Decision making processes in the fruit fly: a computational model

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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. A decision making process has been identified in the flies that had been trained to avoid objects with specific visual features. In presence of a feature the fly has to decide which features are the most relevant to make a choice. The decision making strategy is guided by a pre-wired hierarchical categorization of the features that, for instance, leads the fly to give more importance to color with respect to shape. 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. hybrid robot, visual cue-based navigation, spiking neurons, *Drosophila* melanogaster.

1. Introduction

Visual learning is an important aspect of fly life. Flies are able to extract visual cues from objects and associate a meaning to them depending on other proprioceptive and exteroceptive stimuli. The relevant brain center responsible for the long term aspect of visual memory has been identified in the Central Complex [1].

Another interesting aspect of the insect brain is related to decision making processes that, is related to the visual sensory modality, were found to depend on another relevant brain neuropile, called the Mushroom Bodies. The number of experiments related to this process are limited due to the complexity of the set-up that needs to exclude a multitude of possible concurrent variables to perform a correct analysis of the results. However an interesting experiment was performed by Tang and Guo (2001) [2]: they trained stationary flying flies, using a heat beam, to avoid a visual pattern in a choice situation where two times two pairs of objects are presented. One pair of objects was green and had an upright-T shape and the other pair was blue and had an inverted T-shape. In the test situation the colors were switched between objects. This feature mixture creates a conflict-

[1]The authors acknowledge the support of the European Commission under the project FP7-ICT-2007-1 216227 SPARK II and FP7-ICT-2009-6 270182 EMICAB.

ing situation for the flies. Is the predictor of heat the form or the color of the previously punished object? Wild-type flies took their decisions to avoid the previously punished objects based on the color of the objects, showing a strong preference in following the color information. An interesting behavior arises when the level of color saturation decreases during the experiments. The dilemma is therefore created not only switching the colors between the landmarks, but also fading the level of saturation. Below a certain threshold for color saturation wild-type flies suddenly and consistently select the shape instead of the color of the objects to be avoided. There was always a clear decision in all flies of the population. Mushroom Bodies-less flies had no clear decision point at which they would switch from color to shape. Rather their population average started with short preference for the color at full saturation and then gradually shift towards shape as the color fades. Therefore Mushroom Bodies (MBs) can be considered as a relevant center for visual-based decision making processes. A bio-inspired architecture has been proposed to model the fly behavior and experiments on a dynamic simulation environment were performed.

2. Model Description

In insects and in particular in flies, MBs are a key neural assembly for decision making. Visual information are mainly processed through the Central Complex (CX) [1], [3], [4] but interesting experiments on the fly show that even if no direct connections have been till now discovered between CX and MBs, the latter is responsible for decision making processes also in relation to visual inputs. The role of MBs for generalization with foreground/background separation and in presence of contradictory cues has been demonstrated in different experiments. In particular, modeling the Fan-shaped body, an important element of the CX, it is possible to replicate on a robotic platform the visual conditioning biological experiments carried out on the fly [5]. The proposed model for solving decision making problem in visual-related experiments in flies is shown in Figure 1. The visual information, acquired through the fly's compound eyes, is elaborated in the CX to be used for the final behavior selection. Beside this direct path a secondary one through the Mushroom Bodies is estabilished. Only a limited number of relevant information are acquired from the visual preprocessing layer to be used to modulate the CX response. The MBs is assumed to work as a gateway that modulates the response of the CX. This mechanism is not important for such tasks as like visual learning, but nevertheless is fundamental in presence of contradictory visual cues to solve a dilemma. The part of the MBs block devoted to this process, that we called MB3, is important to solve contradictory situations, as will be shown, but it is not essential for other more common visual functions, like visual orientation, targeting and learning. As depicted in Figure 1, the direct path through the CX and the indirect path through the MB go to the Behavior Selection Network (BSN) that does not yet correspond to any real physical structure of the brain: it is a block where all the distributed functionalities related to the final behavior choice have been glued. The current implementation of the BSN consists of a two layer spiking network implementing a Winner Takes All - like behavior. The role of MBs in handling visual information, to the best of actual Neurobiological knowledge on the fly brain, is up to now limited to two specific circumstances: in presence of contradictory cues and for foreground/background separation allowing a generalization process. The

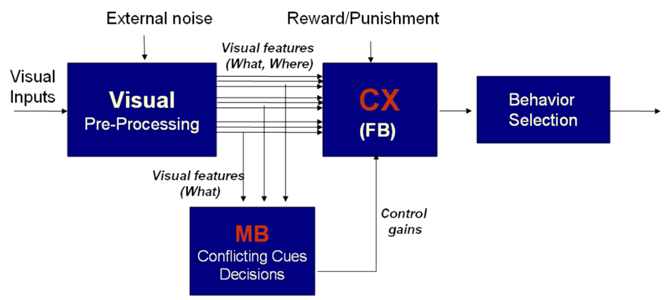

Figure 1. Block diagram of the elements of the insect brain involved in the decision making process in presence of contradictory cues in the processed visual field.

