CrickBot: A mobile robot with a bio-mimetic control architecture

Michele Folgheraiter, Giuseppina Gini, Alessandro Nava, Vittorio Lumare

Department of Electronic and Information, Politecnico di Milano Piazza L. da Vinci, MILANO , I-20133, Italy32

folghera@elet.polimi.it, gini@elet.polimi.it

Abstract

This work is focalized on the study of a bio-inspired neural controller employed to govern a mobile robot. The control architecture is composed of different subnetworks that emulate the functions of some elementary circuits located in the nervous system of simple animals, like arthropods or invertebrates. The neuronal model mimics the behavior of the natural cells present in the animal, and elaborates the continuous signals coming from the robot's sensors. The output generated by the controller, after scaling, commands the wheel rotation and therefore the robot's linear and angular velocity. The mobile robot, thanks to the controller, presents different behaviors, like reaching a sonorous source, avoiding obstacles and finding the recharge stations. In the network architecture different modules, charged of different functionality, are regulated and coordinated using an inhibition mechanism. In order to test the control strategy and the neural architecture, we simulated the system in Matlab and finally in hardware using a mobile platform equipped with microphones and proximity sensors. Results show that the neural controller can govern the robot efficiently with performances comparable with those described about the animal.

Key words: Biorobotics, Neural controller, Robot navigation.

1. Introduction

A crucial problem in mobile robotics is the trajectory planning, usually it is required to represent the environment where the robot is supposed to move and to model properly the obstacles that should be avoided by the system.

When a map is available it is possible to plan a trajectory that allows the robot to reach the target in the more efficacious and efficient way. Up to now many algorithms were proposed in literature to solve this problem and it was demonstrated that they work very well especially in an environments where everything is known. Unfortunately the situation is quite different in real world, the environment is continuously changing, and frequently noise (terrain irregularities, wheels slipping, sensory drift) increases error in the trajectory that the robot performs. Many times this is sufficient to bring the system to fail the task.

If we look at nature, we can see that in very "simple" animal, insects or invertebrates, the deambulation behavior is always accomplished (1),(2).

Biorobotics, in this context, tries to give an answer to these issues mimicking (3), in the machine, the behaviors and the structure of living creatures. Studying the anatomy and the physiology of the animal it is possible to understand how nature has attempted to solve crucial functional issues. Many scientists are focusing their attention on the part of the animal's nervous system that is involved in the sensorimotor coordination. This part, considering the phylogenetic evolution of the living organism, is the simplest and oldest one (4). From the functional point of view, it covers a primary role because it permits the animal to perceive, explore and change the environment where it lives. Because it is relatively simple and accessible, we have a deeper understanding on how it works in comparison with the higher nervous centers.

2. The neural Controller Architecture

Many researchers have considered a bio-inspired control system in order to control a robot (5), (6), (7), (8). Sometimes the animal not only inspires the control strategy for the robot, but also its kinematics and functionalities. In our point of view there are two possible goals for bio-robotics: the first is to use the robotic system to test and validate the models we have for the animals, the second is to use the proposed models to design new kinds of robots. Reaching both these goals at the same time is very difficult and at times dangerous because a compromise is required. In this work we are more focused on the second goal, with the main idea to use the knowledge we have from the biological studies of the animal to synthesize a "better" robotic system. Better, from the functionalities point of view, than a similar system not based on biological knowledge.

The neural controller we implemented is based on the early studies conducted by Braitenberg (9) twenty years ago on very simple automata vehicles, and on the more recently studies that Barbara Webb et al. (10),(8) carried out on a robot cricket, whose principal behavior is to follow sonorous sources.

Inspired by these studies we tried to implement new paradigms that do not have any evidence in the biological studies of the animal. Sometimes it is near impossible to perform a complete comparison between our model and the biological model, since we are more interested in the robotic functionalities than in mimicking the animal. Nevertheless we are convinced that studying the living organism gives us a big opportunity to synthesize new kinds of "intelligent" machines.
In the neural architecture we propose (Figure1) it is possible to individuate two neuron layers: a sensory layer and a motor layer. The sensory layer is composed by 7 neurons connected with different sensors: contact sensors, sound sensors, energy stations sensors, and an energy level sensor. The motor layer is composed by two neurons whose outputs, opportunely scaled, control the velocity of the two robot's wheels. The synapses of each neuron can be excitatory or inhibitory, so to regulate the activation level and therefore the neuron output.
In the network we can also distinguish four principal parts that are assigned to four different behaviors: collision avoidance, reaching the sound emitter, reaching the recharge platforms, energy level monitoring. In the next four paragraphs we will enter in detail in each of these single parts.

