Visual learning in Drosophila: application on a roving robot and comparisons

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ABSTRACT

Visual learning is an important aspect of fly life. Flies are able to extract visual cues from objects, like colors, vertical and horizontal distributedness, and others, that can be used for learning to associate a meaning to specific features (i.e. a reward or a punishment). Interesting biological experiments show trained stationary flying flies avoiding flying towards specific visual objects, appearing on the surrounding environment. Wild-type flies effectively learn to avoid those objects but this is not the case for the learning mutant rutabaga defective in the cyclic AMP dependent pathway for plasticity. A bio-inspired architecture has been proposed to model the fly behavior and experiments on roving robots were performed. Statistical comparisons have been considered and mutant-like effect on the model has been also investigated.

Keywords: STDP, hybrid robot, visual cue-based navigation, spiking neurons, drosophila.

1. INTRODUCTION

Visual learning is an important aspect of fly life. Flies are able to extract visual cues from objects (e.g. colour, center of gravity position and others), and associate a meaning to them depending on other proprioceptive and exteroceptive stimuli.

In an interesting paper Liu and coauthors[1] trained flies to avoid flying towards specific visual objects appearing on a surrounding white cylinder. If flies approached such an object a heat beam was automatically activated punishing the on-going behavior. Wild-type flies effectively learn to avoid those objects but this is not the case for the learning mutant rutabaga defective in the cyclic AMP dependent pathway for plasticity.

The dangerous and the harmless objects shown on the cylinder were characterized by distinct visual features: their height over ground, their angular orientation or their size. Interesting biological experiments using a partial rescue technique for localizing the memory in the fly brain show that the object features are stored in the fan-shaped body (i.e. part of the Central Complex, a brain structure present in insects). Using the currently known information available through the experiments a model of the part of the Central Complex involved in visual learning has been designed.

Experiments on a roving robot were performed to evaluate the proposed architecture. An artificial insect brain model has been realized and implemented in order to control the behavior of the robot. The experimental set-up includes an arena where some objects are present. These objects are different but they also have common features. We assume to consider dangerous one of the possible features (for example, the green color). Every time the robot tries to approach a green object, it will be punished. Every time the robot detects an object, it switches the behavior in order to approach the selected object. The Fan-shaped Body will work as a classifier increasing or decrease the weights relative to each feature of the detected objects. In this way the robot learn to avoid dangerous objects and to recognize the dangerous features.

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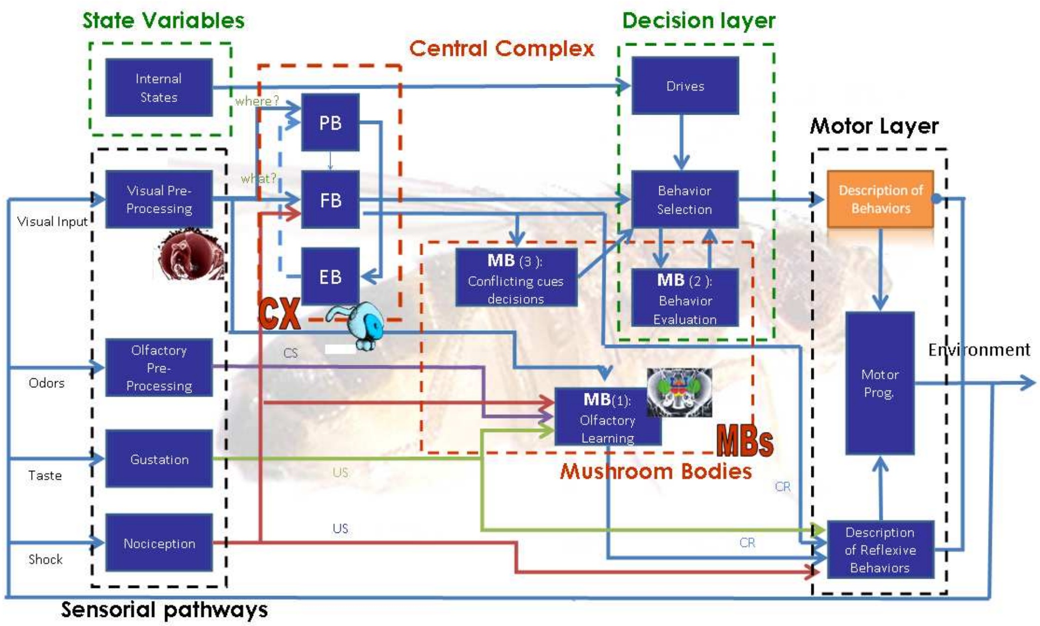


Figure 1. Block diagram of the insect brain model.