model proposed to deal with the decision making process in presence of contradictory cues is reported in the following and the structure has been modeled on the basis of the fruit fly experimental results reported in [2]. The whole network is depicted in Figure 2 It basically consists of three modules: the BSN block, already introduced, the CX block, used for visual learning via classical STDP-based conditioning and the MB3 block. The fruit fly is normally attracted from landmarks acquired through visual cues. Here we used the color and the shape as the most relevant visual information. Since attraction is the default behavior, in Figure 2 an approach bias current is used to implement the approach behavior as the default one. Of course, a rewarding signal can contribute to enhance the approaching behavior through STDP. On the contrary, if an object is punishing through a particular feature (e.g. color and/or shape), a shock signal is released to the network through a proper neural input. This elicits, via fixed synapses, an escape response and also a conditioned learning in the color and/or shape subnetwork of the CX takes place. This dynamics is biased by the MB3 via axo-axonal connections which modulate the axons to the escaping neurons according to the color saturation value. After the experimental results on the fly, we hypothesize that explicit information about the color saturation level is resident into the MB cells which receive this information from the optical lobes, together with a few other information. Moreover we suppose that the color saturation information is transmitted via non spiking neurons. Axo-axonal connections are well known to modulate (i.e. facilitate or depress) post synaptic cells, and were recently found in the fly MBs. The MB3 function is here modeled using two neurons with a sigmoid-like activation function of the color saturation level. Their axons directly affect the axons to the escaping neuron via fixed weights (see Figure 2). The so-called MB3 network works as a gateway that modulates the information from the FB to the BSN depending on specific input signals. The key information processed at this level is the color saturation that allows to sharply decide the most convenient behavior to be performed. The visual preprocessing block is able to extract the relevant features from the segmented objects present in the scene and the FB associates a meaning to the visual data depending on the rewarding or punishing signals coming from the environment via classical conditioning. Finally the acquired information compete at the behavior selection block in choosing the final robot behavior. The experiments were performed both in simulation and on real robots using a SW/HW framework that allows to perform dynamic simulation on a 3D environment [6].

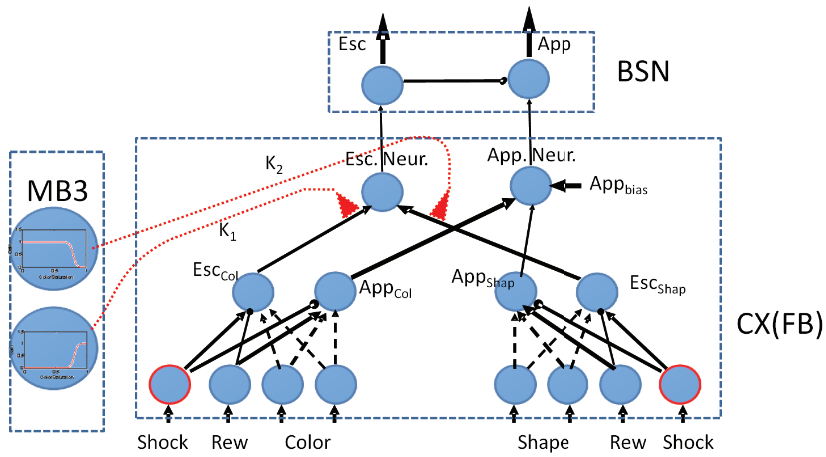

Figure 2. Interaction between the FB, MB3 and BSN blocks, the presence of MB3 is important for the final behavior selection as part of the decision making process.

3. Simulation Results

To evaluate the performance of the proposed control system, a virtual arena similar to that one used for the biological experiments has been considered. The rectangular arena contains two pairs of landmarks placed on the opposite walls. The simulated robot, depending on the received punishment signals, modifies its behavior as shown in Figure 3 where the robot activity is summarized in windows of 5 minutes for a total of 15 minutes of simulations. The robot trajectories, together with the gaze direction for each time window are reported. The robot, during an initial exploration phase, learns to avoid the red squares that are associated to a punishment.

The time evolution of the gaze direction distribution is shown in Figure 4 where it is evident that in a few minutes the simulated robot learns to avoid the red square. A very similar behavior is reached also when the information about the object shape is missing (e.g. all the objects have the same rectangular shape) as shown in Figure 5 where the gaze direction in time is similar to the previous case.

Another interesting case is obtained when the shape is the only distinct feature between the landmarks, for instance introducing in the arena red circles and squares. Only the square objects produce a punishment to the robot. The gaze direction is reported in Figure 6 and the behavior is similar to the other illustrated cases.

