Neural Mechanisms of Learning and Control in Mobile Robotic Systems

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Abstract - 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 (i.e. analyzing "inputs" and "outputs" of their behavior) roboticists can gain insights into how to organize "intelligence". This paper proposes a strategy for mobile robot control that naturally integrates intelligent techniques for autonomous navigation. A new application of artificial neural networks for autonomous navigation of mobile robots in a reactive way is depicted here. In the perception of the sensory information of different modalities that defines the mobile robot environment, the major learning strategy seems to be biologically characterized by sensory information categorization and classification. Therefore neural networks models of self-organizing type were used in order to establish and adapt a place representation through a progressive learning process in which fast learning takes place.

Keywords: mobile robots, cognitive models, perception, behavior, neural networks control, autonomous navigation

I. 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.

Cognitive robotics integrates results from the neurosciences and information technologies aiming to develop hardware / software products which "live and grow", i.e incorporating auto-adaptive and evolving artifacts, based on pure programming.

In this framework, the purpose of this paper is to propose new ideas for using artificial intelligence techniques in certain areas of mobile robot control and to demonstrate the validity and performance of such an approach on a real world control problem. The paper is organized as follows. Section II briefly introduces some recent advances in neurophysiology that raise issues in transferring animal models of behavior to robots, helping to formalize aspects of behavior. Section III presents a formalization of mobile robot navigation by landmark recognition by using schema theory. Previous research results that make use of fuzzy logic control [3] are extended here in order to incorporate learning. 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. Here, perceptual and motor schemas are particularized and implemented by using artificial neural networks of clustering type. Section IV presents obtained results and section V gives some conclusions and directions of further research.

II. ANIMAL BEHAVIOR AND ROBOTICS

By conceptualizing different aspects of intelligence by exploring biological and cognitive sciences for insights in intelligence, an abstract intelligent system can be defined as an agent. 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. The modern approach to artificial intelligence (AI) is centered around the concept of a rational agent. An agent is anything that can perceive its environment through sensors and act upon that environment through actuators.

The possibility of intelligent behavior is indicated by its manifestation in biological systems. The word intelligent in this definition implies that we expect to achieve some resemblance to the intelligence demonstrated by living creatures, primarily by humans. Animal behavior defines intelligence. Therefore, neuroscience, psychology and ethology offer a suitable starting point for the study of behavior robotics.
At present, strong evidence exist in biology that shows the fact 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.

As was suggested by recent results in neurophysiology, the cerebellum and basal ganglia are both involved in different aspects of motor control. 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 [4], [5], see figure 1.

The locations in the brain where a place mapping representation is formal are believed to be in the hippocampus [6] 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 where places were located and with navigating accurately between them [7].

Transferring these concepts to mobile robotics means that detecting unique features in the world - landmarks - allows to anchor the navigation system within the world itself. Provided that the robot is able to identify landmarks unambiguously, navigation is achieved with respect to the world, rather than with respect to an internal frame of reference. Therefore, for mobile robots, navigation can be accomplished by means of perceptual landmarks, that means an uninterpreted, location-dependent sensory patterns such as sonar range patterns or images perceived at a particular location [11].

Mobile robotic systems benefit of an extremely big 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. Nehmzow [11] proposed a formalization of mobile robot landmark-based navigation by using artificial neural networks of self-organizing type.

There are also applications of the Adaptive Resonance Theory Networks (ART) associated with the pioneer of neuromodelling, Stephen Grossberg. In fact, the ART network has been advanced as a theory of perception and classification in biological systems and this is a valuable exploration of its practical application. Frequent reference is made to the construction of a cognitive map in the hippocampus of the animal nervous system.

We define here a landmark 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.

In the context of the mobile robotic terminology, a mapping of sensory inputs to a pattern of motor actions which are used to achieve a task is called behavior.

![Fig. 1. Brain learning-oriented specialization](image-url)
By means of behaviors a set of relations between the robot and the environment can be established that would further govern the activity of the robot [3]. Therefore, the internal representation can be compacted to the minimum necessary for the agent to react to received stimuli from the environment for the sake of survival [12].

This work proposes a navigation strategy based on landmarks recognition for autonomous navigation of the mobile robots. An ART2 neural network (i.e. an artificial neural network of the self-organizing type) is used here in order to implement the perceptual part of a behavior in the framework of schema theory [13]. 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.