2. THE INSECT BRAIN ARCHITECTURE

The development of an insect brain model is a complex task that can be handled and then evaluated considering several different prospectives. The research was principally directed towards the fly *Drosophila melanogaster* and the neural blocks identified and modeled are often tuned in the fly direction.[2] Our objectives are mainly directed toward the formalization of an architecture, looking at the neural assemblies rather at a functional level, trying to formalize the fly brain from the dynamical system prospective considering the reaction-diffusion paradigm. The direction followed in the architecture evaluation process, consisted into comparing the results obtained by neurobiologists in fly experiments with the robot behavior when performing the same tasks.

Biological experiments that involves flies are mainly based on behavioral analysis; this approach motivates the use of statistical analysis of the insect behaviors in order to obtain the relevant key parameters filtering out noise and the fact that only few variables are considered in each experiment discarding the other intrinsic internal variables. These results have been replicated on the robot obtaining a good match between fly and robot behaviors. Moreover another interesting useful aspect for the model evaluation consists in the analysis of the mutant fly behavior. Several experiments concerning fly can be replicated using, instead of Wild type exemplars, genetically modified lines where either specific blocks of the brain or basic learning mechanisms are altered (e.g ablating neural assembly in the brain or using gene expressed toxins that can modify specific learning cascades making the fly deficient in specific behaviors). Experimental results obtained with mutant flies can be obtained also by using the insect brain model following the same alteration that neurobiologists perform on real insects. This is an added value that can be used to further justify the feasibility of the developed structure.

A block diagram of the final implementation of the insect brain architecture is reported in Fig. 1.

In the model, it is possible to distinguish four main sensorial pathways; the olfactory and the visual pathways allow to percept the environment while the gustation and the nociception are indispensable to obtain information about the goodness or badness of the current situation. The learning is obtained using mechanisms based on classical conditioning. Moreover, the own state can be monitored through a set of virtual proprioceptive sensors, that could be chosen according to the application.

Every living being has to know both the external and its internal states to survive in the environment. An internal state is supposed to be directly related to drives: hunger, thirst, the will to sleep etc. are used by animals to know their state and to adapt the behavior accordingly to it. These kinds of drives can be easily transferred to robots: the need for power supply is the most evident example. In order to satisfy its needs, the robot has to choose a behavior from a pre-defined number of available behaviors. Behavior is meant, for the time

