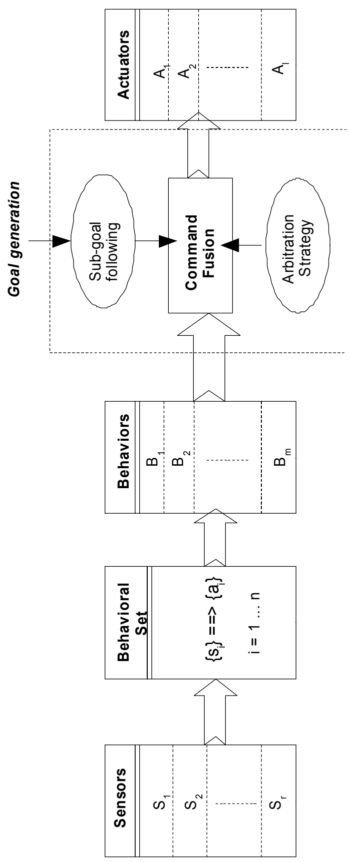


Fig. 3 Behavior-based organization; $\{s_i\}$ is the set of sensory situations, $\{a_i\}$ is the set of reactions

The *arbitration strategy* decides which behaviors should be activated depending on the current goal and on the environmental aspects.

As shown in Fig. 3, a behavior may have several sensory situations, a set of actions and a mapping between the two sets (Dragoicea, 2003).

Several behaviors may be concurrently activated: in these cases, some form of *command fusion* (or a *combinator*) is needed to combine the results from these behaviors into one effector command (Dragoicea, 2003). Many proposals in the autonomous robotics literature adhere to this scheme, but differ in the emphasis put on each part.

The *behavior-based approach for reactive control* reduces the cost of building and maintaining internal representations of the environment. The agent is considered as an inseparable part of its environment; and there is a relationship between the agent and the environment that governs the behavior of the agent.

The agent can retain its relationship to the environment by using a set of behaviors each of which maintains a mapping from sensory information to some control parameters for actuators.

As shown in Fig. 3, the minimum representation required in this approach consists of two parts: sensory situations representing stimuli, and situation to reaction mapping.

The action executed in the actuators may contain the overall, or a part of the, effect of the actions resulting from behavior programs. By using the exteroceptive sensors, the agent acquires a model of the workspace as it is at the moment when the task must be performed.

Behavior-based robotic systems would start with crisp sensor readings (e.g. numeric values from proximity sensors). Artificial neural networks, fuzzy control or genetic algorithms could be further used in order to interpret the data and control the vehicle in an autonomous way, as further depicted.

5. INTELLIGENT BEHAVIORS IN REACTIVE CONTROL

The entire mobile robot control problem is based on presenting different methodologies for developing complex techniques of providing a desired degree of autonomy in navigation. They should take into consideration the fact that the only information available is the subjective (egocentric) perspective of the autonomous robot, constructed from a sequence of measurements, considered as their observable dynamics.

This presentation can be oriented towards some specific directions, listed under the following categories:

- the derivation, following the results obtained in (Dragoicea, 2000), of some new aspects of process control using neural networks;
- neuro-fuzzy integration for collision avoidance and navigation.

A1. Adaptive neural network strategy for mobile robot control

Autonomy requires some abilities like learning in presence of unknown "situations". Here we define a "situation" as being either a special feature of the environment for which the mobile agent was not engineered in advance (e.g. unknown static or moving obstacles in the environment) or some special operating condition of the mobile platform itself (here one intends to take into account inherent parametric uncertainties that obviously interfere in the process of mobile structure modeling).

Considering the second case, it seems attractive to initiate an adaptive control for parameter uncertainties (e.g., unknown mass, wheel-radius, friction effects, unknown inertia parameters, etc) at the lowest level (the execution level).

Different neural network architectures and algorithms were used since the early days of mobile robotics. The mobile robot OBELIX (Mahadevan, 1991) uses reinforcement learning (Q-learning) to acquire a box-pushing skill. The walking robot GENGHIS (Maes, 1990) learns also by Q-learning to co-ordinate its leg movements so that a walking behavior is achieved.

Perceptrons and multilayer perceptrons can be used for simple obstacle avoidance (Nehmzow, 2000). Typical applications of the **S**elf-**O**rganising and **F**eature **M**ap (SOFM) networks (Kohonen, 1988) are for clustering an input space to obtain a more meaningful, abstracted representation of that input space.