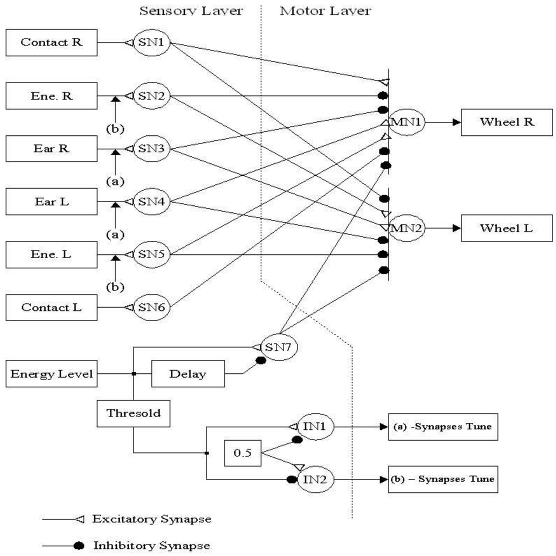

Figure 1. The Neural Controller Architecture

2.1. *Collisions Avoidance*

This behavior involves the action of neurons SN1, SN6, MN1, and MN2 (Figure 1). In particular SN1 and SN2 have only an excitatory input that receives the signal directly from the sensors. The output of SN1 excites the motoneuron MN1 and inhibits the motoneuron MN2, making the robot to turn left when the right contact sensor (**Contact R**) is activated by the collision with an obstacle. The output of SN6 excites the motoneuron MN1, and permits the robot to turn right when an object is revealed by the left contact sensor. As in the schema, there is an asymmetry in the cross inhibition; this is necessary in order to force a left turning when an object is encountered exactly in front of the robot. Depending on the synapses value, the robot turn with less or more strength when it encounters the obstacle.

2.2. *Reaching the Sound Emitter*

The principal goal of our robot is to reach a sound source, mimicking the behavior of the cricket female in tracking the male position. This behavior is possible thanks to the neurons SN3, SN4, MN1, MN2. As we see from the schema (Figure1), SN3 realizes an inhibitory synapse with MN1 and an excitatory synapse with MN2, so the robot turns right if it receives n the right ear (EAR R) a signal stronger than the one received by the left ear (EAR L). The other two connections (SN4-MN1 and SN4-MN2) of this sub-network are completely symmetric, and permit the robot to turn left if the sound signal

perceived by the left ear is stronger than that of the right ear.
In this network the symmetry in the direct inhibitions works because we want to reach the source, not to avoid it.
In reality it is possible to use this kind of architecture to develop other kinds of behaviors if we use also other kinds of sensors.

2.3. *Recharge Platforms Reaching*

The *Recharge Platforms Reaching* behavior, with the *Energy Level Monitoring*, is critical for the robot "life", to guarantee energy for some activity. The corresponding behavior in the animal behaviors is searching for food, that the animal can perceive using olfactory or chemical receptors.
The sub-network involved in this task is that one constituted by neurons: SN2, SN5, MN1, MN2. The architecture is similar to that one which permits the *Sound Emitter Reaching* behavior, but now only the energy-stations sensors are involved.

2.4. *Energy Level Monitoring*

This sub-network, located in the bottom part of figure 1, has a key role in the control system. It permits to regulate the priority of the concurrent behaviors: *Sound Emitter Reaching* and *Recharge Platforms Reaching*. They are concurrent because it is not possible to follow two different targets at the same time .
The neural circuit contains two different parts: one constituted by neurons SN7, MN1 and MN2, and the other by IN1 and IN2. Both these circuits receive as input the signal coming from the sensor that measures the available energy. When the energy level goes below a fixed threshold, a signal reaches both the excitatory synapse of neuron IN1 and the inhibitory synapse of the neuron IN2. Because of this, the neuron IN1 increases its membrane activity and IN2 decreases it. Their outputs go directly to influence the synapses values of neurons SN2, SN3, SN4 and SN5. When IN1 is activated, and therefore IN2 results deactivated, the *Sound Emitter Reaching* behavior is suppressed and the *Recharge Platforms Reaching* behavior takes control of the motoneurons. Note that this mechanism doesn't control the *Obstacles Avoiding* behavior, because it needs to be active also during the energy stations tracking.
When the robot needs energy it is attracted by the energy stations, the more the energy level is low the more the *Recharge Platforms Reaching* behavior takes control of the robot. When the robot reaches a recharge station, the changing level of energy is perceived by the neuron SN7 that becomes active and rises its output. This causes the motoneurons inhibition and therefore the robot remains motionless until the recharge is complete.