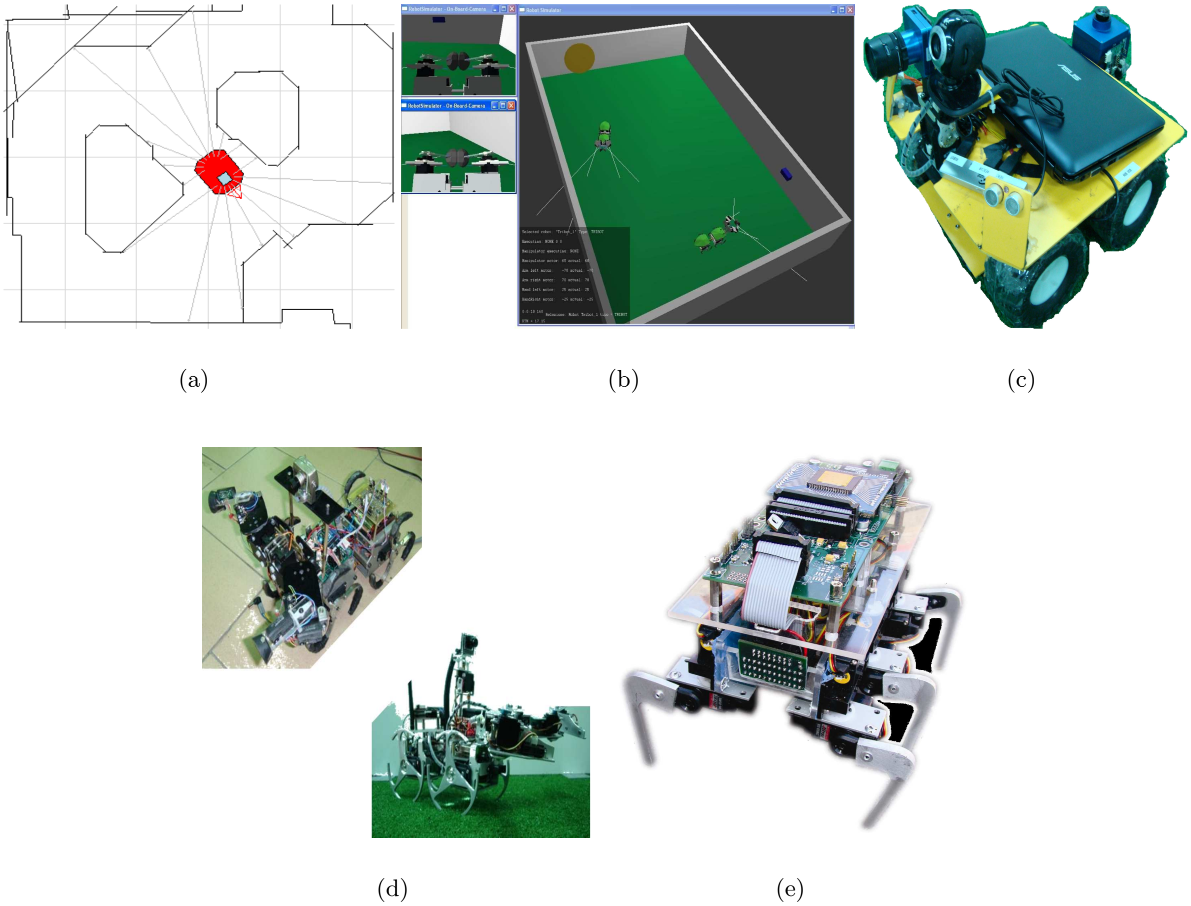


Figure 2. The experiments have been performed both in simulation, using a 2D simulation environment (a) and a 3D dynamical simulator (b) and by using robotic prototypes: (c) a rover, (d) hybrid robots (Tribot I and II) (e) and a hexapod (MiniHex).

being, like a sequence of programmed actions. Each behavior is oriented to satisfy one or more drives. Even if there are not specific experiments that can demonstrate the existence of such a network in the *Drosophila* brain, an artificial Behavior Selection Network (BSN) was supposed and implemented. The BSN was thought as a two layers neural network, in which each unit is an Izhikevich Tonic Spiking neuron.[3] The number of neurons in the first layer matches the number of drives the robot has to satisfy. The number of neurons in the second layer corresponds to the number of available behaviors. Every drive is represented by a current, that is then converted in a spike-rate by the corresponding first layer neuron. The efficiencies of the synapses connecting the first and the second layer neurons are chosen according to the capacity of each behavior to satisfy each drive. Synaptic efficiencies are fixed: no learning is considered at this step. The second layer is a Winner Takes All (WTA) network; during every simulation step the neurons in the second layer are competing and only one neuron can win the competition: the behavior represented by the winning neuron is the selected behavior for the next robot step.

The Central Complex is the brain structure mainly involved in visual tasks; it is composed by three neuropils, namely the Protocerebral Bridge,[4] the Ellipsoid Body[5] and the Fan-shaped Body. In particular, The Fan-shaped body model allows the robot to implement a visual conditioning. This model and its connection with the rest of the insect brain will be described in the following section.

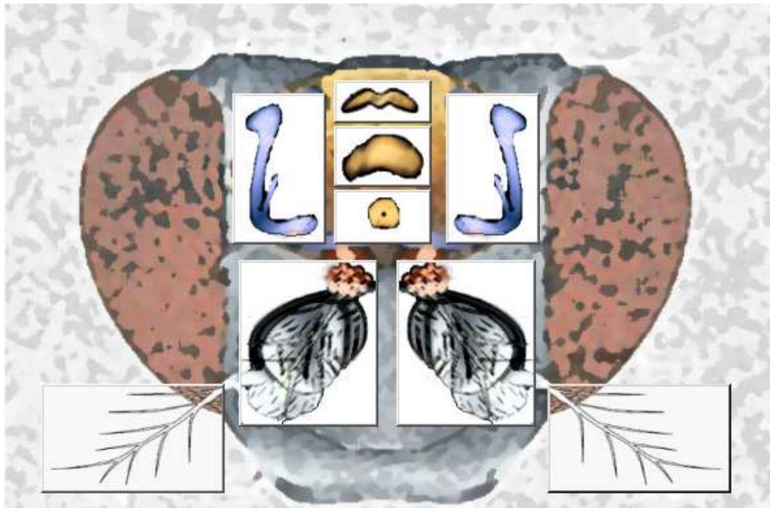


Figure 3. Graphical interface where the active elements of the insect brain are visible during the experiments.

