A Solar Powered Autonomous Mobile Vehicle for Monitoring and Surveillance Missions of Long Duration

Antonio Guerrero-González[1], Francisco García-Córdova[1], Francisco de Asis Ruz-Vila[2]

Abstract –*In this paper, an autonomous vehicle capable of operating during large periods of time for observation and monitoring is proposed. The vehicle integrates photovoltaic panels and a methanol fuel cell, together with a neurobiological inspired control architecture for intelligent navigation. In this work, the autonomy of the vehicle is evaluated in several scenarios, when the vehicle is moving in mission and when the vehicle is not moving. The energetical management module generates recharge missions with a variable priority level depending on the batteries level to the mission planner. The biologically inspired neural network architecture proposed for nonholonomic mobile robots makes the integration of a kinematic adaptive neuro-controller for trajectory tracking and an obstacle avoidance adaptive neuro- controller possible.*

***Keywords**: Solar Powered Autonomous Vehicles, Neuro-controller, Fuel Cell, Power Management*

I. Introduction

The integration of renewable energies on autonomous vehicles has become a common practice in recent years. A large number of recent projects, seek that the autonomous vehicles not only have autonomy from the point of view of control and navigation, but also having the ability to self-generate energy, which allows to perform tasks and / or mission of long-duration. The use of photovoltaic solar energy is the most widely used for these purposes, applying to different types of autonomous vehicles regardless of the medium in which they work (land, sea and air).

I.1. Solar Powered Autonomous Mobile Robots

The need for different data collection in situ, at different scales of time and space, has promoted an effort to develop different types of autonomous vehicles that enable the collection of such data. These platforms have varying capabilities of each communication, durability, mobility, capacity and autonomy. Within these different platforms, are in addition to others, autonomous underwater vehicles (AUV) and Autonomous Surface Vehicle (ASV). According to D. Blidber *et al.* [1], there are three main limitations for autonomous underwater vehicles: energy, navigation for a long time and long distances, and user communications with the platform. He argued that the use of solar energy begins to overcome these limitations, adding the submarine's ability to regenerate energy when needed, giving the ability to last for weeks and months on mission, instead of hours. D. Blidber *et al.* [2] discuss the power management in different situations and find an optimum combination of the size needed to store energy, and the travel distance measurement and / or works to be undertaken by the vehicle this depending on the solar energy available in the area. Special effort is made in the balance between displacement (speed and distance), and tasks (duration and frequency of measurements, number of sensors on board). In their study raises a number of scenarios, where the energy distribution is done in different ways, according to the needs of the mission in question, but it is possible to select different settings for each case scenario.

In [3] the vehicle SAUV II is described, which is an autonomous underwater model that uses solar energy for long duration missions that require monitoring, surveillance, with bi-directional communication in real time and underwater instrumentation.

As an alternative to traditional research ships, with their high operating costs and buoys, which are expensive to build, deploy and maintain, J. Higginbotham *et al.* [4] proposes the Intergration Ocean Atmosphere Sensor System (OASIS), a project for an ASV low-cost, reusable, reconfigurable and long-term that is capable of in situ measurements, independently and for long periods of time.

Another vehicle surface, the AAS Endurance, is detailed by H. Klinck *et al.* [5], as a project to develop in three years driven by the Austrian Society for innovation in computer science, State University of Austria and the Oregon State University. It is an autonomous sailing boat, which uses sensors, actuators and intelligent control system to manage without being driven. This autonomous marine vehicle has special equipment for the study of marine mammals. It is noteworthy that it has solar panels that generate up to 285W, and a methanol fuel cell, that supplies auxiliary 65W.

In this paper, an autonomous vehicle capable of

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operating during large periods of time for observation and monitoring is proposed. The vehicle integrates photovoltaic panels and a methanol fuel cell, together with a neurobiological inspired control architecture for intelligent navigation. In this work, the autonomy of the vehicle is evaluated in several scenarios, when the vehicle is moving in mission and when the vehicle is not moving. The energetical management module generates recharge missions with a variable priority level depending on the batteries level to the mission planner.

I.2. Autonomous Navigation with obstacle avoidance using neural networks

Several heuristic approaches based on neural networks (NNs) have been proposed for identification and adaptive control of nonlinear dynamic systems. More recently, the efforts have been directed toward the development of control schemes which, besides providing improved performance, can be proved to be stable [6], [7].