There are also applications of the **A**daptive **R**esonance **T**heory (ART) that has been advanced as a theory of perception and classification in biological systems and this is a valuable exploration of its practical application.

Frequent uses of this neuro-model is made to the construction of cognitive map in the hippocampus of the animal nervous system (Li, 1999).

In (Dragoicea, 2000) neural networks of multilayer perceptron type were used in order to implement an adaptive control strategy able to cope with parameter uncertainties at the execution layer.

The trajectory controller implemented following (Kanayama, 1990) proved to be able to tune the velocity references for the velocity controller (the feed-forward neural network controller) so good results were obtained solving trajectory-tracking problems with different initial conditions. This work was further continued in (Dragoicea, 2001).

A2. Neural Networks for Reactive Navigation

The behavior-based approach consists of several layers, each of which may be composed of a set of functional units, namely modules. All layers work in parallel and have access to all sensory inputs. Each layer takes parts of the sensory information as input and generates an output of that layer. This layered architecture operates on the basis of a behavior-based hierarchical task decomposition: lower level layers deal with more primitive behaviors (e.g., the reactive behavior in the collision avoidance module), while higher level layers undertake more advanced functionality (e.g. path-planning or sub-goal following modules).

Therefore, one may use *gating techniques* to regulate the information flow between layers so that system level behavior can emerge from interactions among various layers and modules (Pasquier, 1998), (Li, 1996).

Different mappings that involve learning tasks could enrich the level of autonomy for a mobile robot. A mapping from the sensory information categories to the place representation is required for localization (Dragoicea, 2000) while a mapping from the sensory information categories to the motor action representation is essential for implementing the function of collision avoidance.

Supervised or unsupervised learning mechanisms could be used as well for each of these tasks.

A3. Neural mechanisms of learning and control in mobile robotics

Often, *artificial neural networks* can be used *to generalize representation of landmarks*. Among these are neural networks of the multilayer perceptron type, especially used as a pattern associator, and also of the self-organizing feature map (SOFM) due to Kohonen.

Nehmzow (Nehmzow, 2000) proposed a formalization of mobile robot landmark-based navigation by using artificial neural networks of self-organizing type.

As mentioned before, there are also applications of the Adaptive Resonance Theory Networks (ART) associated with the pioneer of neuromodelling, Stephen Grossberg.

A *landmark* can be defined as being *a set of raw sensory patterns*, based on which a motor decision is made. In this way, each place (or pattern) in the environment is defined by a specific set of sensory patterns. The main advantage of this approach is that the representation is dynamic in order to allow structure expansion for the incorporation of newly identified places.

Given a description of mobile robot's sensing abilities, its task and environment*, a set of behaviors* will be further defined using *schemas* to accomplish the task. A behavior could be composed of two schemas, a *perceptual schema* and a *motor schema* (Arbib, 1991).

In (Dragoicea, 2003b) *a navigation strategy based on landmarks recognition* for *autonomous navigation* of the mobile robots was proposed. An ART2 neural network is used in order to implement the perceptual part of a behavior in the framework of schema theory (Arbib, 1991).

Using artificial neural networks for the clustering of the environment and for the generalization of landmarks representation naturally allows the integration of a *learning* dimension into the navigation ability of the mobile robot.

The navigation by landmark recognition phase implies activities by which the robot will attempt to recognize distinct places of its perceptual space that were previously identified and learned..

This requires that some *generalization* regarding the internal representation within the navigation mechanisms is possible. By learning raw sensory perceptions of certain landmarks the robot might learn to recognize landmarks on subsequent visits.

The ART2 neural network learns to classify the sensory patterns that the eight proximity sensors produced during the reactive exploration stage (Fig. 4).

The motivation for choosing self-organization is that clustering the robot's perceptions autonomously using a self-organising classifier helps to avoid the problem of matching individual environmental features against an internal world model. There is no attempt to recognize specific objects in the robot's environment, rather the raw sensor readings are grouped according to their similarity.

This means that the robot's perceptual groupings (ART classifications) may bear no direct translation to obvious human categorisations of the environmental features (e.g. "corner", "wall", "box", etc.).

In each of the conducted studies the mobile robot showed useful learning in an impressively small number of trials (Fig. 5).

