A Survey on Neurorobots: Integrating Neuroscience and Robotics

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***Abstract*—Since its beginning, robotics has been inspired by attempts to emulate biology. However, current autonomous agents have not achieved the flexibility and survival capabilities that animals or insects with nervous systems have demonstrated when dealing with complex living conditions. The field of Neurorobotics investigates the use of biological intelligence by embodying models of the brain on robotic platforms. As a consequence, these neurorobots have become powerful tools for studying different neural functions expanding our knowledge about how these functions work. Furthermore, these cognitive-robots have provided to engineers biological inspired solutions to diverse exciting practical problems. In this work, we explore three projects on Neurorobotics to highlight the benefits of integrating robotics and Neuroscience to build autonomous platforms that operate in complex environments.**

***Index Terms*—Robotics, Neuroscience, Neurorobotics.**

I. Introduction

In the last decades, robotics have become a key field in different areas in human society. Industry, security, defense, entertainment and household chores are some examples of these areas. For instance, there are now robotic vacuum cleaners and autonomous vehicles on the ground and even in the air and beneath the ocean. However, these artificial systems do not emulate the flexibility and survival capabilities of biological organisms which can adapt to dynamic and complex environments. This is one of the motivations behind Neurorobotics. This field can be defined as the design of computational structures for robots inspired by the study of the nervous system of humans and other animals [1]. Neurorobotics crosses a wide variety of disciplines like neuroscience, computer science and electrical engineering, so it is known with other names: neuromorphic robotics, cognitive robotics, brain-based robotics, and many others [2], [3].

In a neurorobot, algorithms are replaced by high dimensional dynamical systems based on neural subunits which range in complexity from leaky-integrate models to integrate-and-fire models [4] like the Hodgkin-Huxley model [5] and the Izhikevich model [6]. Furthermore, Neurorobotics pursues two objectives: to develop better autonomous agents which employ the principles of neural computation and to improve the understanding of how the brain works by using these bio-inspired robots [1], [3], [4], [7]. In biological systems, the brain is embedded in the body and the body interacts with the environment. This embodiment is crucial for the construction of intelligent behaviors through the interactions with its surroundings. Therefore, neurorobots can exhibit how the mind is constructed from the interplay with the body, environment and other agents in real world situations. Also, brain-based robots can be tested in ways that have not been possible to achieve in experiments with human and animal subjects.

Arguably, Neurorobotics may have begun with the work made by William Walter [8]. He described two biologically inspired electromechanical turtle robots: the *Machina speculatrix* and the *Machina docilis*. *Machine speculatrix* used one vacuum tube to simulate two interconnected neurons. It also had two sensors and two motors. The first sensor was a photocell and it was connected to the drive and steering the motors. The second sensor was a contact switch that indicated that the robot bumped into obstacles putting the amplifiers into oscillation and changed the direction. This circuitry allowed the turtles to wander a room and return to a hutch to recharge their batteries. Under normal operation, the steering motor turned slowly producing an arcing motion. When the photocell detected a bright-enough light, the turning stopped and the robot headed towards it. This demonstrated a simple light-attracted behavior. Once the light detected by the photocell became too bright, the steering motor began turning demonstrating light-avoiding behavior. If the turtle struck an object, then the system would oscillate until it successfully avoided the object. The second robot, *Machina docilis* was produced by adding to *Machina speculatrix* a sound detector and an analog electronic circuit designed to form conditioned reflexes known as CORA (Conditioned Reflex Analogue). The CORA circuitry could be trained to establish learned connections between the sensors and the motor drive oscillators. This new configuration resulted in the ability to learn different behaviors which could be initiated by sounds, light or bumpers.

The controllers of Walter's robots were simple and did not come from a strict neural analysis, they illustrated how adding simple mechanism can yield a variety of bio-inspired robot behaviors. In this spirit, the fascinating experiments presented in [11] have inspired the use of synthetic methodology to study together the brain, the body and the behavior. Intuitively, synthetic methodology can be seen as understanding through building. Indeed, one can expect to learn a good deal of a target biological organism by assembling a robot model which mimics sufficiently some aspects of the body, brain and behavior of the original creature. In fact, this in the canon of Neurorobotics.