The study of autonomous behaviour has become an active research area in the field of robotics. Biological organisms are a clear example that this short of learning is possible in spite of what, from an engineering standpoint, seem to be insurmountable difficulties: noisy sensors, unknown kinematics and dynamics, nostationary statistics, and so on. A related form of learning is known as operant conditioning [8]. Chang and Gaudiano [9] introduce a neural network for obstacle avoidance that is based on a model of classical and operant conditioning.

In the classical conditioning paradigm, learning occurs by repeated association of a Conditioned Stimulus (CS), which normally has no particular significance for an animal, with an Unconditioned Stimulus (UCS), which has significance for an animal and always gives rise to an Unconditioned Response (UCR). The response that comes to be elicited by the CS after classical conditioning is known as the Conditioned Response (CR) [10]. Hence, classical conditioning is the putative learning process that enables animals to recognize informative stimuli in the environment.

In the case of operant conditioning, an animal learns the consequences of its actions. More specifically, the animal learns to exhibit more frequently a behaviour that has led to reward in the past, and to exhibit less frequently a behaviour that led to punishment. In the field of neural networks research, it is often suggested that neural networks based on associative learning laws can model the mechanisms of classical conditioning, while neural networks based on reinforcement learning laws can model the mechanisms of operant conditioning [9]. The reinforcement learning is used to acquire navigation skills for autonomous vehicles, and updates both the vehicle model and optimal behaviour at the same time [11]-[15].

In this paper, a biologically inspired architecture that makes possible the integration of a kinematic adaptive neuro-controller for trajectory tracking and an obstacle avoidance adaptive neuro- controller is proposed for nonholonomic mobile robots. The kinematic adaptive neuro-controller is a real-time, unsupervised neural network that learns to control a nonholonomic mobile robot in a nonstationary environment, which is termed Self-Organization Direction Mapping Network (SODMN), and combines associative learning and Vector Associative Map (VAM) learning to generate transformations between spatial and velocity coordinates. The transformations are learned in an unsupervised training phase, during which the robot moves as a result of randomly selected wheel velocities [14]. The robot learns the relationship between these velocities and the resulting incremental movements.

The obstacle avoidance adaptive neuro-controller is a neural network that learns to control avoidance behaviors in a mobile robot based on a form of animal learning known as operant conditioning. Learning, which requires no supervision, takes place as the robot moves around a cluttered environment with obstacles. The neural network requires no knowledge of the geometry of the robot or of the quality, number, or configuration of the robot’s sensors. The efficacy of the proposed neural architecture is tested experimentally by a differentially driven mobile robot.

II. Description of the Solar Powered Autonomous Mobile Robot (CHAMAN)

The biologically inspired proposed control algorithm, power management and monitoring modules are implemented on a mobile robot from the Polytechnic University of Cartagena (UPCT) named “CHAMAN”.

The solar powered autonomous mobile platform has two driving wheels (in the rear) mounted on the same axis and two passive supporting wheels (in front) of free orientation. The two driving wheels are independently driven by two DC-motors to achieve the motion and orientation.

The solar vehicle has two panels of 593x502x22.6 mm, in serial connection providing a charge current of 1.78A at 24 volts. Indeed, the vehicle incorporates a methanol fuel cell providing 2.20A at 24 volts. The currents flows are analysed in line with current sensors connected with a measurement system based in the Compact RIO technology of National Instruments. Some perception elements can be disconnected to reduce the consumption in the vehicle (see Figure 1).

Fig 1. Solar Vehicle in operation.

The vehicle has a CAN bus network as an internal field bus. This network carries sensorial information as motor data and commands and ultrasonic measurements. The ultrasonic system consists on a ring of ultrasonic sensors, four in the sides and one in the front. As a processing unit the vehicles incorporate an embedded computer and a programmable automation controller for energy monitoring. The vehicle incorporate an internal Ethernet network, the main devices connected are a video server, a switch, the embedded computer and de PAC. This internal network is connected to the local network of our laboratory via WIFI. The vehicle includes an inertial unit with accelerometers and gyrostats in the 3 axis for positioning. From this unit the system obtains the inclination, and relative orientation and positioning. The vehicle incorporates also a magnetometer in the front part of the vehicle to obtain an absolute orientation reference based on the earth magnetic field. For surveillance, monitoring and obstacle avoidance the vehicle includes a Laser sensor and a video camera. The video stream is stored in the hard disk of the embedded computer; also the system can make photos of scenes (see Figure 2).