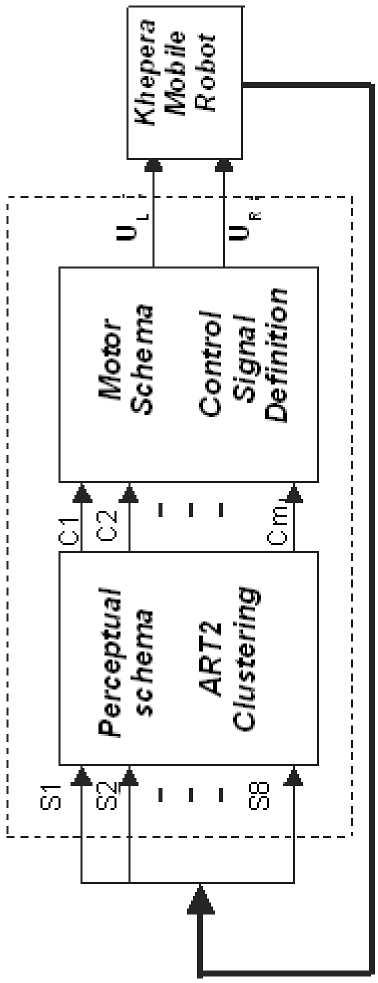
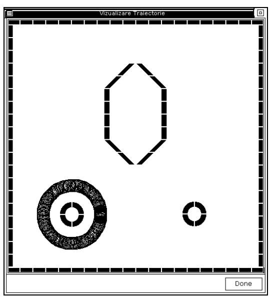
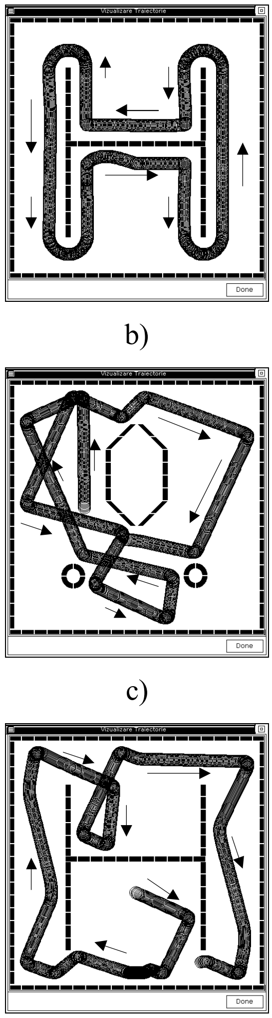


Fig. 4 Neural controller based on perceptual clustering by an ART2 neural network

The evolution of the robot was tested on a number of simulated *worlds* as well as on the real Khepera mobile robot.



a)



b)

c)

d)

Fig. 5 Mobile robot evolution, a) and b) with supervision (ART2 controller), c) and d) with a Braitenberg controller

A4. Fuzzy Reactive Behaviors

Fuzzy logic controllers incorporate heuristic control knowledge in the form of IF-THEN rules, and are a convenient choice when a precise linear model of the system to be controlled cannot be easily obtained.

The first and the most common application of fuzzy logic techniques in the domain of autonomous robotics is the use of fuzzy logic control to implement individual behavior units. Some authors used fuzzy control to implement complex behaviors that take multiple objectives into account (e.g. following a given path while avoiding unforeseen obstacles in real-time).

Fuzzy controllers are typically designed to consider one single goal. There are two options if someone wants to consider two (or several) interacting goals.

- first of all, we can write a set of complex rules whose antecedents consider both goals simultaneously. This approach was used for navigating to a target while avoiding obstacles (Skubic, 1993). (Skubic, 1993) used a miniature infrared-based robot, while (Li, 1994) used a simulated sonar-based robot. (Altrok, 1992) used it for a car following a wall-bounded race track while compensating for the skidding and sliding due to the high speed;
- second, we can write two sets of simple rules, one specific to each goal, and combine their outputs in some way. This approach was used by (Yen, 1995) and (Baxter, 1993) for integrating path tracking and obstacle avoidance, and by (Maeda, 1995) for integrating vision-based wall following and obstacle avoidance on a Hero 2000 robot.

Layer integration, i.e the problem of how to link the different levels of representation and reasoning that must be present in an autonomous agent, is a very important aspect of today's mobile robotic research.

However, while fuzzy logic gives us a valuable tool for writing co-ordination strategies, it does not give a solution to the general problem of behavior co-ordination. For example, we still don't know how to discriminate a situation where different commands proposed by different behaviors should be averaged, from one where they should be regarded as a conflict to be resolved in some way.

These problems are inherent to any form of local combination, and can be seen as instances of the general problem of relating local computation (or action) to global results (or goals, as specified by the path-planning and sub-goal following modules). These problems can only be solved by a careful integration between local and global reasoning.