This work provides an overview of this nascent research field by exploring three research projects that show how robot agents are being used to investigate the roots of biological intelligence. Indeed, we summarize their methodologies and results to provide concrete examples of the two main objectives of Neurorobotics: the development of intelligent machines based on neurobiological principles and using these intelligent bio-inspired agents, to get a further understanding of how the brain works. The first project [12], [13] extends the definition of Neurorobotics to Virtual Neurorobotics by introducing a project brain-based robot. The second one [14], [15], [16] focuses on the rat whisker system to implement biomimetic technology for

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active touch. The third project [17], [18] pursues the use of neuromodulation, a brain-inspired strategy, for controlling autonomous robots. The remainder of the paper is organized as follows. Section II provides an overview of the approach and methodology followed for each one the projects; while, Section III outlines their main experimental tests and results. Discussion and comments about the studies and results of the three reviewed projects and their relationship with Neurorobotics are presented in Section IV. Concluding remarks in Section V close the paper.

II. Approaches

A. Virtual Neurorobotics (VNR)

By employing spiking neural models as the processing elements for robotic agents, researchers are attempting to explore theories that span the depth of robotics and neuroscience. Understanding neurological processing often requires the coupling of neural systems with some form of physical actuation. An example of this interaction is the concept of Virtual Neurorobotics [12], [13]. A VNR system is based on the viewpoint that a truly intelligent system should be driven by emotion incorporating intrinsic motivation and intentionality rather than programmed tasking.

The framework of VNR combines a neural model, a virtual robotic avatar and a human participant. In fact, the definition of Virtual Neurorobotics is given in [12] and it is *a computer-facilitated behavioral loop wherein a human interacts with a projected robot that meets five criteria:*

1) *the robot is sufficiently embodied for the human to tentatively accept the robot as a social partner,*
2) *the loop operates in real time, with no pre-specified parcellation into receptive and responsive time windows*
3) *the cognitive control is a neuromorphic brain emulation incorporating realistic neuronal dynamics whose time constants reflect synaptic activation and learning, membrane and circuitry properties,*
4) *the neuromorphic architecture can potentially provide circuitry underlying intrinsic motivation and intentionality, using "emotional" rather than rule-based drive, and*
5) *the neuromorphic architecture is expandable to progressively larger scale and complexity to track brain development.*

Notice that VNR expands the definition of Neurorobotics, which would imply just the third criterion, to the interaction with a human. Additionally, it requires that the robotic system demonstrates sufficient physical and cognitive realism, so the human sees the robot as a partner deserving an emotional reward, see first and fourth criteria. The robot-human interaction needs to occur in a real-time loop, see second criteria, with a cognitive architecture potentially extensible to a more complex and larger scale, see the fifth criterion.

The components of the real-time loop of the VNR system proposed in [12], [13] are the SCENE, the ACTOR and the ROBOT. The SCENE is the realistic content environment which may be affected by the actions of the ACTOR and/or the ROBOT and it may include other ROBOTs or multiple ACTORs. The ACTOR is the human participant, child or adult depending on the type of target intelligence. The ROBOT is the neuromorphic system whose central nervous system, labeled as BRAIN, may include neocortex, hippocampus, basal ganglia, and/or other limbic regions relating to attention, reward and fear. Also, a repertoire of sensors, expressions and behaviors need are in proportion with the physical and brain complexity of the ROBOT.

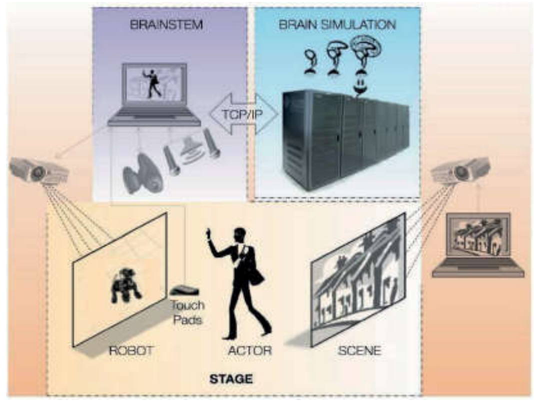
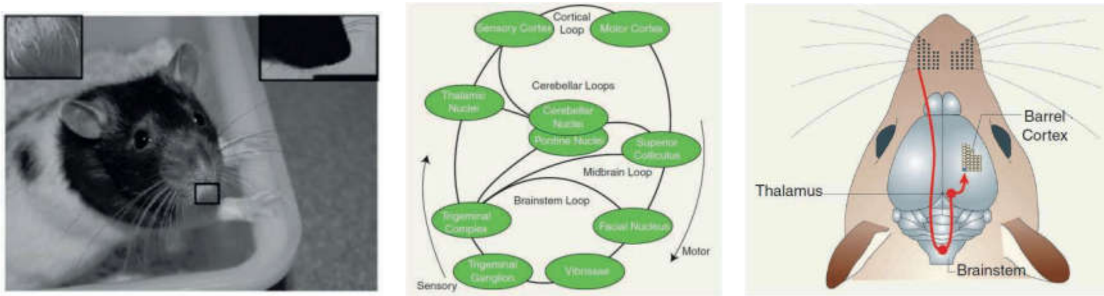


Fig. 1. Sketch of a fully-implemented VNR system. Adapted from [13].