3. The Neurons Model

Each neuron in the neural controller is modelled using equations 1, where **P** is the membrane potential and **Y** the neuron's output. The potential changes depend on the excitatory inputs x_i and on the inhibitory inputs x_j, weighted by We_i and Wi_j respectively. The term $-P$ performs a forgetting mechanism. This permits the neuron to avoid the saturation, and therefore to adapt to different stimulation patterns (11). The constant K regulates the dynamics of the neuron, the more it is hight and the more the neuron is faster in following the input signals.

$$\begin{cases} \dot{P} = k(\sum_{i=1}^{n} We_i x_i - \sum_{j=1}^{m} Wi_j x_j - P) \\ Y = Th(P) \end{cases} \tag{1}$$

In this neuron model the activation function is a piecewise linear function (Equation 2), that bounds the output in the range 0 - 1, and at the same time keeps the system linear. Usually, in many neural networks architectures(12), a non linear activation function is introduced to improve the performance of the network in approximating non linear functions. But here what is important is to avoid the neuron saturation and therefore the network instability.

$$Th(P) = \begin{cases} 0 & P \leq 0 \\ P & 0 < P \leq 1 \\ 1 & P > 1 \end{cases} \tag{2}$$

In figure 2 we can see the potential and the output of the neuron when stimulated with one excitatory and two inhibitory signals.

3.1. *Variable Synapse*

Describing the network architecture, in paragraph 2.4, we indicated the capability of IN1 and IN2 to change the input synapse value of the neurons SN2, SN3, SN4 and SN5. This is possible modelling the synapse with a first order differential equation (Eq.3).

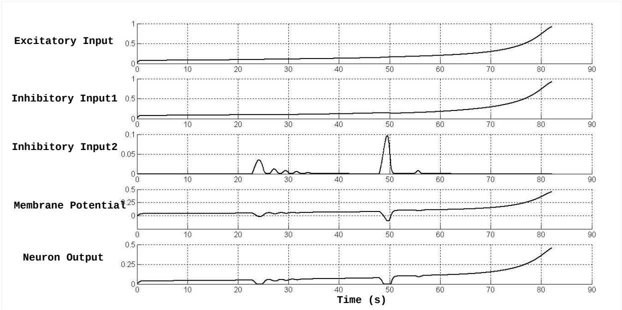

Figure 2. The neuron signals.

$$\begin{cases} \dot{W}_s = W_c - k_d \\ W = Th(W_s) \end{cases} \quad (3)$$

where W_s is the synapse internal state, W_c is the tuning signal coming from the neuron IN_i, K_d a term that allows the depolarizing mechanism, necessary to decrease the synapse value when the tuning signal is low, and finally Th is the function described in equation 2. In figure 3 we see that, when the signal W_c decreases to zero also the weight decreases, and therefore the excitatory input of the neuron doesn't have influence on its potential.

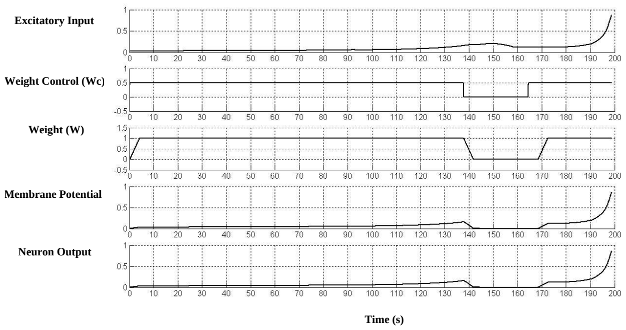

Figure 3. The weight tuning mechanism.

This inhibition mechanism is very important to regulate and coordinate the robot behaviors. What is interesting here, is the possibility to modulate the behaviors in a continuous way, this means that it is possible to switch from a behavior to another with a smooth trend.

