An insect brain computational model inspired by *Drosophila melanogaster*: architecture description

P. Arena, C. Berg, L. Patané, R. Strauss and P.S. Termini

***Abstract*— The fruit fly *Drosophila melanogaster* is an extremely interesting insect because it shows a wealth of complex behaviors, despite its small brain. Nowadays genetic techniques allow to knock out the function of defined parts or genes in the *Drosophila* brain. Together with specific mutants which show similar defects in those parts or genes, hypothesis about the functions of every single brain part can be drawn. Following these experiments, a computational model of the fly *Drosophila* has been designed with a view to its robotic implementation.**

I. INTRODUCTION

ROBOTS can be used to reproduce animal behavior in order to study their interaction with the environment. Robots help to improve the understanding of animal behavior and animals help to create efficient robots. The study of animal brains leads to new control systems that could allow robots to be able to orient themselves in complex environments, to take decisions, to accomplish dangerous missions, in other words to be completely autonomous. Robot implementation of biological systems could also lead to predictions for basic sciences, e.g. when investigating the emergent properties of models. Several attempts are present in the 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]. Looking into the insect world different research groups around the world are trying to design models which are able to reproduce interesting behaviors shown by insects: cooperation mechanisms in ants [2], navigation strategies in bees [3], looming reflex in locusts [4], homing mechanisms in crickets [5], central pattern generator and obstacle climbing in cockroaches [6], [7], reflex-based locomotion control in the stick insect [8], just to cite some examples. It is evident that the effort is focused on specific peculiarities associated with the different insect species that can be also useful for robotic applications. Nevertheless, a more challenging task consists of trying to model the main functionalities of an insect brain, looking from an higher level, trying to identify the mechanisms involved in the sensing-perception-action loop.

The goal of this work is to develop a simplified model of the brain of *Drosophila melanogaster*, amenable to a robotic implementation. This fly has a small brain that brings about a great variety of complex behaviors. Moreover, genetic techniques allow to remove or to inactivate parts of the *Drosophila* brain, creating mutants. The analysis of mutant behaviors can lead to hypotheses about the functions of the single brain parts. Moreover, the so-called *partial rescue* technique, allows to activate genes needed for a structure or a biochemical pathway only in a selected part of the brain, whereas the rest of the fly is still mutant for that gene. This technique is used to definitely establish the one-to-one correlation between that brain part and the behavior it is responsible of. Biological experiments on the fly Drosophila have been conducted and analyzed in an accompanying paper by Strauss et al. [9]. Neurobiological functional models are being discussed there. Following the functional, neurogenetic and behavioral analysis of the *Drosophila* brain, a general computational architecture has been designed and implemented in a robot simulator. This important step allowed starting to compare some of the main behaviors met in the real fly with the simulation. The *Drosophila melanogaster* brain structures responsible for perceptual and motor control capabilities, namely the Central Complex and the Mushroom Bodies, are briefly described in Section II. Section III is related to the presentation of a computational model of the fruit fly brain, while Section IV introduces the model implementation on real and simulated robots. Finally, section V draws the conclusions. Moreover, in a companion paper [10] the simulation results about the validation of the model and a possible application in a real-life scenarios are presented.

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II. BIOLOGICAL BACKGROUND

The *Central Complex* and the *Mushroom Bodies* are the most striking structures of the *Drosophila melanogaster* brain, located in the *protocerebrum*. The *Drosophila* brain is estimated to contain about 100 000 neurons. The *ventral ganglion* might add another 20 000 neurons.

A. Central Complex

The Central Complex (CX) resides in all insect brains at the midline of the brain between the protocerebral hemispheres. It is composed of four main regions, as shown in Fig. 1. It has been studied anatomically using Golgi analysis [11]. The *fan-shaped body* (FB) is the largest neuropil which possesses eight fans in the latero-lateral extent, six layers in the dorso-ventral direction and four shells in the anterior-posterior direction. The *ellipsoid body* (EB) has a perfect toroid shape and possesses 16 segments and it has two radial zones. The paired *noduli* reside ventral to the fan-shaped body just dorsal to the oesophagus. The *protocerebral bridge* (PB) is a rod-like neuropil composed of a chain of 16 glomeruli just posterior to the fan-shaped body. There are no direct tracts from any sensor systems which would bring