A sketch of the implementation of the VNR system described in [12], [13] is shown in Figure 1. The virtual neurorobot is a pseudo-3D screen projection of the physical robot which participates in real-time interplay with the human participant. A tracking pan-tilt-zoom camera and spaced stereo microphones are the robot's eyes and the robot's ears, respectively. These sensors capture the movements of the actor and his/her voice in the context of a background scene that is projected independently. The capturing, pre-processing and conversion into probabilities of spiking as well as the execution of changes in the behavior of the virtual neurorobot are administrated synchronously by BRAINSTEM [19], a multithreaded C++ program. The BRAINSTEM handshakes with a spiking neural brain simulator at every time step. Indeed, the authors developed this simulator, named as NeoCortical Simulator (NCS) [20], which can learn as a result of using the reward stimuli offered by the voice of the ACTOR or stroking of a touch pad. NCS development is motivated by the need to model the complexity of the neocortex and hippocampus systems. It emulates clock-based integrate and firing neurons based on Hodgkin-Huxley formulations. Synapses are conductance-based with Hebbian Spike-Time Dependent Plasticity (STDP) [21] and phenomeno-logical modeling of depression, facilitation and augmentation. NCS provides reports like membrane voltage, spike-event only timings, and synaptic dynamics parameter states of any fraction of neuronal cell groups at any specified interval. An Internet protocol port-based input-output mode is employed to handshake NCS with the BRAINSTEM subsystem. The results from the demonstration of the VNR system in a scenario considering a human actor and a virtual robotic dog are presented in Section III-A.

Biomimetic Whisker Robots

The Whiskerbot/SCRATCHbot project [14], [15], [16] is a collaborative between robotics engineers, computational neuroscientists and ethologists to build a neurorobot based on the whisker system or the vibrissal system of a rat. This project has two principal motivations:



(a) (b) (c)

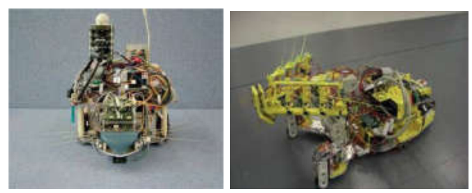
Fig. 2. (a) Macro and micro-vibrissae, the left inset shows a closed up of the outlined region on the main image and the right inset shows the micro-vibrissae being used to investigate a coin lying on the floor. (b) Sensory-processing centers with brain structures involved in controlling the movement of the whiskers and the head. (c) Sketch of the vibrissal sensory-processing pathway. Adapted from [15], [16].

1) by the implementation of a bio-inspired whisker sensory system, test existing models more thoroughly in order to obtain new hypotheses for vibrissal sensory processing, and
2) tactile whiskers could be useful for general mobile robotic sensory deployment.

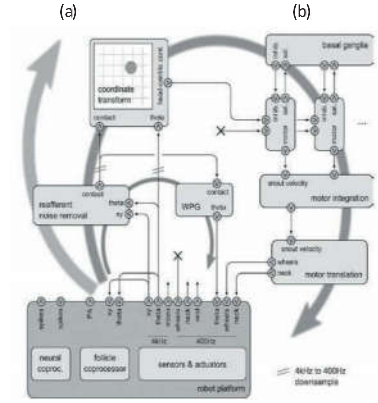
Rats are endowed with prominent facial whiskers or vibrissae which they use to explore the environment immediately surrounding their head, see Figure 2(a). Long whiskers, known as *macro-vibrissae*, are arranged into a regular grid of rows and columns on each side of the snout. These are actively moved back and forth in a regular sweeping pattern for sensing purposes at relative high speeds, 5-25 times/s [15]. This behavior is known as *whisking*. In an adult rat, the long whiskers form a grid where each row contains between five and nine whiskers up to 5 cm long and increasing in length from back to front, see Figure 2(a). Each whisker is curved and tapers from a diameter of less than 1 mm at the base to a vanishing narrow tip [14]. When one or more macro-vibrissae touches an object, the rat tends to orient its snout towards the contact region proceeding to do a fine investigation employing a second group of whiskers known as *micro-vibrissae*, see Figure 2(a). These ones do not have musculature and are distributed on the front and underside of the snout. Therefore, the macro- and micro-vibrissae together function as an integrated active touch sensor to detect and investigate from large-scale properties, like shape, down to fine-grained properties, like roughness, of the environment structure.

