An insect brain inspired neural model for object representation and expectation

Paolo Arena, Luca Patané and Pietro Savio Termini

Abstract— **In spite of their small brain, insects show a complex behavior repertoire and, in these last years, are becoming a reference point in neuroscience. In particular, it is very interesting to analyze how biological reaction-diffusion systems are able to codify sensorial information with the addition of learning capabilities. In this paper we propose a new model of the olfactory system of the fruit fly *Drosophila melanogaster*. The architecture is a multi-layer spiking neural network, inspired by the structures of the insect brain mainly involved in the olfactory conditioning, namely the *Mushroom Bodies*, the *Lateral Horns* and the *Antennal Lobes*. The Antennal Lobes model is based on a competitive topology that transduces the sensorial information into a pattern, projecting such information to the Mushroom Bodies model. This model is based on a first and second order reaction-diffusion paradigm that leads to a spontaneous emerging of clusters. The Lateral Horns have been modeled as an input-triggered resetting system. The structure, besides showing the already known capabilities of associative learning, via a bottom-up processing, is also able to realize a top-down modulation at the input level, in order to implement an expectation-based filtering of the sensorial inputs.**

I. Introduction

One of the primary goals in studying animal brains consists in improving the existing knowledge about learning processes in living beings. Analyzing and modeling the behaviors of animals and the neural structures involved are challenging tasks, because of the brain complexity. Several attempts are present in literature related to algorithms or bio-inspired networks able to mimic the functionalities of parts of the brain. A lot of work has been done in several animal species belonging to mammals, molluscs and insects [1]. Insects are inestimable elements for research in neuroscience; in fact, even if their brain structure is very small, there are several insect species able to show complex behaviors that can be hardly reproduced by other animals like mammals or even humans [2]. In particular, the worker honeybee is certainly a well-known organism for studying the fundamental principles of color vision, pattern recognition, learning and memory, flight control, and navigation [3], [4], [5], [6]. In insects there are neurobiological evidences of processes related to spatio-temporal pattern formation and learning mechanisms that could be used to solve even complex tasks like sequence learning. The most plausible brain structures involved in these processes are the *Mushroom Bodies* (MBs) that together with the *Lateral Horns* (LHs) are principally devoted to olfactory learning. MBs are important neuropils that are also known to be involved in learning and memory with particular attention to olfactory signals. The spatio-temporal olfactory information coming out from the Antennal Lobes are processed and stored in spatial patterns [7], [24]. The MBs neural structure in *Drosophila melanogaster* is known to be able to perform associative learning for odor conditioning [8]. Recently neural models inspired by the *Drosophila melanogaster* brain anatomy were proposed using roughly the same number and connectivity as the olfactory biological counterpart. The spatio-temporal coding in such neural structures has been investigated in [9], where a model for codifying spatio-temporal patterns into spatial patterns has been implemented. In that paper the structure exploited autonomous clustering capabilities and no learning algorithms were added to it. The authors already introduced learning capabilities in a model made of spiking neurons and based on the MB structure; this model was applied to tasks like real time visual feature learning, recalling and forgetting [10], [11]. These structures were successfully applied to enhance the capabilities of an autonomous robot, but they were really far from the insects skills, which are able to show other interesting capabilities like attention and expectation based behaviors. To host such skills, the traditional model, mainly based on feedforward connections from the sensory to the classification layer, should also host other kind of feedback connections, able to affect the input sensitivity to particular expected sensory feature. Feedback connections from Mushroom Bodies to the Antennal Lobes have been found [12], where a functional role of such connections in filtering input information is hypothesized. This fact opens the way to refine the models previously introduced to try to lead to the emergence of new capabilities.

Starting from these principles, we want to analyze the possibility to create a new artificial model of the *Drosophila* olfactory system with enhanced capabilities.

The complexity of the environmental conditions requires, in certain animals, the presence of more sophisticated learning mechanisms. The possibility to make predictions and to modulate sensorial input through expectations is the key point of this work.