III. LANDMARK NAVIGATION STRATEGY

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 [13].

In this work, perceptual schema embodies the sensing, while the motor schema represents the template for the physical activity (figure 2). The two stages considered here to be necessary in order to design the control system for autonomous navigation are the reactive exploration phase and the navigation by landmark recognition phase.

A. The reactive exploration phase

The reactive exploration phase implies different experiments conducted with the robot initially under manual control. Under manual control the robot is moved to a randomly chosen position in its environment and receives different control signals (i.e. control signals for the two wheels). The robot trajectory could be controlled by manual setting of the two wheels velocities.

By actively exploring the environment, the mobile robot accumulates evidence through its sensors, making a correspondence between sensory inputs and motor actions. In this way the further navigation process is governed by simple rules referred to as behaviors that would lead quickly to useful patterns of autonomous action and navigation.

B. The navigation by landmark recognition phase

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.

One way to do this is to use information concerning the neighborhood relationships between certain landmarks the robot perceives. Such topological mapping occur, for example, in animals and humans in the mapping of sensors onto the cortex, as it was mentioned in the previous section.

Therefore the exploration phase is completed with a learning process in which an Adaptive Resonance Theory self-organizing neural network (ART2) is used in order to cluster the perceptual space of the mobile robot.

Figure 3 presents the ART2 neural network controller for navigation based on perceptual clustering of the environment.

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Fig. 2. Behavior based navigation by using schemas theory
The ART2 neural network learns to classify the sensory patterns that the eight proximity sensors produced during the reactive exploration stage. The motivation for choosing self-organisation 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 recognise 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.). Suitable perceptual landmarks emerge rather than being defined arbitrarily by a human designer. In the wider context of the map-building and localisation competences the ART network is effectively used as a "black box" for classifying sensor patterns.

The ART2 network of Carpenter and Grossberg [14] type is designed to categorize continuous-valued input patterns that represent raw sensory measurements.

Figure 4 shows an example of categorization of the analog patterns by the ART2 neural network. The 68 patterns of sensory inputs, drawn as bar graphs, are finally grouped by network learning into 34 recognition categories, named C_1, … C_34.

The number of raw sensory data that are used in order to train the ART2 network is heuristically chosen, based on the complexity of the task that has to be achieved and also on the experience of the designer of the application.

Category 14 - Avoid obstacle that stands right - back (at the end of a corridor, half-way of a complete turn)

Category 22 - Avoid obstacle that stands close left - front - right (at the end of a narrow corridor)

Category 29 - Avoid front obstacle

Fig. 4. Categorization of sensory inputs by ART2 network
For each category two clustered sensors are explained. The following parameter values were used throughout all of the experiments and simulations (for the update rules see [15]):

\[
a = 10, b = 10, c = 0.1, d = 0.9, e = 0.01, \alpha = 0.6, \theta = 0.09, \rho = 0.97
\]

The vigilance parameter \( \rho \) proved to be a critical parameter for the category forming process. As it was observed, only the values close to 1 influence the formation of the clusters.

Through experiments, the optimum value was determined as being \( \rho = 0.97 \). For lower values of \( \rho \), the network formed less categories, that means important evidence about the environment was missed.

As can be seen in figure 5, the differences in the output of the clustering process depending on the values of the vigilance parameter are displayed.

As can easily be seen, higher values of \( \rho \) resulted in a fine categorization (a much more relevant similitude between continuous-valued raw sensory inputs) and lower values in a coarse categorization.

The motor schema part of controller (see figure 3) associates the ART2 categories to some control signal in order to steer the mobile robot with the desired movement. For example, for the above explained categories the following correspondence will hold:

<table>
<thead>
<tr>
<th>Category number</th>
<th>Control signal ( U_l )</th>
<th>Control signal ( U_R )</th>
</tr>
</thead>
<tbody>
<tr>
<td>14</td>
<td>-M</td>
<td>+M</td>
</tr>
<tr>
<td>22</td>
<td>-M</td>
<td>-M</td>
</tr>
<tr>
<td>29</td>
<td>-M</td>
<td>-M</td>
</tr>
<tr>
<td>31</td>
<td>-M</td>
<td>+M</td>
</tr>
<tr>
<td>34</td>
<td>+H</td>
<td>-H</td>
</tr>
</tbody>
</table>

where M stands for a medium value of the wheels velocity, H for higher value, etc.