Section A2 introduced methods in which neural network controllers proved to be a suitable choice for realizing reactive behaviors as a mapping from input to output. Behaviors could be formulated as well using fuzzy "perception-action" rules, which are then applied periodically to control the vehicle. Systematic exploration strategies can be devised, defining different behaviors such as wall following behavior, obstacle avoidance behavior, steering and tracking behavior.

(Pasquier, 1998) proposed a fuzzy inference engine that processes all these fuzzy control rules aggregated within a single rule base. In (Dragoicea, 2003), (Dumitrache, 2002) and (Dragoicea, 2004) a method to implement a hierarchical version of the system, where each behavior could be realized as a separate FLC is proposed.

Reactive behaviors should be guided using intermediate sub-goals (from the sub-goal following module, see Fig. 3). As was described in Fig. 3, a combinator will mediate the drive coming from the collision avoidance module and the sub-goal following module and will generate velocity and orientation references to the execution layer (Dragoicea, 2000).

This approach will endow the mobile robot with a set of skills implemented as reactive behaviors and complemented with global exploration strategies.

The multiple outputs would be supervised by a supervisory module. In this way the arbitration mechanism could be under user control, in order to modulate the importance that is given to each behavior accordingly to the given evolution context (Dragoicea, 2003), (Dragoicea, 2004).

A fuzzy control system for behavior-based robotic systems would start with crisp sensor readings (e.g. numeric values from proximity sensors), translate them into linguistic classes in the fuzzifier, fire the appropriate rules in the fuzzy inference engine, generating a fuzzy output value, then translate these into a crisp values representing actuator control signals (see Fig. 6).

Fuzzy logic allows a certain type of discrete encoding of the (situation, reaction) pairs by using rule-based systems.

The collection of IF - THEN rules that take the general form:

IF antecedent THEN consequent

where the *antecedent* consists of a list of preconditions that must be satisfied in order for the rule to be applicable and the *consequent* contains the motor response.

The discrete set of possible responses corresponds to the set of rules in the system. More than one rule may be applicable for any given situation.

The strategy used to deal with conflict resolution typically selects one of the potentially many rules to use based on some evaluation function.

Fig. 6 presents a fuzzy logic control system architecture for elementary behavior implementation that consists of the following parts:

- fuzzifier: it maps a set of crisp sensor readings onto a collection of fuzzy input sets;
- fuzzy rule base: it contains a collection of IF - THEN rules;
- fuzzy inference engine: it maps fuzzy sets onto other fuzzy sets according to the rule base and membership functions;
- defuzzifier: it maps a set of fuzzy output sets onto a set of crisp actuator commands.

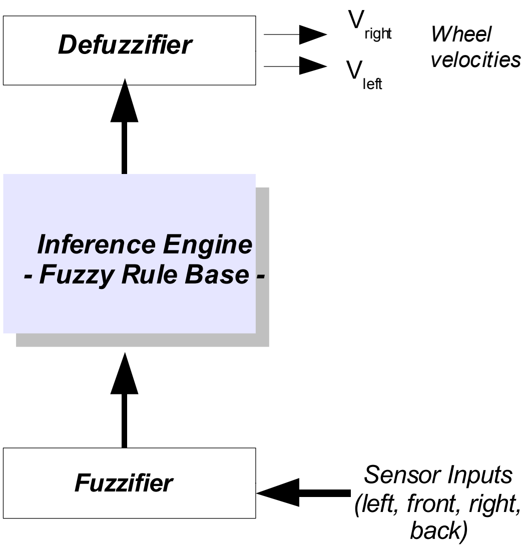


Fig. 6 Fuzzy logic control system architecture for behavior implementation

The main advantage of the proposed reactive multi-control strategy based on elementary behaviors (Dragoicea, 2003) is that the arbitration mechanism (i.e. a function of type PLAN) is under user's control, that means it is possible to give more importance to a specific behavior or even rule according to the context in which the robot evolves (i.e. task to be fulfilled and environment conditions). In this approach fuzzy rules of the general form are used:

IF path_cond THEN command1
IF obstacle_cond THEN command2

As an example, table 1 shows practical rules that implement a wall following behavior on our robot test-bed, the mobile robot Khepera:

Table 1 Fuzzy rules for a wall following behavior

IF (dist_front_OK ∧ dist_left_far) THEN turn_medium_left
IF (dist_front_OK ∧ dist_left_OK) THEN turn_smooth_left
IF (dist_front_small ∧ dist_left_medium) THEN turn_smooth_right