The proposed model is a multi-layer spiking neural network basically inspired to [8], and including the recent findings in [10]. Here an extra layer is also added in order to have conditioning and a direct output to the motor layer. The first layer represents the Antennal Lobes model: inputs are decomposed in main *features*, represented by feature-specific groups of neurons within an input layer. Here a locally competitive topology is implemented, as suggested by Neurobiology [13]. This layer randomly projects connections to the second layer, which models the functionalities of the

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Mushroom Bodies. Each neuron of this layer is connected through fast excitatory synapses to its neighborhood and, within the same layer, through fast inhibitory synapses to the rest of the network. In order to have a symmetric set of connections, a toroidal shape was implemented in this layer. This layer shows interesting clustering capabilities and represents the core of the system in terms of spatio-temporal patterns formation. Recurrent connections are present from Mushroom Bodies to the Antennal Lobes. The Lateral Horns model, as suggested from Neurobiology [14], has been thought as an input-triggered system that provides a delayed global inhibition to the Mushroom Bodies network.
The paper is divided into five sections: Section I presents the biological background of the work and the state of the art regarding artificial models of insects brain. In Section II the proposed architecture is introduced and described while Section III discusses the architecture designed and also introduces preliminary potential applications of the model on simulated robots. Finally, Section IV draws the conclusions.

II. Biological Background and State of the Art

Mushroom bodies (MBs) and *Lateral Horns* (LHs) are neural structures of the insect brain, able to codify the spatio-temporal information coming from the glomeruli of *Antennal Lobes* (ALs). They create a spatio-temporal representation of the incoming information in the insect brain. Antennal Lobes project olfactory information to the higher level structures of the brain. Mutual inhibitory connections between the glomeruli have been founded very recently in neurobiological studies on *Drosophila*, as discussed in[13]. These competitive topology allows the creation of odor-evoked patterns of excited and inhibited glomeruli. Mushroom Bodies are a paired structure of the protocerebral hemispheres spreading out in three dimensions. The role of MBs in olfactory learning is fundamental as demonstrated in experiments using MB-defective mutant flies [22]. The MBs "frame" the *Central Complex* without known direct connections. In the fly *Drosophila melanogaster*, the most important constituents of the MBs are the 2500 Kenyon cells per side which run in parallel from the *calyx* through the *peduncle* and to the *lobes*. There is a prominent olfactory input from the Antennal Lobes into the calices. Input from other sensory modalities is not obvious in *Drosophila*, but tasks of the MBs related to vision are described for flies [15]. In honeybees, MBs receive prominent visual [16], gustatory, and mechanosensory [17] input. In flies and bees, the MBs lobe region receives information on sugar reward (via octopaminergic neurons) or electric shock (via dopaminergic neurons). There is an output of the MBs to pre-motor areas of the brain. Inside the MBs the information flow is through the Kenyon cells from the calyx towards the lobes. Very recently, recurrent connections between MBs and ALs have been found. The presence of this functional feedback from the MBs to the ALs suggests top-down modulation of olfactory information processing in *Drosophila* [12]. Olfactory information flows in parallel from the ALs to the MBs and LHs (Fig. 1). Connections

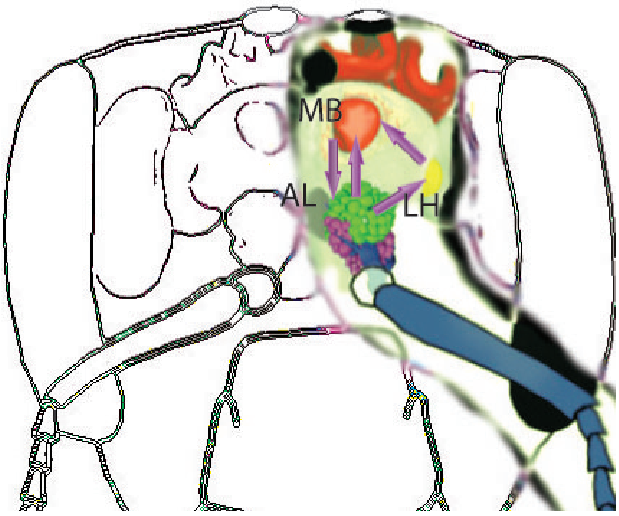

Fig. 1. **Sketch of an insect brain**. Scheme of the centres involved in the olfactory processing The Antennal Lobes (ALs) project olfactory information into the Mushroom Bodies (MBs) and Lateral Horns (LHs) through the Projection Neuron (PNs). In locusts, the LHs inhibits the MBs activity.

from LHs and MBs have been found. The entity of these connections in *Drosophila* are not well known. In locusts, LHs offer an inhibitory effect to the MBs Kenyon Cells[14].
An implementation of the olfactory system of locusts has been illustrated in [9]. In this model the inhibitory effect of the LHs circuit on the MBs cells is underlined. Each Kenyon cell is strongly connected with the cells of its neighborhood, and in this model the Antennal Lobes layer randomly projects to the Kenyon cells layer. A coincidence detection mechanism allows the model to codify sequences of events in spatial patterns of firing neurons. No learning is implemented in the model proposed in [9], whereas the system architecture discussed in this paper includes also learning mechanisms to allow pattern reconstruction and expectation capabilities.