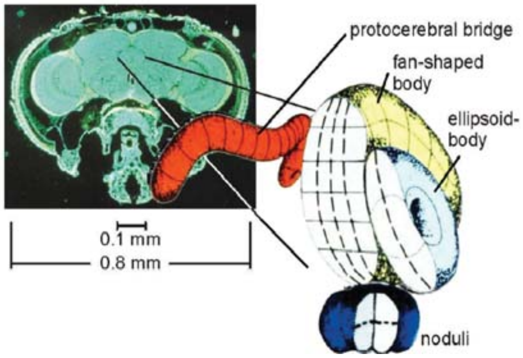

Fig. 1. *Drosophila* Central Complex, after Strauss 2002 [12]. The CX is composed by four major regions, the *fan-shaped body*, the *ellipsoid body*, the *noduli*, the *protocerebral bridge*. The input into the CX seems to be highly preprocessed because there are no known projections from primary sensory areas.

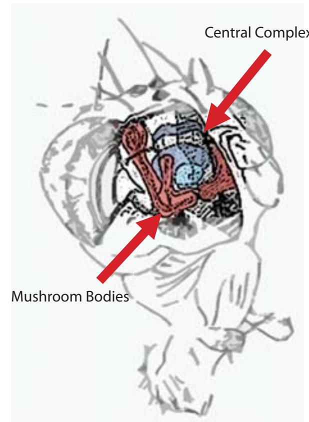

Fig. 2. *Drosophila* Central Complex and Mushroom Bodies. The MBs frame the CX without known direct connections.

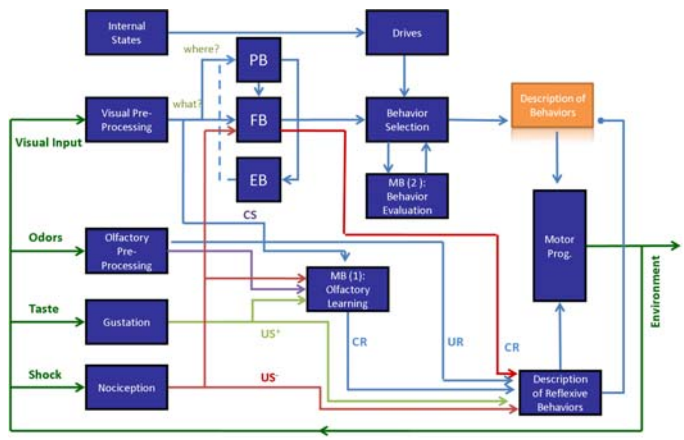

Fig. 3. Computational architecture of the *Drosophila melanogaster* brain. The olfactory and the visual pathways are modulated by drives in order to select the winning behavior. Learning is present in the MBs and FB blocks and it gives to the model its plasticity. The reflexive pathways allow the fast realization of the most basilar behaviors, like escaping reactions.

unfiltered information from sensors to the Central Complex. There are, however, two accessory areas of the CX. The *lateral triangles* are the starting point of input into the ellipsoid body, and the *ventral lobes* are a major input and output region for the fan-shaped body. Because there are no known projections from primary sensory areas to the CX, the input into the CX seems to be highly preprocessed. Experimental evidence from *Drosophila* and many different insect species demonstrate that primarily visual information is processed in the CX [13], [14]. In *Drosophila melanogaster*, the CX is composed of about 2000 to 5000 neurons. Details can be found in [9].

B. Mushroom Bodies

The *Mushroom Bodies* (MBs) are a paired structure of the insect protocerebral hemispheres spreading out in three dimensions. The MBs “frame” the CX without known direct connections (Fig. 2). 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*. In flies, 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. In honeybees, MBs receive prominent visual [15], gustatory, and mechanosensory [16] 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 flow of information is through the Kenyon cells from the calyx towards the lobes.

The MBs in *Drosophila* can be conveniently ablated chemically [17]. The method is not universally applicable to other neuropils because those do not usually have a unique time window for their neuroblasts to divide.

III. Computational Architecture

The main parts of the insect brain have been modeled and integrated into a computational architecture. This global computational model inspired by the *Drosophila* brain is presented in Fig. 3. It has been designed in order to be directly linked to a robotic implementation.
The main parts of the whole architecture are described in the following.

A. Sensorial pathways and internal states

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.