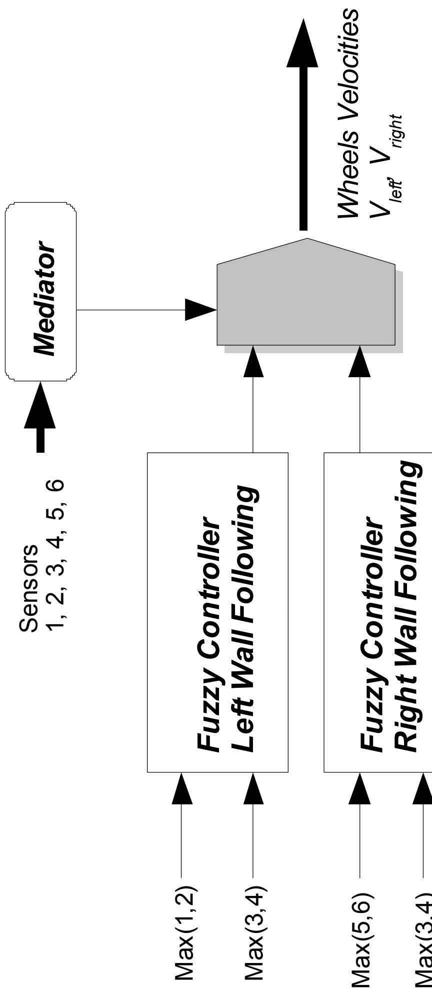


Fig. 7 A schematic diagram of the wall following fuzzy hierarchic controller for a Khepera mobile robot

A wall following behavior is a tracking control mechanism able to follow any continuous surface at some fixed distance from contact, a feature that is most useful when mapping an unknown environment.

The fuzzy controller that implements this behavior may consist of two controllers, one for right wall following, the second one for left wall following (Fig. 7).

Therefore, the mobile robot will also be able to enter a corridor and to execute a movement between two walls.

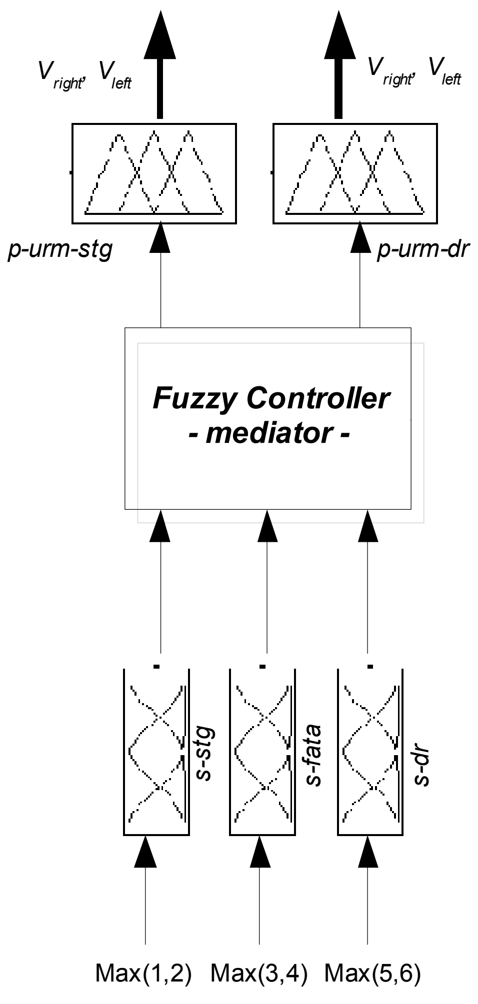


Fig. 8 A fuzzy mediator for the wall following behavior

The inputs for the two fuzzy controllers, as well as for the mediator, is the information received from the distance sensors of the robot (Dumitrache, 2002). The two outputs of the left / right wall following fuzzy controllers are the two wheels velocities, V_{left} and V_{right}.

The mediator for the wall following behavior (see Fig. 8) realizes a weighting action of the control signal generated by the two fuzzy controllers (for left and right wall following).

The weighting strategy will influence one of these two controllers, according to the context in which the robot evolves (i.e sensors measurements). The inputs to the fuzzy mediator are the values of the left, right and front sensors, and its outputs are the weights for the two fuzzy controllers for left and right wall following. For more details, notations, and results, see (Dragoicea, 2003) and Fig. 9.