III. The Proposed Neural Architecture

On the basis of the biological evidences concerning insect expectation capabilities and the identification of neural structures responsible for these processes, in this work a new model, endowed with learning, is proposed. The model is directly inspired to the MBs structure, with enhanced top-down connections to the Antennal lobe, including the global inhibitory effect of the Lateral Horn. The proposed neural architecture is a two layers recurrent network in which each neuron is an artificial spiking neuron. An output layer can be added in order to link the behavior of the second layer to a motor or pre-motor area. Similar attempts were already carried out for different blocks of the insect brain leading to applications on robotics [23]. The developed neural structure even if inspired by the insect olfactory system, can be used for processing different sensorial stimuli (e.g visual features can be easily used in robotic scenarios) . For this reason in the rest of the paper generic object features will be taken into consideration.

A. Neural and Synaptic Models

The proposed model is an artificial neural network, and each unit is an Izhikevich spiking neuron [18]. The model is represented by the following differential equations:

$$\begin{aligned} \dot{v} &= 0.04v^2 + 5v + 140 - u + I \\ \dot{u} &= 0.02(-0.1v - u) \end{aligned} \tag{1}$$

with the spike-resetting

$$\texttt{if } v \geq 0.03, \texttt{ then} \begin{cases} v \leftarrow -0.055 \\ u \leftarrow u + 6 \end{cases} \tag{2}$$

where v is the membrane potential of the neuron, u is a recovery variable and I is the synaptic current. Izhikevich neural models are well-known in literature and offer many advantages from the computational point of view.
Neurons are connected through synapses. The synaptic model transforms the spike-rate of the pre-synaptic neuron into a current that excites the post-synaptic one. Here is the mathematical response of the synapses to a pre-synaptic spike:

$$\varepsilon(t) = \begin{cases} Wt/\tau \exp(t/\tau), & \texttt{if } t > 0 \\ 0 , & \texttt{if } t < 0 \end{cases} \tag{3}$$

where t is the time lasted from the spike, τ is the time constant and W is the efficiency of the synapse. This last parameter can be modulated by learning.

B. Hebbian Learning and Spike Timing Dependent Plasticity

Hebbian learning, introduced by Donald Hebb in 1949, is a mechanism where the synaptic efficiency increases through coincident stimulations of the postsynaptic and presynaptic cell. The theory is often summarized as *"cells that fire together, wire together"*.
The Spike Timing Dependent Plasticity (STDP) can reproduce Hebbian learning in biological neural networks [19], [20] and has been used for learning in robot applications [25]. The algorithm works on the synaptic weights, modifying them according to the temporal sequence of occurring spikes. The updating rule can be expressed by the following formula:

$$\Delta W = \begin{cases} A^+ \exp(\Delta t/\tau^+), & \texttt{if } \Delta t < 0 \\ -A^- \exp(\Delta t/\tau^-), & \texttt{if } \Delta t > 0 \end{cases} \tag{4}$$

where Δt is the time delay between pre and post synaptic spikes. In this way the synapse is reinforced if the pre-synaptic spike happens before the post-synaptic one, it is weakened in the opposite situation. Parameters τ_+ and τ_- represent the slope of exponential functions, while positive constants A_+ and A_- represent the maximal variations of the synaptic weight.