Whisker deflections are transduced into neural signals whose processing for tactile perception and control can be seen as a series of layers or nested sensorimotor loops connecting sensing to actuation at all levels of the rat brain from the brainstem through to the cortex [22], see Figure 2(c). In fact, Figure 2(c) illustrates the pathway from the vibrissae to the sensory cortex via the brainstem and thalamus. This nested-loop architecture appears to be the typical organization of sensorimotor control systems in mammals. Thus, progress in vibrissal robotics offers the prospect of not only developing novel tactile sensor devices, but also contributing wider insights into the brain function.

Two examples of robotic platforms bio-inspired in the rat whisker system are the Whiskerbot [14], Figure 3(a), and the SCRATCHbot [16], Figure 3(b). For both neurorobots, the base platform layout is a two-wheel differential drive unit with artificial whiskers mounted in rows in either side of the head. Also, optical encoders are located on the shaft of each whisker to derive its absolute angle θ with respect to the head unit. Even though both platforms have the previous similarities, the SCRATCHbot is mechanically and electrically a more refined version of the Whiskerbot. For instance, the SCRATCHbot has a three degree-of-freedom neck and an array of micro-vissae while the Whiskerbot has a fixed head.



(a) (b)



(c)

Fig. 3. (a) Whiskerbot. (b) SCRATCHbot. (b) Diagram of the control architecture of Whiskerbot/SCRATCHbot (mainly the configuration for the SCRATCHbot is shown). Adapted from [16], [23].

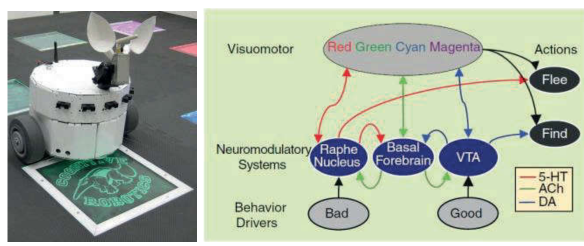
Due to the lack of biological materials and engineering practicalities, artificial whiskers do not accurately mimic the properties of the natural ones and the tissues that supports them. The whisker shaft is made of materials, *e.g.*, glassfiber, with lower sensitivity and lower damping than the ones displayed by the real whiskers. About the signal transduction from the whisker deflection, it is employing resistive strain gauges bounded directly to the base of the artificial whisker to measure the strain in two axis: anterior-posterior (AP) denoted as x and dorsal-ventral (DV) denoted as y. This configuration was implemented in the Whiskerbot, but it got damaged under large deflections. Therefore, the signal transduction was improved for the SCRATCHbot by designing a base which adds a soft polyurethane insert and a disk magnet to the base of the whisker. In this way, the whisker can return elastically to its rest position when it is released and a miniature tri-axis Hall-effect sensor (HS) can be positioned under the base to generate two voltages related to the displacement in the two axes x and y.

An overview of the robot control architecture is depicted in Figure 3(c) that is mapped loosely onto the parts of the biological architecture of Figure 2(b). The main control hardware resource of both neurorobots is a PC-104 single-board computer with expansion slots for FPGA modules. The larger neural models are offloaded onto FPGAs to maximize computational throughput using parallel computing. The motor control board of the motors is based on a dsPIC microcontroller that communicates with the PC-104 board via a SPI bus. A Proportional derivative feedback controller for each of the two motors is running on the dsPIC.