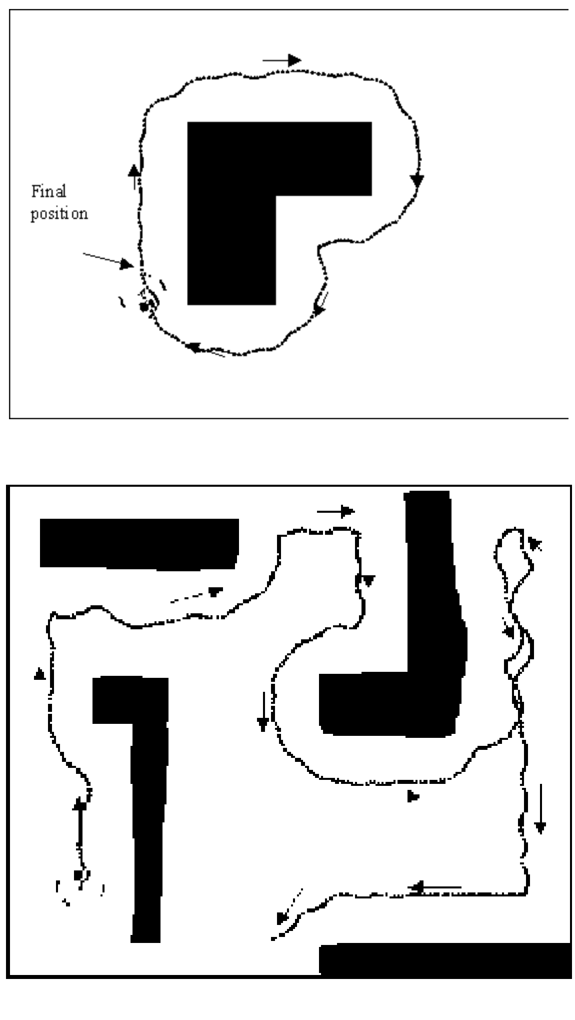


Fig. 9. Complex behaviors with fuzzy implementation

Therefore, following a more general deliberative / reactive approach, the robot has the possibility to plan (in a deliberative way) the most suitable way to split its global task into subtasks, i.e. to make a mission plan. Then it can determine the suitable behaviors in order to fulfill the sub-tasks. These behaviors are to be executed in a reactive way, as it was previously mentioned.
Based on this strategy, more complex behaviors could be accomplished, like position tracking and position tracking with collision avoidance behaviors (Dumitrache, 2002).

A5. Neuro-fuzzy Approaches for Multi-Agent Team Design

Multi-robot team design is challenging because performance depends significantly on issues that arise solely from interaction between agents. These interactions complicate development since they aren't obvious in the hardware or software design but only emerge in an operating team. Co-operation robot-robot, interference and communication, for instance, are not considerations for a single robot, but are crucial in multi-robot systems.

To date, some researchers started to investigate learning in multi-robot systems (Mataric, 1992), (Mataric, 1994), (Parker, 1994). Parker developed the ALLIANCE architecture for controlling teams of physically heterogenous robots. The system was built on the behaviour-based subsumption architecture (Brooke, 1986). At Georgia Tech, Arkin and Balch have investigated several homogenous strategies for robot foraging (Arkin, 1993), (Balch, 1995). Recent interest has sparked more research in robot soccer. Kitano and Asada (Kitano, 1997) promote the Robot World Cup as a vehicle for multi-agent research.

Researches carried out in the last years started to investigate specific tasks for collective robot teams, like robot foraging, robot soccer and formation maintenance. Behavior-based approaches are currently studied in correlation with these tasks.

Up to now, many existing behavior-based robotic systems are comprised of hand-coded behaviors. For dynamic environments, learning is necessary, as mentioned before (Dragoicea, 2000). (Balch, 1998) was the first to concentrate his research on reinforcement learning in behavior-based multi-agent robot teams.

When a behavior-based approach is applied, the behaviors that are used to fulfill each tasks are to be accomplished in at least two steps:

- a perceptual process (determines the robot's proper position in formation based on current environmental data), and
- the motor process (generates motor commands to direct the robot toward the correct location). Several motor schemas (e.g. move-to-goal, avoid-static-obstacle, avoid-robot, maintain-formation) will implement the overall behavior for a robot to move to a goal location while avoiding obstacles, collisions with other robots and remaining in formation.

The above mentioned strategies based on fuzzy and neural approaches could be easily integrated in a multi-agent design methodology in order to implement individual – elementary – behaviors.