Eventually the role of the MB3 block, that works as a gateway modulating the information generated by the FB, is evident in the case of a dilemma. The robot after learning in the arena shown in Figure 3, is facing a new scene where the visual features associated to the objects are contradictory if compared with the first arena, in fact a yellow square (placed in the top and bottom side of the arena) and a red circle (placed left and right in the arena) are now present: the color was switched with the shape. In Figure 7 the behavior of the robot is shown through the gaze direction obtained in three different simulations that differ for the value of the color saturation. When the color saturation (CS) is high ($CS = 1$) the robot has a preference to choose the color as the most meaningful feature and avoids red objects. Decreasing the saturation ($CS = 0.8$) the robot has no clear preference and tries to escape from the objects, finally for low level of color satura-

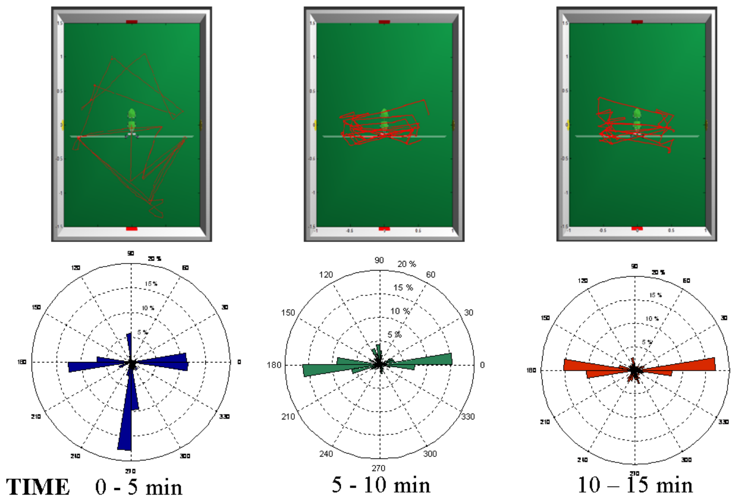

Figure 3. The behavior of the robot in terms of followed trajectories and gaze distribution, is acquired in windows of 5 minutes. The red squared landmarks in the bottom and upper part of the arena are dangerous and the robot learns to avoid objects with these features.

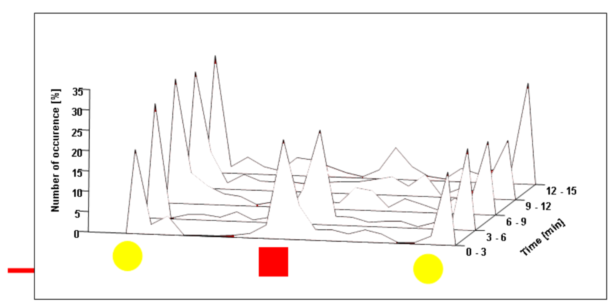

Figure 4. Evolution of the gaze distribution in time. After a few punishment events, the robot avoids to direct its attention to the red squared object.

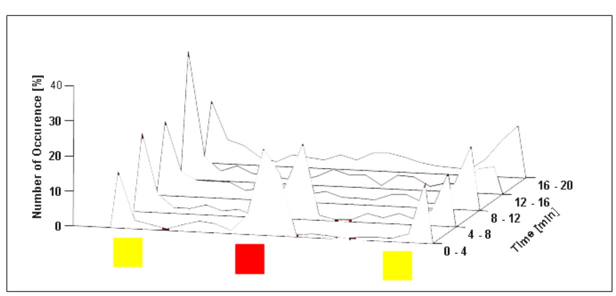

Figure 5. Evolution of the gaze distribution in time when the objects have the same shape but different colors.

tion ($CS = 0.5$) a preference for the shape arises. Going deeper in details analyzing the critical case of $CS = 0.8$, it is possible to evaluate the temporal evolution of the robot

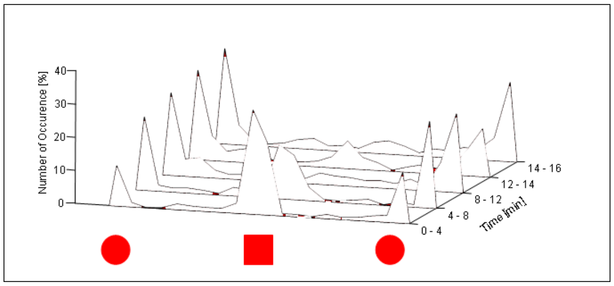

Figure 6. Evolution of the gaze distribution in time when the objects have the same colors but different shapes.