3. EXPERIMENTAL RESULTS

3.1 Robotic Environment

The experiments were performed both in simulation and on real robots. The developed SW/HW framework includes a 2D simulation environment useful for roving robots (see Fig. 2 (a)) and a 3D dynamic simulator based on ODE, where legged and hybrid robots can interact with objects in a virtual arena (see Fig. 2 (b)). Different robotic platforms used during the experiments are: the roving robot equipped with an on-board PC (Fig. 2 (c)), two different prototypes of the hybrid robot Tribot (see Fig. 2 (d)) and a six-legged robot called Minihex (see Fig. 2 (e)).

The framework developed to test the insect brain, includes a graphical interface that allows to identify the different active blocks while the robot is performing the experiment as shown in Fig. 3.

3.2 Results

Experiments carried out on visual learning show the fly capability to associate either attractive or repulsive behaviors to specific objects or even single features if a training stage is performed using a reward or punishment-based procedure.
The proposed model inside the insect brain to demonstrate these cognitive processes, is mainly related to the Central Complex (CX) block. In particular the Protocerebral Bridge (PB), the Fan-shaped Body (FB) and the Ellipsoid Body (EB), are able to support this new process. The objects placed just in front of the robot are segmented and all the relevant features are extracted. The visual preprocessing phase, that mainly involves the optic lobe, has been performed both using standard libraries developed inside the framework and by means of the Eye-Ris visual system. Concerning the Fan-shaped body, the relay station role performed during the visual orientation, is now integrated and augmented with storing capability together with learning mechanisms. The FB model is a multi-network architecture in which each subnetwork is a spiking structure as shown in Fig.4 where unconditioned stimuli (i.e. reward and punishment) are used to trigger a spike timing dependent plasticity (STDP)[6] based learning. Each subnetwork manages a particular feature (i.e. color, shape).
The first layer of the network receives in input the visual pre-processed signals and is connected to a second layer with two neurons associated to the two main behaviors that can be elicited at this level: escaping and approaching. In particular, analyzing the synaptic connections, we can underly that the shock neuron is connected through an excitatory synapsis to the escaping neuron and inhibits the approaching neuron. This is justified because in presence of a dangerous condition the robot escapes without taking into account the other sensory signals. The depicted connections are fixed (not subject to learning) because represent the basic level of apriori knowledge present in the system for safety reasons.

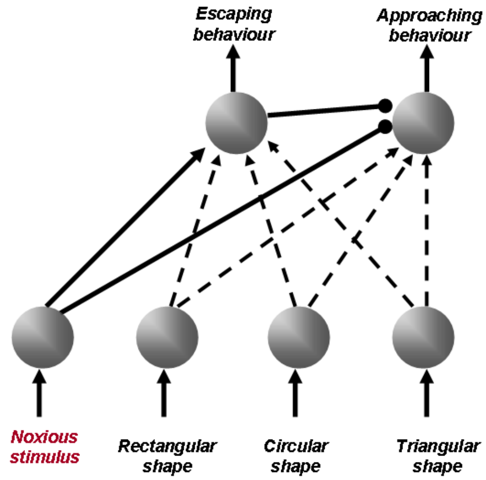


Figure 4. Elementary block of the FB structure. Unconditioned stimuli (e.g. an electric shock) guide the learning of a spiking network that associates a meaning to visual features extracted in the FB. The example refers to shapes, solid lines represent fixed synapses whereas dashed lines indicate plastic connections subject to learning through STDP.