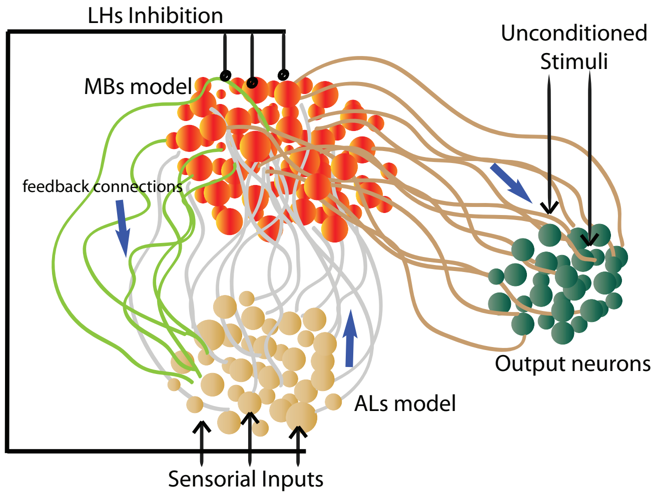

Fig. 2. **Neural structure inspired by the insect olfactory system.** . The Antennal Lobes model is directly connected to the output of the sensorial system (Antennas). We can assume that the activity of each neuron codifies the presence of a particular value for a specific feature. Neurons in the ALs are organized in groups. A competitive topology is implemented between neurons in the same groups, while plastic excitatory synapses link neurons from different groups. Synapses from the Antennal Lobes model to the MBs model are randomly chosen, with a given probability of connectivity. The MBs model is a spherical lattice, with local excitatory and global inhibitory synapses. The major peculiarity of this neural layer is a spontaneous clustering, due to the competitive topology. The Lateral Horns periodically inhibits the MBs neurons. Feedback plastic connections links clusters in the MBs to the ALs neurons. Local connection in the ALs and in the MBs are not reported in the figure.

C. Antennal Lobes Model

The input layer of our neural model is a sensing layer. Inspired by the Antennal Lobes (ALs) of the *Drosophila melanogaster*, we can assume to have a layer able to codify the interesting *features* of objects. As in the insects Antennal Lobes each glomerulus is able to detect a peculiar component of an odor, in our model each neuron (or group of neurons) in this layer encodes a particular aspect related to a detected object.
Neurons within the ALs model are organized in groups. Each group codifies a kind of feature (examples of features could be color, shape, etc.), and neurons in the same group codify different values of that feature (i.e. different colors or shapes). Moreover, neurons in the same group are linked together through inhibitory synapses. This topology implies that, when the ALs layer is stimulated, after a short transient time, only one neuron in each group remains excited, according to a Winner Takes All topology. Neurons in different groups are linked together through plastic synapses, reinforced when neurons are firing together, according to the Hebbian paradigm. Therefore, when an object is presented to the network, the ALs model decomposes that object in its relevant features, and the corresponding neuron of each group is excited through a constant input current.
The plastic connections between groups of neurons allow the model to temporarily retain the presented objects through all its features and, as outlined below, to reconstruct the

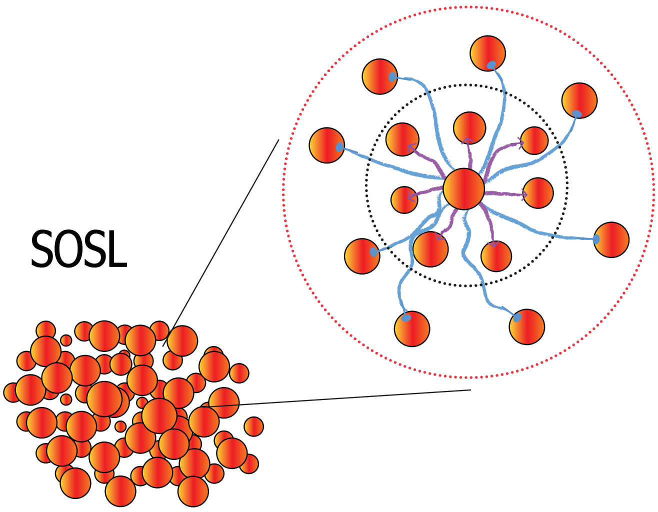

Fig. 3. **Self Organizing Spiking Layer**. SOSL is a spherical lattice, with local fast excitatory and global fast inhibitory synapses. This set of synaptic connections gives the network its major peculiarity, the spontaneous clustering capability. Another set of plastic delayed synapses links each neuron of the SOSL to the other neurons of the same lattice, in order to have the possibility to temporally link different clusters, allowing short term prediction and expectation capabilities of the neural architecture. In the figure, the inner circle indicates the locally excitatory neighborhood, whereas the outer circle includes all the SOSL network where a global inhibitory effect takes place.

feature in case of incomplete or noisy detection. The ALs layer projects excitatory synapses to the MBs model. Each neuron of the ALs is connected with each neuron of the MBs model with a given probability of connection.