B. Drives and Behavior Selection Network

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

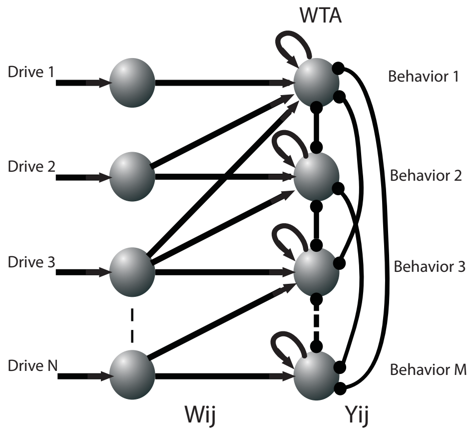

Fig. 4. Spiking network used to simulate the Behavior Selection functionalities. Drives are represented by input currents. Each drive can excite more than one behavior. Synaptic efficiencies between the input layer and the WTA layer represent the influence that each drive has in each behavior. Only the most excited behavior can win the competition and can be selected.

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 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 Class I spiking neuron [18], having the following equation:

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

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. In Fig. 4 an example of BSN is shown. 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 weights W_{ij} represent the importance of drive i for the behavior j. 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. To avoid a continuous switching among the selected behaviors, an auto-excitatory synapse has been introduced in each neuron of the second layer of the BSN. In this way, if a behavior has been selected during a simulation step, the probability to be selected again is increased at the next step the robot takes. Synaptic weights Y_{ij}, i≠j , represent the inhibitory synapses between neuron i and j in the WTA layer. Synaptic weights Y_{ii} represent the auto-excitatory synapses of neuron i in the WTA layer. The last point to clarify is how to transform drives in an input current. Let's imagine having the drive "recharge", the robot analogue to "sleep", strongly connected to an internal sensor that measures voltage in batteries. It is possible to implement a transfer function that takes as input the battery level and gives as output a numerical evaluation of the "sleep" drive. Other methods for behavior selection have been used in literature, in particular for sequence learning [19]. The proposed approach could be modified in order to implement sequence learning, but up to now there are no biological evidences about the capabilities of *Drosophila* in learning sequences of behaviors.

C. Central Complex model

1) Protocerebral bridge model: Object detection and distance estimation are functions related to the PB in fruit flies. Mronz and Strauss proposed a simple model based on parallax motion [20] that can be used to model these functions and a hardware implementation for an autonomous roving robot has been proposed in [21]. However, it is possible to use a generalized PB model, made of a cascade of three simple blocks:

- *Object Detection Block*. This block takes input from the visual system and is used to detect the presence of an object.
- *Distance Estimation Block*. When an object has been detected, this block estimates its distance from the robot. In real flies, distance is estimated using a parallax motion approach.
- *Object Position Block*. It is possible to reproduce fly behavior assuming as interesting objects those standing in the compartments ranging from the frontal direction to 100 degrees in the two lateral sides and repulsive ones those standing in the compartments from 100 degrees to 160 degrees on the rear part of the robot. Objects at angles exceeding 160 degrees cannot be seen.

2) Fan-shaped Body model: The fan-shaped body model has been designed as a cascade of two sub-blocks, a feature extraction and a feature evaluation element.

- *Feature Extraction*. Once an object has been detected, the Feature Extraction Block classifies it by using a series of features. As underlined in focused experiments with flies [22], the following features can be considered:

– *Color*. Using a HSV representation, it is assumed to consider only the Hue value.
– *Orientation*. Orientation is meant as the angle between the vertical direction and an axis that represents the direction in which an object is mainly distributed.
– *Size*. Size is meant as the portion of total visual area of the robot occupied by the object, normalized with respect to the distance from the robot.
– *Center of Gravity*. This feature is given by the height of the center of gravity normalized with respect to the vertical dimension of the visual area and the distance from the robot.
– *Wideness*. Wideness is meant as the maximal horizontal extension of the object, normalized with respect to the total horizontal dimension of the visual area and the distance from the robot.
– *Height*. Height is meant as the maximal vertical extension of the object, normalized with respect to the total horizontal dimension of the visual area and the distance from the robot.

- *Feature Evaluation.* The robot collects features and is able to associate features to punishment or neutral situations. Every feature has a *punishment value*: if this value exceeds a threshold, the robot escapes every time it meets an object with that feature. The punishment value of a feature decreases if the robot is not punished when that feature is encountered. When the robot meets an object, it evaluates its Escaping Value: this is a weighted sum of the punishment values of the features of that object. When the Escaping Value is high enough, the robot escapes from the object, even if not punished. This is the simplest way to implement a classifier. Other, more performing and sophisticated algorithms, either bioinspired, or more information theory-bases, like the Neural Gas [23], could be implemented to add plasticity to this simple, starting point model.