4. The Robot Model

In order to test our controller we developed a virtual world where the robot can move and interact with objects.
The arena (10x10 meters, see figure 4) contains obstacles represented by circles of different diameters, a sound source (the target position for the robot) and two recharge platforms.
The mobile robot (0.6x0.4 meters) has two wheels in a differential drive configuration; controlling independently the velocity of the left and right wheels the robot can move forward, backward, turn left or turn right. The robot direct kinematic can be solved using the system of equations 4 :

$$\begin{cases} x(t) = \frac{1}{2}\int (v_l(t) + v_r(t))\cos(\theta(t))dt \\ y(t) = \frac{1}{2}\int (v_l(t) + v_r(t))\sin(\theta(t))dt \\ \theta(t) = \frac{1}{2}\int (v_l(t) - v_r(t))dt \end{cases} \quad (4)$$

where $(x(t), y(t))$ is the robot position, $\theta(t)$ its orientation and v_l, v_r the linear velocities of the left and right wheel respectively, obtained directly from the wheel angular velocities. All of these quantities are respective of an inertial reference system. In this model we neglected the dynamics of the robot, therefore we do not considered mass and inertia. This simplification is plausible, especially if it is possible assume that the robot is very light, nevertheless future models may also include this aspect.
The robot is equipped with two sound sensors located at the right and left side in front of the robot, two energy station sensors located in the same positions, and two circular contact sensors (see figure 4).

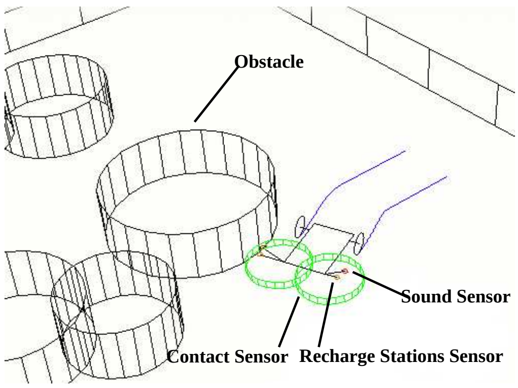

Figure 4. The robot equipped with sensors inside the Arena.

The intensity of the sound signals received by the sound sensors is modelled by equation 5:

$$I_{Received} = I_{Source}\frac{1}{K_1 + K_2 d + K_3 d^2} \quad (5)$$

The intensity of the sound received ($I_{Received}$) by the sensors is directly proportional to the intensity of the sound source (I_{Source}) and inversely proportional to a quadratic polynomial of the source distance d. A similar equation can be used also to represent the signal level received by the recharge-station sensors.

The level of the signal generated by the contact sensor can be model by equations 6.

$$\begin{cases} I_{Received} = K_1 Com + K_2 Com^2 \\ Com = SensorRadius - ObstacleDistance \end{cases} \tag{6}$$

Here Com is the compression of the circular sensor when it encounters the obstacle.

5. Results in Simulation

All the simulations were done using Matlab; for the integration method of the differential equations we used the Runge-Kutta algorithm with an integration step of 0.001s.

The first simulation we performed, was done to test the *Sound Emitter Reaching* and the *Obstacles Avoiding* behaviors. As mentioned before this two behaviors work together to govern the robot movements. The robot moves from a **Start**(in the figure is the star symbol) position to the position of the sound source.

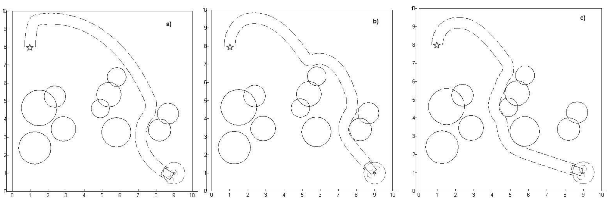

Figure 5. Simulations of the *Sound Emitter Reaching* and the *Obstacles Avoiding* behaviors with different values for the inhibitory synapses.

In figure 5 we see the paths followed by the robot with three different values for the cross inhibition synapses (**a** 0.1, **b** 0.5, **c** 0.6), located in the sub-network that performs the *Sound Emitter Reaching* behavior. Increasing the values for these two synapses makes the robot to narrow the curves. This is useful to more precisely reach the target, however near the sound source a strong inhibition (quite similar in both the motoneurons) slows down the robot velocity.