Nevertheless, further mechanisms for supervision and proper sequencing of individual behaviors are needed. In (Dragoicea, 2005) and (Dragoicea, 2005b) strategies for task coordination in multi-agent systems are proposed, based on finite state machines.

The experiments specifically describe a framework of defining behavior-based strategies for multi-robot tasks, specifically for robot soccer and robot foraging. The research focuses specifically on motor schema-based multi-robot systems, which are an important example of behavior-based control. Individual motor schemas, or primitive behaviors, express separate goals or constraints for a task. Motor schemas may be grouped to form more complex, emergent behaviors. Groups of behaviors are referred to as behavioral assemblages.

Solving complex tasks for mobile robot control implies than developing an assemblage for each sub-task. This the assemblage will be further executed in an appropriate sequence, by temporal sequencing (Balch, 1998). Therefore a resulting task solving strategy can be represented as Finite State Machine.

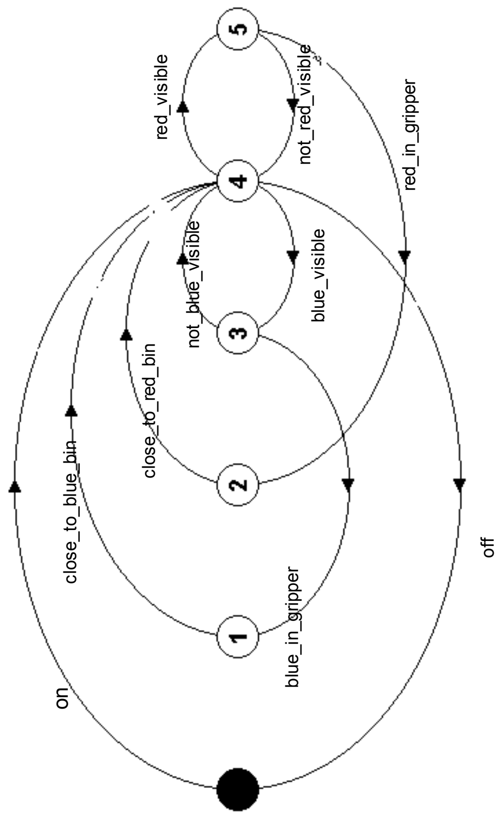


Fig. 10 Behavioral assemblage for homogenous foraging based on finite state machines

Fig. 10 displays an example of behavioral assemblage for a homogenous foraging task (Balch, 1998), that means all the robots collect all the different types of attractor and deliver them to the corresponding color-coded delivery areas. All agents are programmed with the same sequence of behaviors (Dragoicea, 2005).

The behavior assemblage for homogenous foraging can be represented as an abstract model as follows (McGee, 2003):

```
HOM_FOR       = OFF,
OFF           = (on->WANDER),
WANDER        = (red_visible->ACQUIRE_RED
                 |blue_visible->ACQUIRE_BLUE
                 |off->OFF),
ACQUIRE_RED   = (red_in_gripper->DELIVER_RED
                 |not_red_visible->WANDER),
DELIVER_RED   = (close_to_red_bin->WANDER),
ACQUIRE_BLUE = (blue_in_gripper->DELIVER_BLUE
                 |not_blue_visible->WANDER),
DELIVER_BLUE = (close_to_blue_bin->WANDER).
```

Therefore, the Finite State Machine (FSM) that describes the homogenous foraging task is an extension of the behavioral table:

$$M: (K, \Sigma, \delta, s, F)$$

where

$$K = \{\text{off, WANDER, ACQUIRE\_RED, ACQUIRE\_BLUE, DELIVER\_RED, DELIVER\_BLUE}\}$$

are the states the robot should be in (the finite number of discrete states for homogenous foraging is 6).

$$\Sigma = \{\text{on, red\_visible, blue\_visible, off, red\_in\_gripper, not\_red\_visible, close\_to\_red\_bin, blue\_in\_gripper, not\_blue\_visible, close\_to\_blue\_bin}\}$$

is the set of behavioral releasers (that means the inputs of the FSA, also called the alphabet).

δ is the transition function that specifies what state the robot is in after it encounters an input stimulus from Σ.

$$s = OFF$$

is the Start State, and the robot should always start there.

$$F = OFF$$

is the final state that the robot can reach that terminates the task. Here the final state is OFF, that means the robot runs the sequence of behaviors until it is turned off manually.