D. Mushroom Bodies and Lateral Horn Models

The MBs model is based on a competitive topology that we call Self Organizing Spiking Layer (SOSL), the crucial part of the whole neural model. The SOSL is a spherical lattice in which each neuron is connected through fast excitatory synapses with all the neurons of its neighborhood, and through fast inhibitory synapses with all the other neurons of the lattice (Fig. 3). The main capability of the SOSL is a spontaneous clustering of neural activity, driven by a Winner takes all - like structure.

In this way, information coming from the ALs are compressed together into a cluster. In addition to this, a slow and delayed diffusion of the neural activity within the SOSL is present. In fact, another set of plastic delayed synapses links each neuron of the SOSL to the other neurons of the same lattice, in order to have the possibility to temporally link different clusters. These synapses are subjected to the STDP learning algorithm, that allows to discover and retain temporal causality among clusters. These connections have the interesting capability to generate, within the SOSL layer, expectation and short term prediction capabilities. Plastic feedback connections are also present from the MBs model to the ALs model. These connections were never present in any bioinspired model up to now, since only very recently were discovered. Their role is precious to boost the model performance and two main functions have been identified: they are useful to create an expectation-based depolarization of the neurons in the ALs, they are also essential to reconstruct the expected object. The actual model hypothesizes massive feedback connections from SOSL to ALs neurons, even if a probability distribution could maintain the same performance in case of large scale implementation. When a cluster is elicited in the MBs model, the synaptic connection between the neurons of the MB cluster and those neurons which are firing in the AL (due to the synchronous presence of the corresponding input) are raised, according to the Hebbian paradigm.

The Lateral Horns model contribution, after the neurobiological evidence of connections to the MBs in the fly [21], and according to the mainly inhibitory role in the locust, have been modeled as a time-driven resetting system, that generates an inhibitory wave to the MBs. In this way, the SOSL integrates the information coming from the ALs in a given time window and, after the emergence of a cluster, the neural activity of the network is inhibited by the LHs wave. One crucial issue is the synchronization between the delay of the synaptic clusters-linking connection in the SOSL and the LHs induced inhibitory action onset time.

E. Output Layer

The output layer represents the connection of the model to the motor or pre-motor area. Neurons in the output layer are linked to the SOSL neurons through an associative learning.

IV. Simulation Results

In this Section some simulations of the model are presented. These are useful to understand the basic principles that rule the network and its parameters.Under this point of view these have to be considered preliminary, since a further refinement in the immediate future is expected to further boost its potentialities.

A. Network Parameters

The network presents a lot of parameters that can influence its behavior.

The proposed network architecture of course represents a much scaled version of the biological counterpart, and has to be considered as a proof of concept for the basic and enhanced capabilities ascribed to the olfactory insect neural architecture. In these simulations, the first layer is made by a 4x4 lattice. In particular, there are four groups of neurons (f_1, f_2, f_3 and f_4), and each group is made of four neurons (for instance, the neuron "j" in the group f_i will be called f_{ij}). Neurons in the same group are connected each other through inhibitory synapses, with a synaptic efficiency $W_{grp} = -3$. Neurons in different groups that, after the presentation of an object, fire together, increment the efficiency of the synaptic link with a $\Delta W_{obj} = 2$. The initial value of such synapses is zero. When an object is detected the neurons of the first layer that encodes the feature of that object are excited with an input current $I_{in} = 70$. Each neuron of the first layer is connected to each neuron in the second layer with a probability of connection $P_{12} = 0.25$. The increase

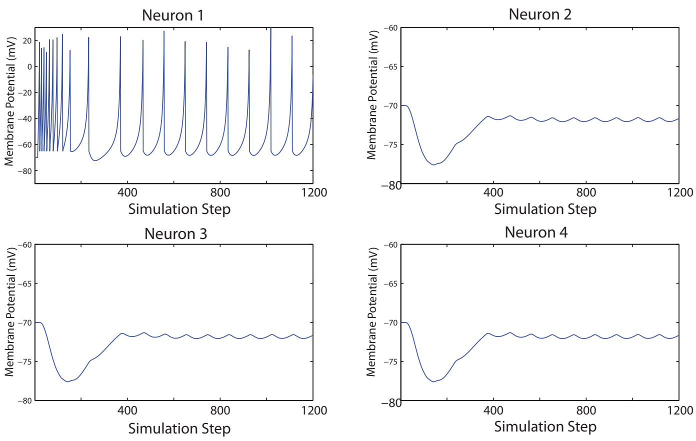

Fig. 4. **Temporal evolution of the first group of neurons in the first layer**. Evolution of the membrane potential of the neurons in the group f_1 of the first layer, during the presentation of the first object. In the case of the first object, no competition is present between neurons, because of the absence of the contribution of the expectation feedback. However, it can be noticed the inhibitory effect of the excited neuron on the others. Input neurons project information to the SOSL.