Another experiment was for testing all the behaviors. Now the robot has a limited amount of energy that doesn't permit it to directly reach the target (sound source). In this experiment we located two recharge platforms at the two side of the upper part of the arena. As we see in figure 6 the robot, at the beginning, performs a trajectory quite similar to that one obtained without considering the *Recharge Platforms Reaching* behavior; however, because now the robot has a finite energy storage, it needs to refill.

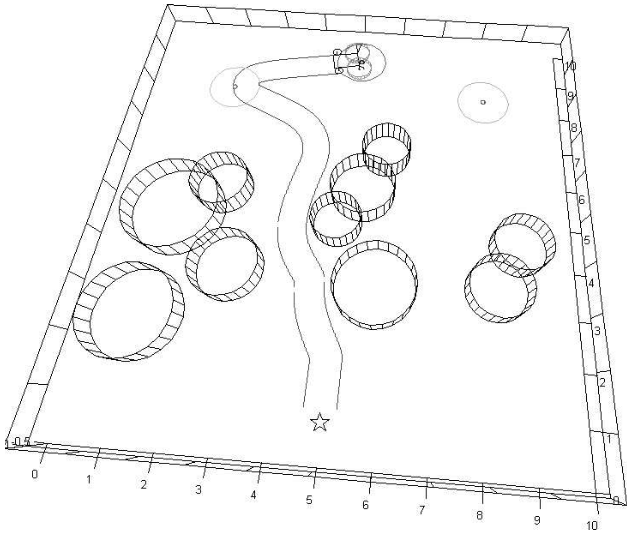

Figure 6. Simulation with all the behavior active (prospect view).

When the energy level is under a certain value the *Recharge Platforms Reaching* behavior takes the control of the robot. Now the robot is more attracted by the energy stations than by the sound source. In the graphs of figure 7 we can see the progress of the energy level and the distance travelled by the robot.

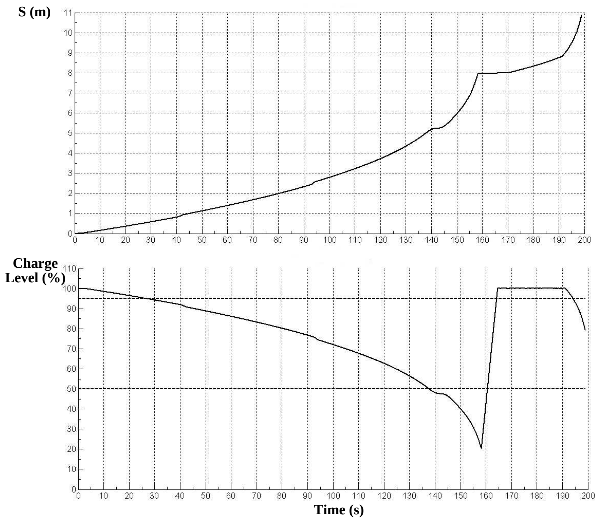

Figure 7. The distance covered by the Robot and its energy level.

After 137 seconds the energy reaches the bottom threshold and the robot changes the direction of movement. At the 158th second the recharge platform is attained and the robot stays for 8 seconds in recharging; after it moves around the platform for 7 seconds. This action is quite strange, it seems that the controller enters in a condition of instability. The phenomenon was interpreted considering that the station can supply a finite level of energy. When the energy is terminated, the robot is not anymore attracted by it and can go to the final target.

6. Experimental Results

In this section we describe the experiments we have done using a mobile platform builded in our laboratory. The main goal was to demonstrate the capability of our neural controller to govern the robot in reaching a real sound source in presence of obstacles located inside the environment.

Another goals is to study the effect of changing the principal synapses of the network. In particular we concentrate our attention on the two inhibitory connection located between the ear sensory-neurons and the two motoneurons. These are crossed in the sense that the inhibition for the right motoneuron came from the contralateral sensory neurons. Experiments evidenced that depending on the synapse values the robot assume different kind of behaviors.