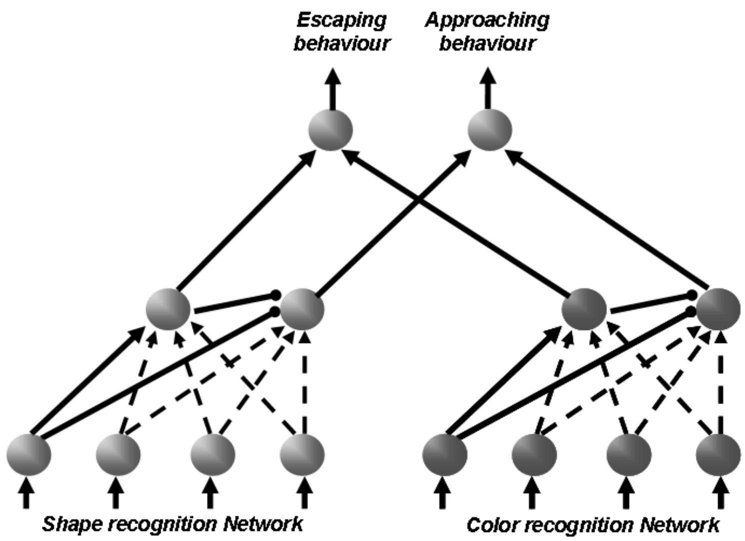


Figure 5. Multiple Elementary blocks of the FB structure can be connected each other through a second layer where visual features are combined.

The other sensing neurons that receive information about the visual features of the object, are connected to both the second layer neurons through excitatory synapses subject to learning. The initial values have a bias toward the approaching behavior giving to the robot an initial preference (i.e. curiosity) to be attracted from the objects in the scene. However the escaping behavior, when elicited, is able to inhibit the object approaching. Similar structures can be replicated for different features in a modular way. Each subnetwork is devoted to handle specific visual features that concur to the behavior selection process through a third layer as shown in Fig.5. The third layer transfers the information processed through the CX to the Behavior Selection Network (BSN), where the merging with the other sensory modalities occurs.

In Fig. 6 the robot behavior when four attractive objects are placed in the arena is shown. In this simulation the robot is able to extract the object features for learning. The final behavior depends on the fact that the robot has been rewarded when reaching all the targets. In contrast, if during the simulation a pair of targets is considered dangerous the final behavior is depicted in Fig. 7 where the robot safely reach the left and right targets while after a series of punishments in the downside one, learn to avoid both the bottom and upper side targets that have the same visual features.

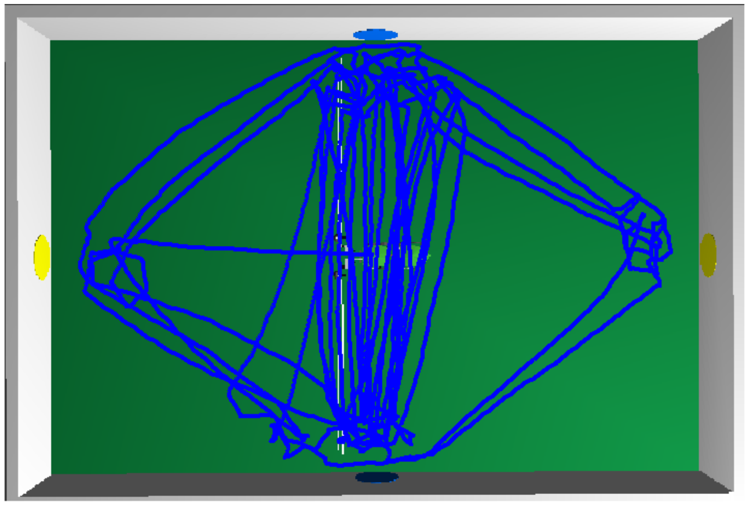


Figure 6. Visual learning experiment. The simulated robot trajectories show the emerging behavior when the robot is rewarded for reaching the targets placed on the center of the walls. The patrolling between the two targets on the farther walls does not emerge due to the preference in reaching the nearest target among the visible ones.