The same procedure based on finite state machines for behavior assemblage definition could be used for robot soccer (Dragoicea, 2005b). For implementation details, see (Dragoicea, 2005) and (Dragoicea, 2005b).

Fig. 11 presents the behavioral assemblages for team members evolution – player and goal keeper in one team.

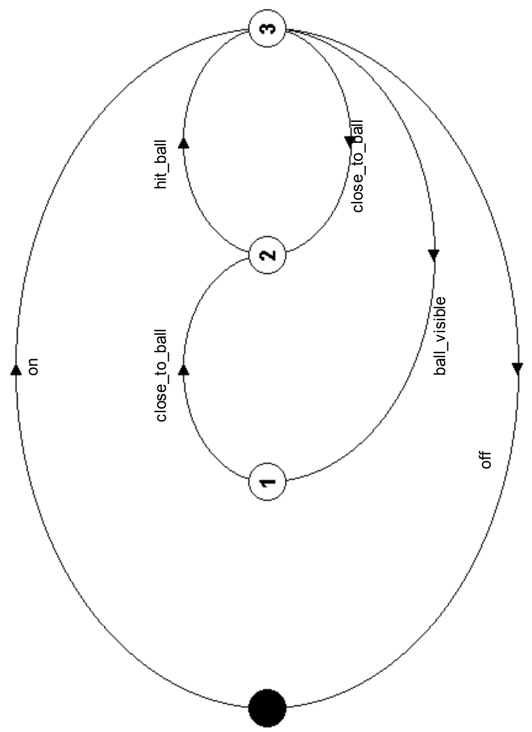


Fig. 11a) Behavioral assemblage for robotic soccer - player (forward)

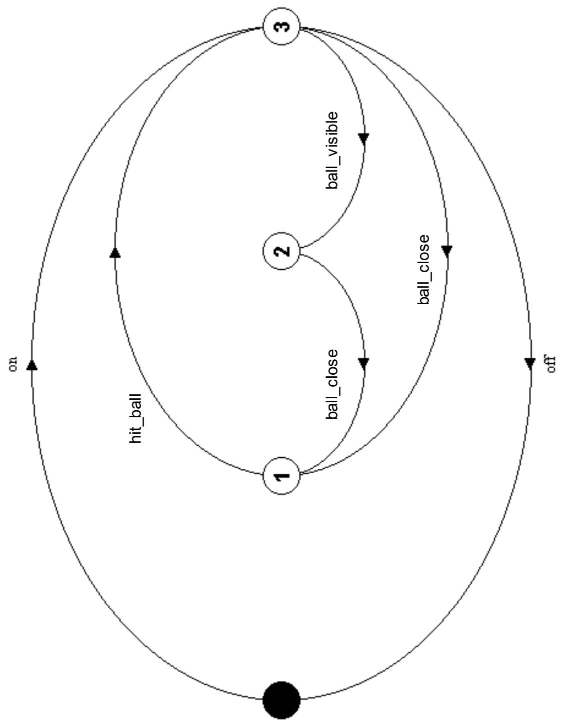


Fig. 11b) Behavioral assemblage for robotic soccer - goal keeper

Each robot selects from a set of behavioral assemblages to complete the task. The behaviors are sequenced to form a complete strategy. In this case, the possible transitions are between the following states (Dragoicea, 2005):

- for the forward player: state 0 = OFF, state 1 = GO_TO_BALL, state 2 = BEHIND_BALL, state 3 = WANDER;
- for the goal-keeper: state 0 = OFF, state 1 = GO_TO_BALL, state 2 = DEFEND, state 3 = WANDER.

Therefore, for sequential real-time system a Finite State Machine (FSM) representation was used, which represent the different states of the robot. Behaviors composing a behavioral assemblage represented by a FSM, as well as releasers, can be further designed using Object Oriented Principles - OOP.

6. CONCLUSIONS

This survey paper tries to do a short presentation of the research state-of-the-art for the mobile robot control systems with some results applications of our team.

We consider that the cognitive and intelligent techniques could be applied with real success to develop a new generation of mobile robots as an intelligent information system highly adapted at the variable and uncertain environments.

The parallel view between mobile robots and biological systems gives us the opportunity to identify the limitations of the actual advanced control systems for robots to realize a complex behavior into uncertain and variable environment taking into account the hybrid paradigm deliberative-reactive.

Some applications of the neural networks, fuzzy logic and knowledge based procedures are presented that implement the main attributes of the intelligent systems in robotic applications.

This paper is only a short synthesis of the research in this very dynamic field of mobile robot control systems.

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