3) Ellipsoid body model: Neuser [14] described the role of the *Drosophila* ellipsoid body in the visual short term memory. That functional analysis leads to the implementation of a model able to create a spatial memory in a robot. By using polar coordinates to code the robot position in the environment, it is possible to design neural architectures inspired by the ant's path integration [24]. However other solutions could be based on a mathematical implementation of a polar path-integration algorithm and this kind of approach (easier and more robust) has been taken into consideration at this stage. A scheme describing the path integration mechanism is shown in Fig. 5. Supposing $\Delta s << r$, defining λ as the direction of the current robot movement and $\delta = \lambda - \nu$, the approximation of the current robot position is recursively given by:

$$r_{n+1} = r_n + \Delta r_n = r_n + \Delta s_n cos(\delta_n) \quad (3)$$

$$\nu_{n+1} = \nu_n + \Delta \nu_n = \nu_n + \Delta s_n sin(\delta_n / r_n) \quad (4)$$

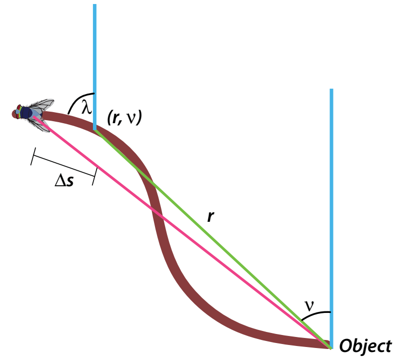

Fig. 5. Path Integration scheme (modified after [24]). The values of r and ν represent the position of the robot from the object. Every robot step r and ν are updated according to the last robot movements, in direction λ by a path increment Δs.

where Δs_n is the length of the robot step of index n and r and ν are the coordinates that represent the position of the robot with respect to the object that is supposed to be the origin of the polar coordinate system.

D. Mushroom Bodies model

The MBs are a key structure of the insect brain. Mushroom Bodies are primarily involved in olfactory learning [25],[26] and in a more complex function that will be called *behavior evaluation* [27]. Because experiments are not able to demonstrate the connection between the two functions, two uncoupled models were implemented.

1) Olfactory learning model: A two layer spiking neural network was designed and implemented to model the olfactory learning function. The Spike Timing Dependent Plasticity (STDP) has been applied as learning algorithm [28], [29]. This algorithm can reproduce Hebbian learning in biological neural networks. The algorithm works on the synaptic weights, modifying them according to the temporal sequence of spikes occurring. The algorithm is represented by the following formula:

$$\Delta W = \begin{cases} A_+ \exp(\Delta t/\tau_+), & \texttt{if } \Delta t < 0 \\ -A_- \exp(\Delta t/\tau_-), & \texttt{if } \Delta t > 0 \end{cases} \quad (5)$$

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.

Each neuron is modeled by an Izhikevich Class I neural model [18]. A scheme of the neural model is shown in Fig. 6. The Shock (Punishment) Neuron takes as an input a current proportional to the value of the robot punishment, while the Good (Reward) Neuron takes as an input a current proportional to the reward. In experiments with *Drosophila*, the punishment could be represented by an electrical shock,

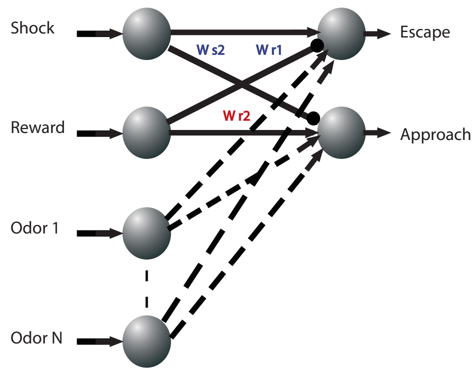

Fig. 6. Olfactory Learning Model. Solid line (dashed) connections correspond to fixed (plastic) synapses; arrows (bullet) correspond to excitatory (inhibitory) connections. The model here presented can be easily extended to the desired number of odors.