Fig 2. Embedded Computer and Power Electronics of the solar vehicle.

III. Power Management of Autonomous Vehicle

The power management module makes measurement of the main voltages and currents of the power systems, and make balances, estimations and predictions about the energy consumption and autonomies of the missions. The power management module generates recharge missions with the solar panels and fuel cell which has a priority level related with the charge level of the batteries (see Figure 3). The power management algorithms are executed over a NI CRIO 9074, and the interaction with the navigation system is made over the internal Ethernet communication channel of the vehicle.

Fig. 3. Hardware for power Management.

The average consumption and energy inputs to the vehicle are shown in Table I. On the other hand, the energy in vehicle is shown in Table II. The power management module estimates the maximum duration of the energy in vehicle depending if the vehicle is resting or in mission. When the vehicle is in mission all the device and modules are running and the consumption is about 4.3A, when the vehicle is resting, the motors and laser sensor are disconnected and the consumption is about 1.3 A. In the resting state the vision system is working, and therefore the vehicle is making visual observation. The management module estimates the energetic autonomy of the vehicle depending on the working state and the solar energetic contribution. If the vehicle is permanently in the resting state, the autonomy is about 120 days, but if the vehicle is permanently in mission, the autonomy is reduced to about 2 days and 13 hours (see Table III-VI).

TABLE I
CONSUMPTION AND ENERGY INPUTS

Elements	Values
Consumption without movement	1.3 A
Consumption with movement	4.3 A
Solar Contribution	1.6 A
Fuel Cell Contribution	2.2 A

TABLE II
ENERGY IN VEHICLE

Elements	Values at 24V
Batteries	90 Ah
Fuel Cell	2.200 Ah

TABLE III
ENERGY BALANCE AT REST FOR ONE DAY

Elements	Values at 24V
Mission Time	24 h
Daily Consumption	31.2 Ah
Solar Contribution	12.8 Ah
Fuel Cell Contribution	18.4 Ah
Duration at rest	119.5 days

TABLE IV
ENERGY BALANCE AT MISSION FOR ONE HOUR WITHOUT SOLAR CONTRIBUTION

Elements	Values at 24V
Mission Time	1 h
Mission Consumption	4.3 Ah
Solar Contribution	0 Ah
Fuel Cell Contribution	2.2 Ah
Generated Energy	2.2 Ah
Batteries Contribution	2.1 Ah
Recharge time mission	58 min

TABLE V
ENERGY BALANCE AT MISSION FOR ONE HOUR WITH SOLAR CONTRIBUTION

Elements	Values at 24V
Mission Time	1 h
Mission Consumption	4.3 Ah
Solar Contribution	1.6 Ah
Fuel Cell Contribution	2.2 Ah
Generated Energy	3.8 Ah
Batteries Contribution	0.5 Ah
Recharge time mission	7.8 min

TABLE VI
ENERGY BALANCE AT MISSION FOR ONE DAY

Elements	Values at 24V
Mission Time	24 h
Mission Consumption	103.2 Ah
Solar Contribution	15 Ah
Fuel Cell Contribution	52.8 Ah
Generated Energy	67.8 Ah
Batteries Contribution	35.4 Ah
Maximum Operation Time	2 days 13 hours

IV. Autonomous Navigation with Avoidance of Obstacle Based on a Neurobiologically Inspired Neural Network Architecture

Figure 4(a) illustrates our proposed neural architecture. The trajectory tracking control without obstacles is implemented by the SODMN and a neural network of biological behaviour implements the avoidance behaviour of obstacles.

IV.1. Self-Organization Direction Mapping Network (SODMN)

The transformation of spatial directions to wheels angular velocities is expressed like a linear mapping and is shown in Fig. 1(b). The spatial error is computed to get a spatial direction vector (DVs). The DVs is transformed by the *direction mapping network* elements V_{ik} to corresponding motor direction vector (DVm). On the other hand, a set of tonically active inhibitory cells, which receive broad-based inputs that determine the context of a motor action, was implemented as a context field. The context field selects the V_{ik} elements based on the wheels angular velocities configuration.