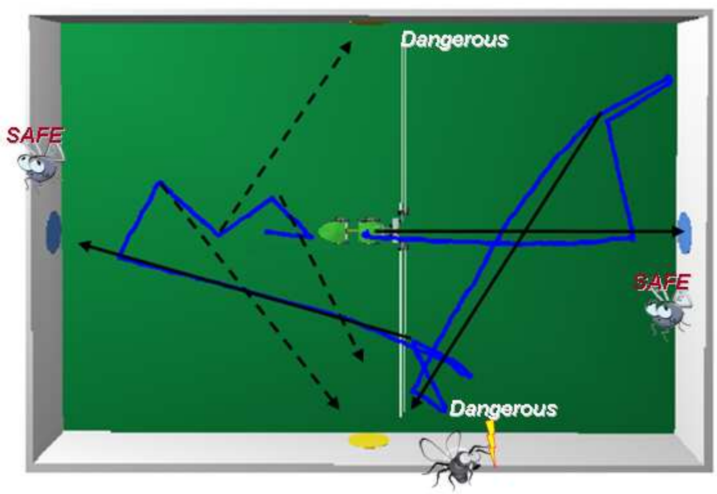
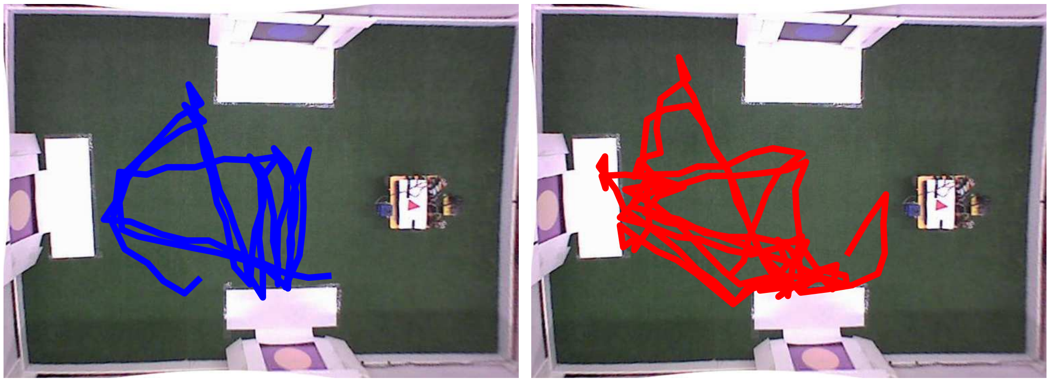


Figure 7. Visual learning experiment. The robot safely reaches the left and right targets (see the solid arrows) whereas is punished when the downside object is reached. The learning process allows the robot to avoid the objects and visual features associated to dangerous events, in this case the bottom and upper side ones (dashed arrows).

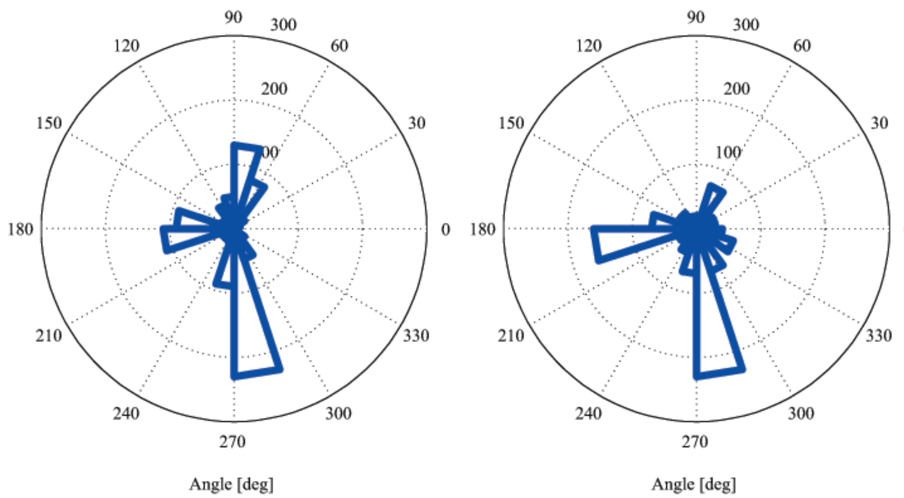
In the following preliminary tests on a roving robot are reported which are currently under evaluation for further optimization. The same set-up used in the dynamic simulator environment has been replicated in the arena for the robot experiments. Two yellow circles have been projected in the screens in the left and right side walls whereas a blue circle is shown in the upside of the arena. The Rover, exploring the arena, is attracted by these targets and is punished when the blue circle is reached. the trajectory obtained during the experiment are reported in Fig. 8. The robot is initially attracted by all the landmarks (Fig. 8 (a)) and then avoids the blue circle (upper wall) due to the punishment signals (Fig. 8 (b)). The changes in the robot behavior are also evident in Fig. 9 where the gaze direction for the first and second part of the experiment is reported.