while the reward is represented by sugar. Each of the remaining neurons of the first layer takes as an input a current proportional to the odors the robot can detect in the environment. Each odor has a corresponding receptor and a neuron that converts the current in a spiking-rate if the current is high enough above the threshold for the Class I Izhikevich model. In a real robotic implementation odors can be substituted with other sensorial inputs, according to the application. Specific neural network composed by Izhikevich neurons and STDP learning were already implemented to realize approaching or escaping behaviors. They are here omitted simplicity [30]. In the present implementation, synapses between the Shock and the Reward Neuron and the output layer have a fixed value. Outputs of the second layer neurons are connected to a Motor Program block. The robot escapes from the actual position if the Escape Neuron is firing, while it begins an approaching algorithm if the Approach Neuron is firing. Synapses between unconditioned stimuli (i.e. shock and reward) and motor neurons are fixed and represent the inherited knowledge whereas connections between conditioned stimuli (i.e. odors) and the motor system are subject to learning, according to the STDP rule. If not reinforced, the efficiency of a synapse decays with time.

2) Behavior Evaluation model: When a behavior is selected, the robot defines a setpoint to be reached. A setpoint is meant as a desired value for a vector of physical quantity linked to the definition of the drives: to satisfy its needs, the robot has to minimize the error between this setpoint and its actual state. For example, let us assume that the robot has a low battery voltage and that a charging-station is present in the environment. In this situation the robot could choose to go to the base station whereas the desired battery level would be the setpoint. If the selected behavior is not able to allow the robot to satisfy its needs, that behavior has to be inhibited: in the opposite situation, if the selected behavior leads to satisfying its needs, that behavior has to be excited. The Behavior Evaluation block inhibits or excites the actual behavior depending on the amount of time already spent and the amount of success reaching the setpoint. Inhibition or stimulation is easily implemented sending a current to the neuron of the WTA layer in the BSN associated to the ongoing behavior. Maybe some additional plasticity could be implemented into the Behavior Selection Network through the Behavior Evaluation model. In particular, the synapses between the neuron related to the selected behavior and drives that represent the setpoint could be reinforced (or weakened) if the last selected behavior has been able (or not) to reach the last setpoint. However, there are no biological evidences about this point.

E. Motor Programs and Description of Behaviors

The Motor Program block describes all the possible elementary actions that the robot can perform. Motor learning is not considered up to now, although it is envisaged to be investigated and added in the near future.

F. Reflexive Behaviors

When the robot is punished in some way it needs to escape as fast as possible from the object responsible for the shock. The *Description of Reflexive Behaviors* is a simple high level block that allows the robot to take the right direction in the case it is punished.

G. Complex Behaviors

The *Description of Behavior* block is a high level part of the complete model that describes the available behaviors that the robot can follow. The choice of the possible behaviors the robot can exhibit depends on the robot applications. Applying a searching strategy to find a charging station could be an example of a typical behavior. The description of each behavior, however, could depend on the robotic structure and the embedded sensorial system.

IV. Simulation - Oriented Drives and Behaviors

The implementation of drives and behaviors on a real robot strongly depends on the field of application in which that robot is involved. The simulation of the general model of an insect brain requires a simulated environment, where behaviors and drives, which the robot has to satisfy, need to be defined. In this section, drives and behaviors that could be chosen for a simulation of the whole model are presented. The focus is to simulate the model in a context that can present analogies with the *Drosophila* real experimental setup, in order to obtain the experimental validation of the model.

A. Drives

A brief description about the suggested drives and their analogies with real fruit flies is presented here.

- *Sleep*. The drive Sleep is assumed to be the need for a robot to charge its batteries. In real fruit flies sleep is indispensable for learning [31]. In common robots we can quantify the drive sleep using a function of the battery level:

$$I_{drive} = K_{drive} \tanh(\Lambda - \chi) + \psi \qquad (6)$$

where K_{drive}, Λ, χ and ψ are the parameters of the function. Through these parameters it is possible to set the maximum and the minimum value of the current and the optimal battery level. An example is shown in Fig. 7. The optimal battery level is represented by the point in which the drive Sleep is equal to zero. If the battery level exceeds the optimal point, the drive becames negative, in order to inhibit a battery charging. In order to simulate the battery level, it is convenient to implement a virtual sensor. The output of such sensor is the estimated battery level. The battery level must decrease each step in which the robot is far from the charging station, and reaches the Max Battery Level after a given time spent in the charging station area. A sleep drive is indispensable for every time it is necessary to have a completely autonomous robot, which must be able to find power supply sources and use them to move for a long time.