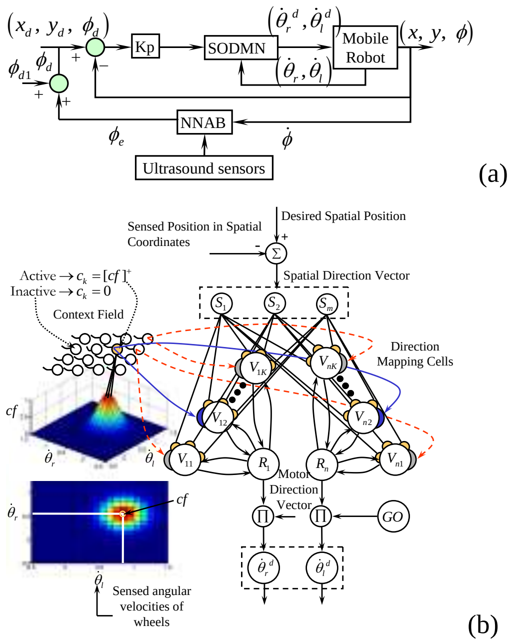


Fig. 4. a) Neural architecture for reactive and adaptive navigation of a mobile robot. b) Self-organization direction mapping network for the trajectory tracking of a mobile robot.

A speed-control GO signal acts as a non-specific multiplicative gate and controls the movement's overall speed. The GO signal is an input from a decision centre in the brain, and starts at zero before movement and then grows smoothly to a positive value as the movement develops. During the learning, the GO signal is inactive.

Activities of cells of the DVs and DVm are represented in the neural network by quantities (S_1, S_2, ..., S_m) and (R_1, R_2, ..., R_n), respectively. The direction mapping is formed with a field of cells with activities V_{ik}. Each V_{ik} cell receives the complete set of spatial inputs S_j, $j = 1, ..., m$, but connects to only one R_i cell. The direction mapping cells ($\mathbf{V} \in \Re^{n \times k}$) compute a difference of activity between the spatial and motor direction vectors via feedback from DVm. During learning, this difference drives the adjustme-nt of the weights. During performance, the difference drives DVm activity to the value encoded in the learned mapping.

A context field cell pauses when it recognizes a particular velocity state (i.e., a velocity configuration) on its inputs, and thereby disinhibits its target cells. The target cells (direction mapping cells) are completely shut off when their context cells are active (see Fig. 4(b)). Each context field cell projects to a set of direction mapping cells, one for each velocity vector component. Each velocity vector component has a set of direction mapping cells associated with it, one for each context. A cell is "off" for a compact region of the velocity space. It is assumed for simplicity that only one context field cell turns "off" at a time. The centre context field cell is "off" when the angular velocities are in the centre region of the velocity space. The “off” context cell enables a subset of direction mapping cells through the inhibition variable c_k, while “on” context cells disable to the other subsets.

The learning is obtained by decreasing weights in proportion to the product of the presynaptic and postsynaptic activities [15]. The training is done by generating random movements, and by using the resulting angular velocities and observed spatial velocities of the mobile robot as training vectors to the direction mapping network.

IV.2. Neural Network for the Avoidance Behaviour (NNAB)

Grossberg proposed a model of classical and operant conditioning, which was designed to account for a variety of behavioural data on learning in vertebrates [7], [9]. Our implementation is based in the Grossberg’s conditioning circuit, which follows closely that of Grossberg & Levine [10] and Chang & Gaudiano [9], and is shown in Figure 5.

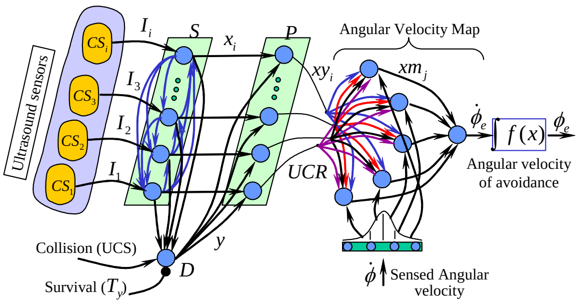


Fig. 5. Neural Network for the avoidance behaviour.

In this model the sensory cues (both CSs and UCS) are stored in Short Term Memory (STM) within the population labelled S, which includes competitive interactions to ensure that the most salient cues are contrast enhanced and stored in STM while less salient cues are suppressed. The population S is modelled as a recurrent competitive field in simplified discrete-time version, which removes the inherent noise, efficiently normalizes and contrast-enhances from the ultrasound sensors activations. In the present model, the CS nodes correspond to activation from the robot’s ultrasound sensors. In the network I_i represents a sensor value which codes proximal objects with large values and distal objects with small values. The network requires no knowledge of the geometry of the mobile robot or the quality, number, or distribution of sensors over the robot’s body.