6.1. *Experiment setup*

The experiment testbed consists in a mobile robot of 33cm of diameter and 15cm hight, a square arena with side of five meters, four obstacles and a sound source that emits a pure sound at 1KHz. The robot we employed has two actuated wheels equipped with incremental encoder. On the top of the robot we installed two vocal microphones (JEFE AVL 508) these devises are hight directionally and permits the robot to localize the direction of the sound source, indeed they are sensible only for sounds that hit the sensors frontally. Microphones are connected to amplifiers located onboard and are prevented from vibration by two neoprene sheet. To isolate the microphones from the robot is very important because motors and wheels generate a noise that will add to the sound emitted by the target, this normally will disorientate the robot. The mobile platform is equipped also with a belt of 18 infrared proximity sensors located in front of it. The frequency for the infrared emitters can assume a values between 32 KHz and 38KHz, this permit us to distinguish between four different values of distances (20cm 15 10 5), the more the object is near to the sensor the bigger is the signal that it generates. For this particular experiment we divide these set in two subset that are suitable to located an obstacle at the left or at the right of the robot, we assumed that the sensor will work like a proportional contact sensor that increase its output according with the distance from the obstacle. This will comply the configuration of the mobile robot we used to perform the simulations.

Sensors and actuators are managed by a microcontroller (Microchip 18F452) which take care also for the communication (RS232) with the host computer. The robot is connected with the host computer by a cable that brings the RS232, the power and the sound signals. To acquire the sound signals we used the sound board inside the host computer and elaborated the signals by Simulink.

As said before the robot arena consists in a square surface of 5X5 meters, were we placed four obstacles with a diameters of 0.5m, obstacles are yellow in order to increase the sensibility of the proximity sensors. The sound source is represented by a pure sinusoid of 1 Khz, sound is reproduced by an mp3 player connected with two amplified speakers.

The neural controller runs on the host computer in real time, to implement the neurons and the sound filter we used Simulink (Matlab). We chose a fixed integration step of 0.5ms and employed Euler algorithm. Thanks to the tool ”Windows Real time workshop” it is possible to compile the Simulink code and execute it in real time, this means that every 0.5ms the control system acquires the input signal from the robot calculates all the signals that flow in the network and resend the output to the robot.

The sound signals are acquired using the sound board that equip the host computer with a frequency of 3.2 Khz, this in order to accomplish the Shannon theorem. In order to filter noises that can be located inside the environment, for example from people that are speaking or from the wheels of the robot, we used a bandpass filter implemented via software, it lets pass the frequencies between 0.9 and 1.1 KHz, outside the signal magnitude is reduced of -80dB. During each experiment the sound intensity is maintained constant.

6.2. *Methodology*

In order to prove the efficacy of the neural controller in governing the robot and to better understand the inhibition mechanism that acts in the middle level of the network, we performed a set of repeatable experiments.

Synapse	MN1	MN2
SN1	0.1	-0.7
SN3	-w	1
SN4	1	-w
SN6	-0.8	0.1

Table 1
The synapses values,SN1 and SN6 are the contact right and left sensory-neurons and SN3 SN4 the right and left ear sensory-neurons

In each test we started with a well defined initial condition: each time we positioned the robot in a fixed initial position and orientation, we regulated the sound source at a fixed level of intensity and located the obstacles in the same position. To simplify the experiment we also excluded the part of the network which is devoted to monitor the energy level of the robot and to switch from the *Sound Emitter Reaching* behavior to the *Recharge Platform Reaching* behavior.

Because we wanted to analyze the effect of the inhibitory synapses that connect the Ear sensory-neurons to the contralateral motoneurons, for these set of experiments we keep fixed all the other synapses that interests the net. In table 1 we reported the values for the connections between the sensory-neurons and the motoneurons, negative values indicate that the synapse inhibits the neuron, we keep the same nomenclature used in figure 1. We indicated with a variable **w** the synapses tha we changed during the experiment. The other synapse that interest the sensory-neurons inputs are all settled t the maximum value 1.

As is possible to note we chose different value for th inhibitory synapses SN1-MN2 and SN6-MN1 in orde to force the robot to turn right if both the contact sensor are activated at the same value

We want to change the inhibitory synapses that ar located between the sensory neurons and the motoneurons. We will change their values between 0.5 to 0.7 to 1 and to from 0.5 to 0.3 to 0.1, so in total we will perform five experiments.

Increase these synapses will make the robot turn mor for the same sound intensity and source position, whe the robot is oriented in front of the source these synapse will decrease the speeds proportionably to the invers of the distance between the source and the robot. Th more the inhibitory synapses are hight the more tim the robot will requires to reach the sound source.