IV. SIMULATION STUDIES

In each of the conducted studies the mobile robot showed useful learning in an impressively small number of trials. The evolution of the robot was tested on a number of simulated worlds as well as on the real Khepera mobile.
robot. In order to test the newly proposed navigation techniques a real-time simulator was developed using the real-time facilities of the QNX operating system (see figure 6 for the application main window).

In this way, an autonomous navigation ability can be obtained, by which the mobile robot can execute different kind of operations, like left or right wall following, obstacle avoidance, etc. The type of operation is defined by the set of raw sensory data that defines a certain landmark, for example left corner, right corner, straight corridor, round obstacle, etc.

The motor schemas editor is a powerful tool that allows the user to associate to the different categories realized by the ART2 clustering controller wheels velocities, in order to implement autonomous behaviors in the environment. Therefore, a communication function can be easily implemented between the human operator and the mobile robot. One can "program" the robot to follow a wall, to avoid obstacles, or to go to a target.

The two panes of this communication window allows the association between category and velocities (the Controller ART2 pane) and to test the category to which a certain set of sensor values belongs (the Cluster Test pane).

The overall control framework allows the mobile robot to act in an intelligent way. Control algorithms configuration and communication are possible through the motor schemas editor (figure 7). Adaptivity skills are provided through the ART2 clustering - perceptual schema.

Following the general reactive approach, the robot has the possibility to determine the suitable "behaviors" (pattern of motor actions) in order to fulfil the sub-tasks.

These behaviors that integrates memory are to be executed in a reactive way. By combining this kind of associations between the outputs of the two schemas and the odometric readings from the wheels encoders more complex evolutions could be defined.

The neural network controller proved to be extremely efficient in allowing the mobile robot to navigate in a reactive way in the environment. The mobile robot starts from different initial positions, being successful in finding its way through different shapes and obstacles. All the figures shows the same evolution. The robot finds its way in different environments, not previously seen or engineered for its evolutions. A very low sensibility in detecting the contours is displayed in each of these figures.

As can be seen in figure 8, the evolution of the mobile robot following this control framework executes in a clear way. As a test bed, different "environments" were used, that the software simulator provides.

As can be seen in figure 9 the evolution of the mobile robot under a Braintenberg controller supervision is very random.

![Fig. 6. Real-time QNX application for mobile robot control](image-url)
V. CONCLUSIONS AND FURTHER RESEARCH

The cognitive robotics era prefigures into a nearby horizon of time strong correlation with the evolution of the human behavior and cellular intelligence modeling. Building systems based on perception - action activities, including sensorial, cognitive and control aspects which are similar to the visual, hearing, olfactory and tactile biological functions, could represent a tangible target in the context of the evolution of the knowledge and information processing.

Recent advances in cognitive psychology and neurophysiology has led in mobile robotics to an attempt to emulate biology, reproducing the physiology and neural mechanisms. In general, it may not be possible, or even desirable, to duplicate how a biological agent does something. Although "learning from nature" is an old concept, what we can actually learn from biological systems depends very much on the available theories and technologies.
In this framework, a new application of artificial neural networks for autonomous navigation of mobile robots in a reactive way is presented and depicted here. In this context a major role is assigned to the perception and communication functions. In the perception of the sensory information of different modalities that defines the mobile robot environment, the major learning strategy seems to be biologically characterized by sensory information categorization and classification. Therefore neural networks models of self-organizing type were used in order to establish and adapt a place representation through a progressive learning process in which fast learning takes place.

The experiments presented here were chosen to demonstrate the ability of the proposed strategy to allow autonomous navigation in unmodified environments, avoiding the use of pre-installed maps or external devices such as markers or beacons for position evaluation. To be fully autonomous, the robot must rely on its own perceptions for dealing with the interrelated sub-problems of exploration, map-building and re-localisation. To achieve this, proprioception and/or exteroception can be used. For these reasons we have chosen a landmark-based method, accumulating evidence over time, by learning.

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