The drive node D corresponds to the Reward/Punishment component of operant conditioning (an animal/robot learns the consequences of its own actions). Learning can only occur when the drive node is active. Activation of drive node D is determined by the weighted sum of all the CS inputs, plus the UCS input, which is presumed to have a large, fixed connection strength. The drive node D is active when the robot collides with an obstacle. Then the unconditioned stimulus (USC) in this case corresponds to a collision detected by the mobile robot. The activation of the drive node and of the sensory nodes converges upon the population of polyvalent cells P. Polyvalent cells require the convergence of two types of inputs in order to become active. In particular, each polyvalent cell receives input from only one sensory node, and all polyvalent cells also receive input from the drive node D.

Finally, the neurons (xm_i) represent the response conditioned or unconditioned and are thus connected to the motor system. The motor population consists of nodes (i.e., neurons) encoding desired angular velocities of avoidance. When driving the robot, activation is distributed as a Gaussian centred on the desired angular velocity of avoidance. The use of a Gaussian leads to smooth transitions in angular velocity even with few nodes.

The output of the angular velocity population is decomposed by SODMN into left and right wheel angular velocities. A gain term can be used to specify the maximum possible velocity. In NNAB the proximity sensors initially do not propagate activity to the motor population because the initial weights are small or zero. The robot is trained by allowing it to make random movements in a cluttered environment. Whenever the robot collides with an obstacle during one of these movements (or comes very close to it), the nodes corresponding to the largest (closest) proximity sensor measurements just prior to the collision will be active. Activation of the drive node D allows two different kinds of learning to take place: the learning that couples sensory nodes (infrared or ultrasounds) with the drive node (the collision), and the learning of the angular velocity pattern that existed just before the collision.

The first type of learning follows an associative learning law with decay. The primary purpose of this learning scheme is to ensure that learning occurs only for those CS nodes that were active within some time window prior to the collision (UCS). The second type of learning, which is also of an associative type but inhibitory in nature, is used to map the sensor activations to the angular velocity map. By using an inhibitory learning law, the polyvalent cell corresponding to each sensory node learns to generate a pattern of inhibition that matches the activity profile active at the time of collision.

Once learning has occurred, the activation of the angular velocity map is given by two components (see Figure 6). An excitatory component, which is generated directly by the sensory system, reflects the angular velocity required to reach a given target in the absence of obstacles. The second, inhibitory component, generated by the conditioning model in response to sensed obstacles, moves the robot away from the obstacles as a result of the activation of sensory signals in the conditioning circuit.

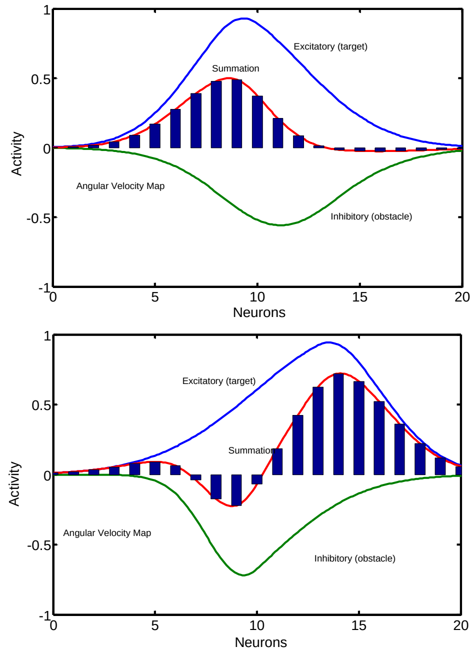
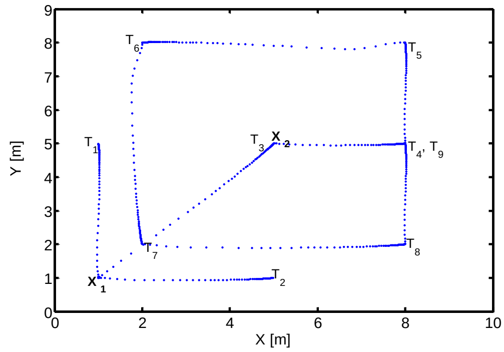


Fig. 6. Positive Gaussian distribution represents the angular velocity without obstacle and negative distribution represents activation from the conditioning circuit. The summation represents the angular velocity that will be used to drive the mobile robot.