In the case the robot is not oriented toward the soun source, for example because is avoiding an obstacle, a big cross inhibition will cause a more robot reaction depending on the difference between the right and left signals.

Before to feed the neural controller each inputs signals is normalized between 0 and 1, after the elaboration the motoneurons outputs are scaled in order to obtain a proper velocity reference for the two motors that equip the robot.

6.3. *Results and discussion*

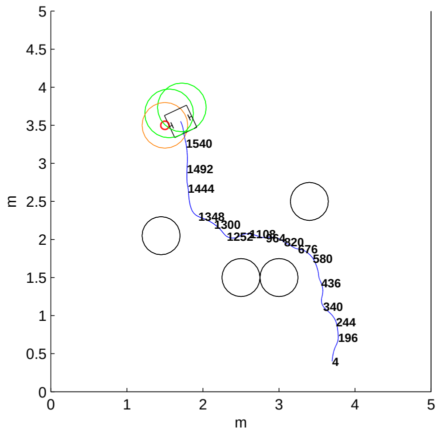

Figure 8. Trajectory followed, inhibitory weight 0.1

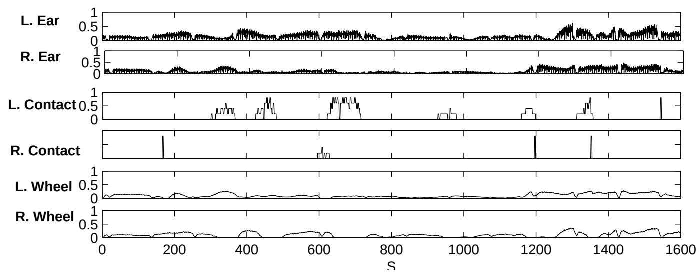

Figure 9. Ear and Bumper Input Signals, and motoneurons outputs, inhibitory weight 0.1

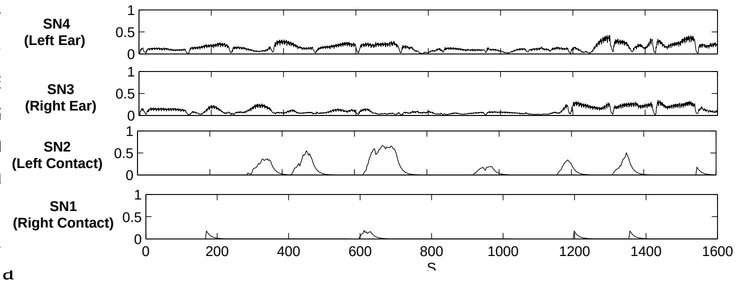

Figure 10. Signals from sensory neurons to motoneurons,inhibitory weight 0.1

7. Conclusion and Future Work

In this paper we presented a bio-inspired neural controller for a mobile robot. The network architecture is organized in two neurons layers: the sensory layer receives the output signals coming from the robot sensors and feeds with excitatory and/or inhibitory connections the motoneurons, the motor layer combine its input signals to govern the robot wheels. Inside the architecture it is present also a sub-network, that using information about the energy level, regulates the robot behaviors. The regulation is based on an inhibition mechanism that acts directly on the synapses of the sensory-motor layer.

From the first results obtained in a simulated environment we have shown that the controller is able to govern the robot in its primary task, that is following a sound source. We changed the values for the inhibitory synapses that connect the Ear sensory neuron to the motoneuron and evaluated the robot performance.

Compared with other neural controllers (8) (10), we introduced a more complex architecture able to perform different kind of behaviors concurrently. This is possible thanks to an inhibition mechanism that modulates the synaptic strength of different sensory-neurons. Related to the subsumption architecture (13), we developed a control system that is more biomimetic, in the sense that the control layers here are represented by different dynamical neural networks that resemble parts of the neural circuits of the insects.

Experiments suggest us to consider and develop a mechanism to adjust the synapses in order to improve the robot performances. The synapse optimization may be done for example on the time needed by the robot to reach the target and on the level of energy consumed to perform this task. Or it is possible to think to use a learning paradigm (14), (15).

After the hardware implementation of the controller using a DSP processor, we can conclude that the time needed to actuate the robot using the neural architecture is absolutely acceptable.

A more realistic scenario to test the robot may be developed to contribute to the wide area of service robots.

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