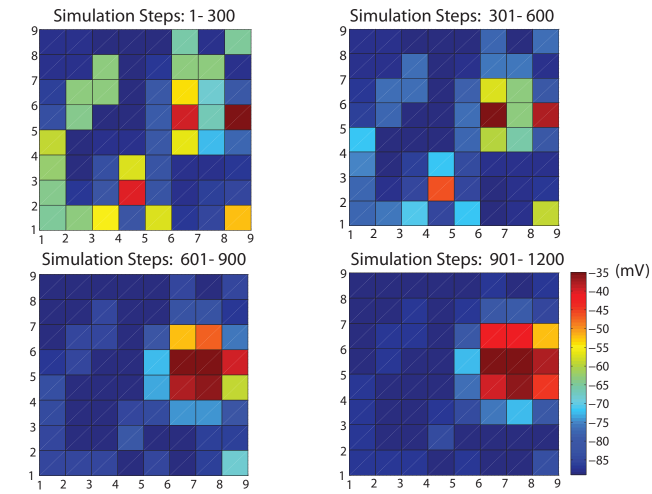

Fig. 5. **Temporal evolution of the SOSL in clusters formation**. Evolution of the mean potential of the neurons in the second layer. The network has been simulated for 1200 steps with an integration time of 8ms. The membrane potential is averaged every 300 simulation steps. At the end of the simulation, only one cluster of neurons remains active.

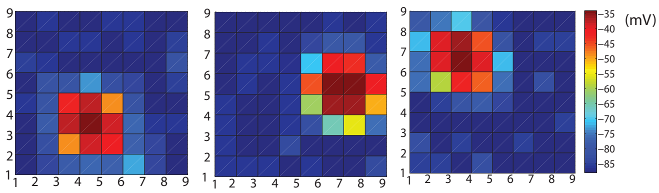

Fig. 6. **Prediction of short sequences**. During the learning phase, three objects are presented to the network. In the test phase each cluster representing a given object excites the cluster that represents the following object in the sequence. Objects can be reconstructed thanks to the feedback connections from MBs to ALs.

of this probability preserves the clustering capabilities, at the expenses of an increased transient time. The synapses between the first and second layer have fixed efficiency of $W_{12} = 10$ and a time constant $\tau_{12} = 1s$.
In these simulations the second layer is a 9x9 lattice with a toroidal topology. The neurons in the second layer are all connected each other according to the paradigm of local excitation and global inhibition. A neighborhood of radius $r = 1$ is defined. In this way, each neuron is connected with the neurons in its neighborhood and with itself through excitatory synapses with an efficiency of $W_{near} = 5$ and a time constant $\tau_{near} = 1s$. It is also connected with the other neurons of the lattice through inhibitory synapses with an efficiency of $W_{far} = -3$ and a time constant $\tau_{far} = 1s$. These set of connections give the network its clustering capabilities.
Moreover, a second set of synapses allows the linking of sequences of winning clusters. Each neuron is connected to each other neuron in the lattice through a time-delayed synapse, subjected to learning. In this case, the most active neurons of two clusters activated sequentially in time reinforce the synapses that connect them according to the STDP rule. The time-delay of these synapses is fixed at $t_{del} = 400ms$ and the initial value of their efficiency is zero. Feedback connections start from a null value. When a cluster is firing together with neurons in the first layer, the corresponding synapses are raised, $\Delta W_{fbk} = 1$. All the equations are solved using the Euler method with an integration time of 8 ms.