- *Hunger*. The need of food can be reproduced putting inside the environment objects or landmarks that the robot should periodically find and/or visit. The drive Hunger could be thought as proportional to the time the robot left the object. This drive is indispensable to obtain a behavior that can match with reality but also to force the robot to find objects that can be periodically useful. The drives Hunger and Sleep have some similarities; their differences would be remarked according to the application.
- *Shelter*. When in danger, a fly looks for a safe place. A fly in open spaces often has the tendency to protect itself, typically aiming to approach and follow walls. Shelter can be related the distances of the robot to the walls.
- *Curiosity*. The drive Curiosity allows a fly to search for other resources when the other drives are satisfied. Curiosity can be quantified with a constant value. From a robotic point of view, curiosity leads the robot to explore the environment and to acquire information about the objects it meets.

B. Behaviors

To make the robot able to satisfy its drives, the following behaviors could be implemented. They would constitute the output of the Behavior Selection Network, discussed in Section III.B.

- *Exploration*. During an exploration behavior the robot tries to find new resources. In flies, the environment exploration is characterized by an increase of the mean-free path algorithm [32]. As in the real flies, during an exploration behavior it is possible to distinguish two behaviors [33]:
  – Sitter larvae behavior: short path length and tight turning angles.
  – Rover larvae behavior: long path length and wide turning angles.

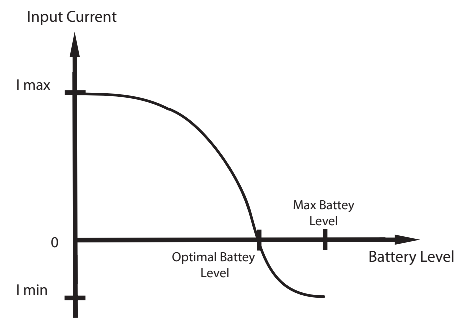

Fig. 7. Example of the transfer function used to model the sleep drive. A low battery level leads to a high value of the current related to the *Sleep* drive. The optimal battery level is represented by the point in which the drive *Sleep* is equal to zero. If the battery level exceeds the optimal point, the drive became negative, in order to inhibit a possible dangerous battery charging.

  Exploration can be thought as a default behavior: the robot could choose this behavior when no particular drives are enabled. Usually curiosity is the drive that mainly influences the choice of an exploration behavior. The implementation of the exploration behavior requires also the management of the obstacle avoidance and object detection. Moreover, the robot must be able to update its position at each step; in our case, the ellipsoid body model is involved.
- *Homing*. The homing behavior is meant as the return to the charging station, from where the robot usually initiates the simulations. Of course, the position of the Home must be known and updated every step. An obstacle avoidance algorithm has to be implemented during the homing behavior. Homing behavior is needed to have an autonomous robot, able to charge its battery before its autonomy is compromised.
- *Landmark Recalling and Achievement*. During the navigation the robot meets objects: if some objects are associated to food, the robot must remember their position in order to reach them when it is needed. The biological plausibility of this behavior is evident. The robot must use the path integration system to update its position from each interesting object.
- *Centrophobism*. A centrophobic behavior has been found in flies [34]. From a biological point of view, centrophobism in flies could be a consequence of the increase of mean-free path in the exploration behavior. A fly uses centrophobic behavior to protect itself in dangerous environments. Shelter is the drive that mainly influences the choice of a centrophobic behavior.

V. Remarks and Conclusions

A simplified computational model of the *Drosophila melanogaster* brain has been designed. Two main centers of the insect brain have been considered: the Mushroom Bodies and the Central Complex.

The Mushroom Bodies model has been splitted into an olfactory learning model and a behavior evaluation model, following the actual neurobiological evidence. The olfactory learning model is a two layer spiking neural network and the STDP algorithm has been used for the learning implementation. Concerning the CX, it has been divided into several blocks. The fan-shaped body has been modeled as a feature extraction block followed by a classifier, while the protocerebral bridge model allows the robot to detect interesting objects. An orientation memory has been implemented into the ellipsoid body model. Moreover a Behavior Selection Network is used by the robot that autonomously chooses the most suitable behavior able to fulfill its drives (i.e. internal motivation mediated by external stimuli). Behaviors allow the robot to satisfy drives. Finally, a list of drives and behaviors has been suggested with a view to the implementation of the model in real robots or robotic simulators. In a companion paper the simulation results about the validation of the model and a possible application in a real-life scenarios are presented.

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