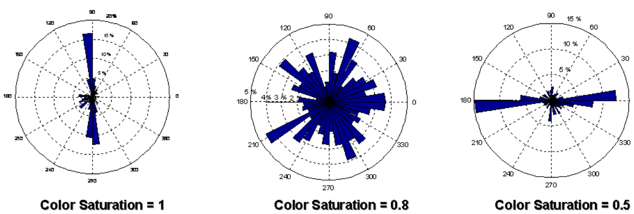

Figure 7. Dilemma test in presence of the MB block. After a learning phase performed in the arena in Figure 3, a testing is performed changing the color feature between the two objects. When the color saturation is high, the robot has a remarked preference for the color, reducing the color saturation (CS=0.8) no preference appears whereas further reducing the color saturation (CS=0.5) a preference for the shape appears.

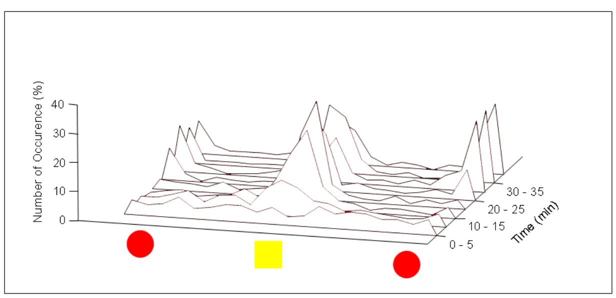

Figure 8. Dilemma test in presence of the MB block. When the color saturation is about CS=0.8, the robot shows no preference but due to a forgetting factor a preference for the shape appears in time and persists if the punishment signal is removed

behavior as shown in Figure 8. During the first 5-10 minutes the robot has no preference for the objects while during time the robot starts to approach objects with square shapes and later on also red objects if the punishment signal is no longer present in the environment. A very interesting result obtained in [2] consists in replicating the Dilemma experiment in a mutant fly with defects in the MB block. We modeled this case deactivating the block MB3. The results obtained while changing the level of color saturation are given in Figure 9, it is interesting to analyze that while for low level of saturation the behavior is very similar, when the color saturation is high the robot is not able to decide which feature is dangerous with respect to the other and tries to avoid both without

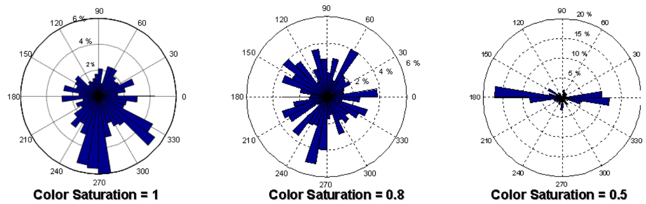

Figure 9. Dilemma test after ablating the MB block. The presence of an high color saturation is not enough to force the robot to make a choice.

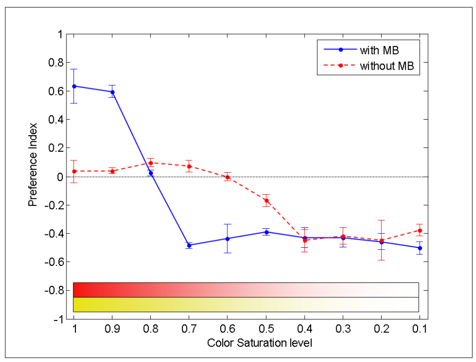

Figure 10. Representation of the robot behavior through the preference index in presence of a dilemma in the proposed simulations. See [2] for biological details and comparisons. Significative differences are visible when the MB block is eliminated from the control loop.

solving the dilemma. To summarize the results and compare the behavior of wild type and MB-defective robots, a preference index has been considered. The index is similar to that one used in the biological experiments in [2], and is calculated considering the time spent observing each object compared with the entire simulation time:

$$PI = \frac{t_{YS} - t_{RC}}{t_{tot}} \tag{1}$$

where t_{YS} is the time spent observing the yellow squared object t_{RC} is the time spent observing the red circular object and t_{tot} is the duration of the experiment. Figure 10 shows the trend of the Preference index for both the simulation. The index is obtained performing a set of 10 simulations of 5 minutes for the different levels of color saturation. The results show that the robot controlled with an insect-like brain structure is able to make a clear decision among the two objects depending either on the color (for $CS > 0.8$) or on the shape ($CS < 0.8$) while the mutant robot, where the effect of the MB block on the decision process is missing, is not able to decide in case of high level of color saturation. Finally also in the mutant experiment when the degradation of the color is high enough, the preference for the shape takes the lead.

4. Conclusion

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. In presence of a conflict the fly has to decide which features are the most relevant to make a choice. A bio-inspired model of the *Drosophila* brain centers involved in this task has been proposed to model the fly behavior and experiments on roving robots were performed. It is composed of three main blocks which interact so as to show an emergent behavior able to solve visual contradictory cues. Results have been compared to biological data. A huge current effort is being paid in order to tray to include into the whole network also other relevant features related to MB functions,like the behavior evaluation and the olfactory learning.

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