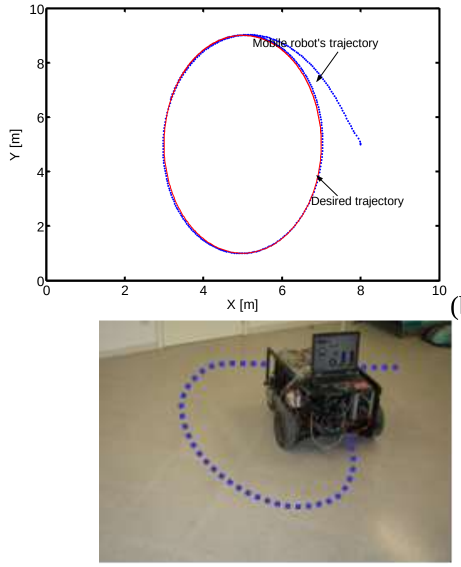
V. Experimental Results

High-level control algorithms (SODMN and NNAB) are written in VC++ and run with a sampling time of 10 ms on a remote server (a Pentium IV processor). The lower level control layer is in charge of the execution of the high-level velocity commands. It consists of a Texas Instruments TMS320C6701 Digital Signal Processor (DSP).

Figure 7 shows approach behaviours and the tracking of a trajectory by the mobile robot with respect to the reference trajectory.



(a)

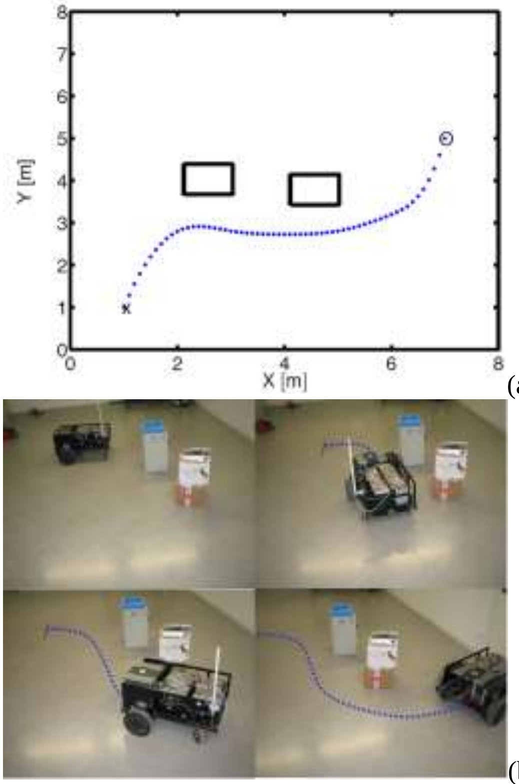


(b)

(c)

Fig. 7. Adaptive control by the SODMN. a) Approach behaviours. The symbol X indicates the start of the mobile robot and T_i indicates the desired reach. b) Tracking control of a desired trajectory. c) Real-time tracking performance.

Figure 8 illustrates the mobile robot's performance in the presence of several obstacles. The mobile robot starts from the initial position labelled X and reaches a desired position. During the movements, whenever the mobile robot is approaching an obstacle, the inhibitory profile from the conditioning circuit (NNAB) changes the selected angular velocity and makes the mobile robot turn away from the obstacle.



(a)

(b)

Fig. 8. Trajectory followed by the mobile robot in presence of obstacles using the NNAB.

VI. Conclusion

The result obtained for this work was to design an autonomous electric vehicle for long-term operations, for which work two aspects: the energy and navigation. The energetic aspect is addressed by including photovoltaic panels, a fuel cell and a module manager, monitor power status of the vehicle and the navigation aspect is addressed by creating a multi-sensory architecture and multi-network on the basis of cortical areas involved in motion planning, trajectory and the task. In this article, we have implemented a neurobiologically inspired neural architecture for trajectory tracking and avoidance behaviours of a solar powered autonomous mobile robot. A biologically inspired neural network for the spatial reaching tracking has been developed. This neural network is implemented as a kinematical adaptive neuro-controller. The avoidance behaviours of obstacles were implemented by a neural network that is based on a form of animal learning known as operant conditioning.

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