B. Analyses of the clustering properties

In these preliminary simulations an object with four different features is presented to the first layer of the network; four neurons are excited, one for each group of input neurons (Fig. 4). The first layer projects the information to the second layer (SOSL), exciting its neurons. After a transient of 1200 simulation steps, the network is able to elicit a winning cluster, as shown in Fig. 5. Moreover, the architecture shows interesting capabilities in storing and recalling short sequences of objects. If, for instance, a sequence of three objects is presented to the network input, a learning phase takes place; the SOSL elicits a winning cluster for each object. The central neurons of each couple of subsequent clusters are linked, increasing the synaptic efficiency of the delayed synapses between them. In the testing phase, presenting to the network only the first object, the network is able to reconstruct the whole sequence, as shown in Fig. 6. At the end of each step of the learning and test phases, the network is inhibited. The synchronization between the inhibition from the LHs model and the excitation between clusters is the main point of the simulation.

C. Expectation through top-down modulation

In this case the simulation is aimed to test the behavior of the expectation system, through the feedback connections. Two subsequent objects are presented to the network. In particular, the first object stimulates the neuron "one" of each group ($f_{11}, f_{21}, f_{31}, f_{41}$), while the second object stimulates neurons f_{11}, f_{21}, f_{32} and f_{42}. During the presentation, the SOSL elicits two subsequent clusters and links them through the delayed synapses. Moreover, the connections between the two clusters and the corresponding neurons in the first layer are raised. Now we want to simulate a test phase, following different possibilities.

1) In this first case, after the presentation of the first object, an object with an incomplete feature - set is presented at the second step. In particular, no neuron in the second group is excited. In this case, at the second step the SOSL network recalls the second object: feedback connections from the MBs to the ALs excite the neurons of the first layer that codify that object and synaptic connections between neurons in different ALs groups allow the reconstruction of the complete object representation. No competition happens in the first layer, but top-down connections allow the recalling of the lost information (Fig. 7).
2) In the second case, after the presentation of the first object, the second object is presented again. In this case, the contribution of the feedback system as an expectation-based filter that enhances the response of the whole architecture. In fact, the cluster in the SOSL is already formed, neurons in the first layer are pre-depolarized and their response is faster. Results are similar to those ones presented in Fig. 4, but with an increased spike rate.
3) In this last case, we want to analyze a peculiar situation. After the presentation of the first object, a second object is presented to the network, but it is different from the object presented in the learning phase. In this case, a competition happens in the first layer. The top-down system enhances enhance the response of the neuron representing the common features between the object just presented (and unexpected) of the test phase and the second object of the learning phase. At the end of the competition, a new cluster is elicited in the SOSL (Fig. 8). This cluster represents the new object, creating a new sequence. The network is then able to store multiple competing sequences and the most reinforced one will be finally stored. Moreover, learning and testing phase case take place concurrently, provided that, at the very beginning, a number of learning examples are repetitively presented.

V. Remarks and Conclusions

Inspired by specific parts of the insects brain, we propose a neural model for expectation-based learning.
The neural architecture is a multi layer network. The first layer is a sensorial layer and it is inspired by the insects Antennal Lobes. The neurons of this layer are able to detect the presence of given features in objects. The information coming from the sensorial system are then projected to the second layer, that is a self-organizing layer (SOSL) and it is inspired by the insects Mushroom Bodies. The competitive topology of this network allows a clustering, in the sense that step by step a winning cluster is elicited. This layer is periodically reset by the Lateral Horns inhibitory action. The basic principle of the architecture is that the expectation for objects can be translated into a sequence of winning clusters in the SOSL, that projects back to the sensorial layer. Simulation results show the suitability of the proposed new network as a bio inspired architecture, in which drawing inspiration by simple beings, emergent capabilities, like expectation and simple sequence recalling tasks can be found. These network capability can be used in robotic applications like landmark recognition and sequence learning for maze solving. Regarding the network topology, the random probability-based connections between the first and the second layer improve the clustering capabilities of the networks; this enables the birth of new a cluster, even if it corresponds to a slightly different object, clustered within an already formed cluster.
Of course this affects the network memory capacity; this