The level of punishment associated to each feature is shown in Fig.10 where the escaping value for each object is also shown.



(a) (b)

Figure 8. Trajectory followed by the robot for the first 100 steps (a) and for other 150 (b). The robot initially attracted by the blue landmark, after several punishments learns to avoid it.



(a) (b)

Figure 9. Gaze direction for the first 100 steps (a) and for other 150 (b).

4. CONCLUSIONS

The study of insects brain is becoming a reference point in neuroscience and bio-inspired robotics. An insect inspired spiking neural architecture has been designed and implemented both in software and hardware robotic environments. This structure has been tested in a biological-like experiment of visual conditioning on roving robots. The STDP paradigm applied to the fan-shaped body network allows the robot to extract dangerous features from objects and modulate behavior of the robot in order to avoid dangerous objects in the environment.

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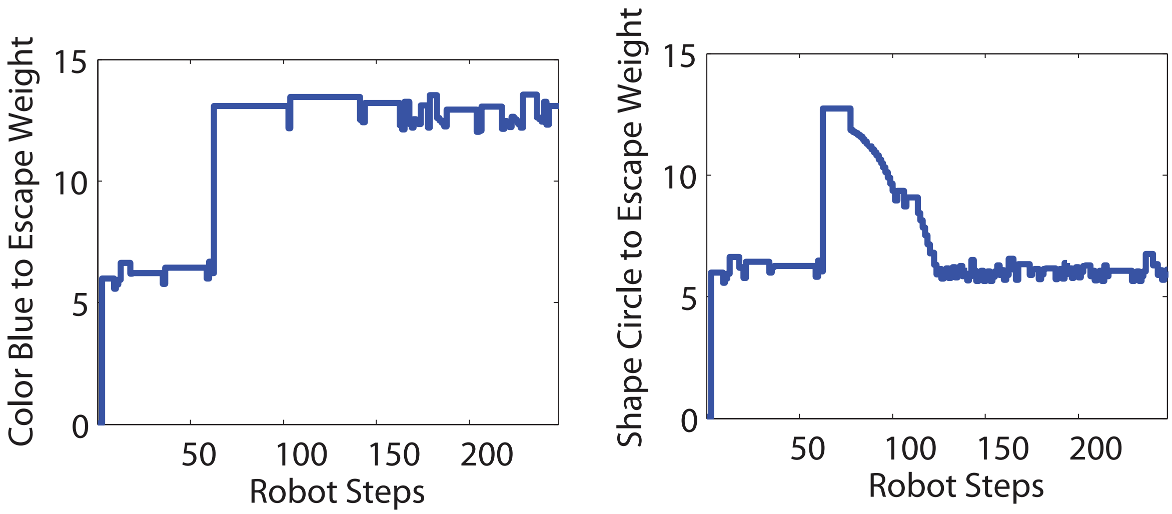

Figure 10. Temporal evolution of the synaptic weights that associate the blue color (left) and the circle shape (right) to the escaping behavior. After 100 steps the robot is able to discriminate the blue circle as dangerous.

REFERENCES

[1] Liu, G., Seiler, R., Wen, A., Zars, T., Ito, K., Wolf, R., Heisenberg,M., and Liu,L., "Distinct memory traces for two visual features in the *Drosophila* brain", Nature 439, pp. 551-556 (2006).

[2] Arena, P., Berg, C., Patané, L., Strauss, R. and Termini, P.S., "An insect brain computational model inspired by *Drosophila melanogaster*: archetecture description", Proc. IJCNN, 1-7 (2010).

[3] Izhikevich, E.M., "Simple Model of Spiking Neurons", IEEE Transactions on Neural Networks, 14(6), 1569-1572 (2003).

[4] Mronz, M. and Strauss, R., "Visual motion integration controls attractiveness of objects in walking flies and a mobile robot", Proc. International Conference on Intelligent Robots and Systems, 3559-3564 (2008).

[5] Neuser, K., Triphan, T., Mronz, M., Poeck, B. and Strauss, R., "Analysis of a spatial orientation memory in *Drosophila*", Nature 453, 1244-1247 (2006).

[6] Song, S., Miller, K.D. and Abbott L.F., "Competitive Hebbian learning through spike-timing-dependent plasticity", Nature Neurosci. 3, 919-926 (2000).