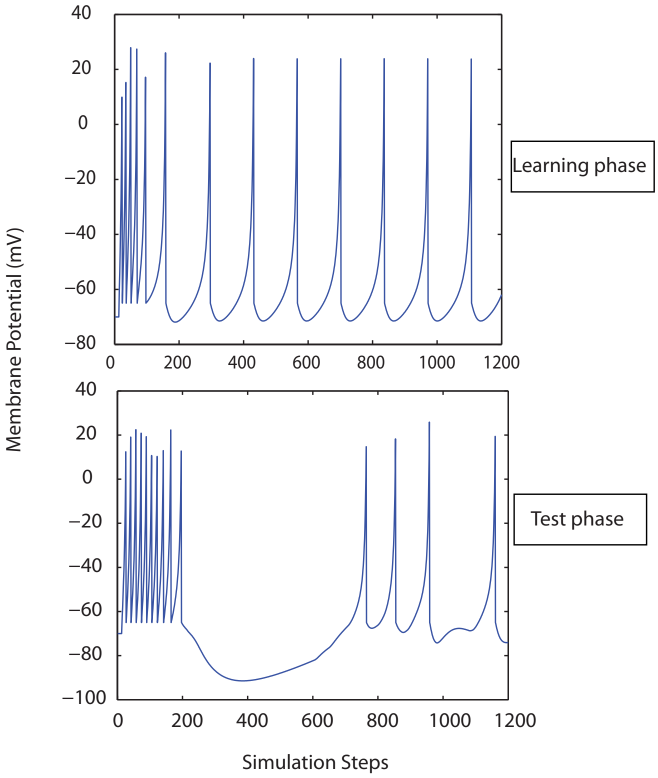

Fig. 7. **Reconstruction of an incomplete input pattern**. During the learning phase, after the presentation of two subsequent objects, the SOSL elicits two subsequent clusters and link them through the delayed synapses. During the test phase, after the presentation of the first object, an object with an incomplete feature - set is presented at the second step. In particular, no neuron in the group f_2 of ALs is excited. In this case, at the second step the network recalls the second object: feedback connections from the MBs to the ALs excite the neurons of the first layer that codify that object and synaptic connections between neurons in different groups allows the reconstruction of the complete object representation. The picture shows the evaluation of the membrane potential of the neuron f_{22}, that represents the missing feature, in the second step of both test and learning phase. The first 200 simulation steps show the activity of all neurons that can be excited according to their initial conditions. This dynamics is subsequently filtered out by the inhibitory connections.

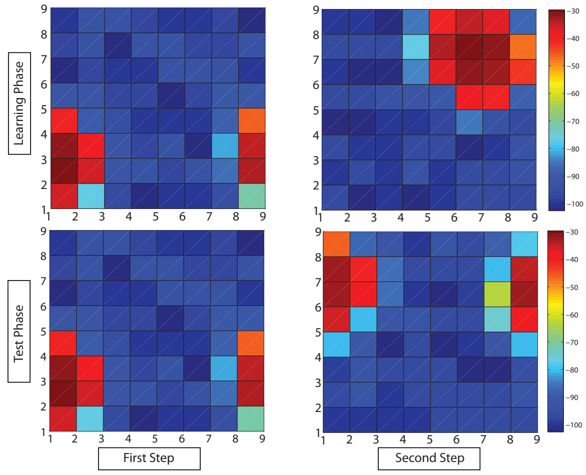

Fig. 8. **Behavior of the network in the case of non satisfied expectation.** During the learning phase, after the presentation of two subsequent objects, the SOSL elicits two subsequent clusters and link them through the delayed synapses. During the test phase, after the presentation of the first object, an object that does not follow the previous stored sequence is presented. In this case, at the second step the network tries to recalls the second object, but the competitive topology in the first layer corrects the prediction and a different cluster is formed in the SOSL.

could be increased, like in the biological case, by scaling-up the network dimensions. On the other side, living beings are commonly able to appreciate even slightly different odorant characteristics.

Moreover, a really added value provided by this simple network is the possibility to reconstruct an expected object. In fact the top-down information stimulates the AL neurons that are considered as representative of the single features that constitute the expected object. The expected object is then projected down at the sensing layer, just like an “imagined” object ,which filters the future objects that the agent expects. So, in case of multiple presented objects, the network will “pay attention” only to the expected ones. So this model could be the starting point of a simple network able to model attention. Finally, the network could learn even without a real input presented, in the sense that, if a suitable level of noise is added in the network in absence of input, for example simulating the overnight autonomous behavior, the noise will excite one set of AL neurons, which will give rise to sequences of network iterations, and this could suitably model the overnight memory consolidation phenomenon, well known to take place in insects.

Of course the simulation results have to be considered preliminary, since, to fully appreciate the potentialities, the dimensions have to be properly scaled, in order to be more and more connected to the biological counterpart.

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