In order to use the Whiskerbot and the SCRATCHbot to investigate embedded neural processing on the real animal, the whisker deflection signals x,y and the whisking angle θ need to be encoded into spike trains using simulated leaky-integrate-and-fire (LIF) neurons. For this purpose, a model of transduction which consists of the two blocks neural and follicle coprocessors [24] is adopted. This model simulates the response to a deflection of a whisker the rat follicle assembly. Furthermore, this model was used for the Whiskerbot but not for the SCRATCHbot because of the interest of investigating more complex algorithms for the Whisker Pattern Generator (WPG). This generator underlies the rhythmic whisker motions observed in the animal giving as output a head-centric space angle that is passed to the corresponding actuators. Its signal is modulated by the *contact* signal which is a free noise version of the x, y raw sensor data. The contact signals from each whisker, in the animal and in the robot, are provided in a whisker-centered frame of reference. Thus, the signals from multiple whiskers should be transformed into a single reference frame and this is the task of the coordinate transform block in Figure 3(c). In the case of the animal, it is hypothesized that this is performed by neural mechanisms detecting coincidences between firing in deflection and angle cells [22]. In the case of the robots, a sheet of LIF cells representing the head frame are driven by deflection and angle cells together. Thus, coincident firing generates activity on a specific region of the sheet indicating contact at the encoded location. The next step is to select an action based on the detection and location of the contact. Appropriate action selection should take into account not only the signal derived from the whisker-environment contact but also internal homeostatic indicators and proprioceptive signals like odometry. In general, one proposal is that these signals are integrated by a collection of brain nuclei known as *bassal ganglia* (BG) which seems to perform efficient selection between competing behavioral alternatives [25]. The model adopted for the BG block in Figure 3(c) considers that each possible action has associated a degree of relative salience that rises and falls depending on the external sensory and internal motivational states [14]. The action with the highest salience at any one time could therefore be classed as the winning action, which is selected by the BG dis-inhibiting the necessary motor commands while strongly inhibiting those desired by other actions. A summary of the experimental tests of the Whiskerbot and the SCRATCHbot will be detailed in Section III-B.

C. Neuromodulation-Based Robot Control

Conventional robots generally require some level of supervision and tuning to work properly in a particular domain, biological organisms have the ability to adapt quickly to a dynamical world. For instance, neuromodulatory systems in mammals signal important exterior events to the rest of the brain causing to focus the attention to important objects ignoring irrelevant distractions and then responding fast and appropriately to the event [26]. Indeed, neuromodulators have a variety of functions ranging from the regulation of neuronal excitability and plasticity to structural modifications in neural circuits [18]. For example, dopamine (DA) has an effect on the organism's curiosity-seeking behavior, *i.e.*, DA drives the reward anticipation, the serotonin (5-HT) can change the level of anxiety or harm aversion, *i.e.*, 5-HT sets the response to risks and threats, and the acetylcholine (ACh) affects the ability to filter out noise and irrelevant events, *i.e.*, establishes a level of attention effort, [17]. The subsystems within the neuromodulatory system associated with each one of these chemicals are the dopaminergic with DA, the serotonergic with 5-HT and the cholinergic with ACh. All these subsystems originate below the cerebral cortex and projects broadly to all regions of the brain. Also they are reciprocally connected with the amygdala, the frontal cortex and the hippocampus which are the cognitive areas of the brain and their effect is to sharpen target neural networks resulting in a winner-take-all response [26].



(a) (b)

Fig. 4. (a) The CARL-1 wheeled robot. (b) Schematic of the neural architecture, the arrows between neural areas denote many synaptic connections between neurons. Reproduced from [17], [27].

The interaction between neocortical executive areas and the neuromodulatory system arises cognitive functions such as attention, goal-directed behavior and decision-making. Therefore, a robot controlled based on the neuromodulation could have advantages respect to conventional systems when dealing with dynamic environments. An example is the work carried out in [17]. CARL-1, the robot used for the experiments, and its neural architecture are shown in Figure 4. CARL1 is a two-wheel base with an RF-CCD camera for vision, IR sensors for obstacle avoidance and a Wi-Fi device for communications, see Figure 4(a). A distributed network of PIC-18F2680 microcontrollers forming a CAN network is employed for reading sensors, control actuators and managing the communications with a computer workstation where the neural architecture was implemented. One of the light panels used for experimental purposes is also shown in Figure 4(a). The color of the panels can be changed in frequency and duration between red, green, cyan, and magenta.

The neural architecture that controlled the CARL-1, Figure 4(b), is formed by a visuomotor area, neuromodulatory systems, action areas, and behavior drivers. In Figure 4(b), each ellipse denotes a group of mean firing neurons whose model is given by [17]

$$s_i(t) = \rho_i s_i(t-1) + (1-\rho_i)\left(\frac{1}{1+\exp(-0.1 I_i(t))}\right), \quad (1)$$

where t is the current time step, s_i is the activation level of the neuron i, ρ_i is the neuron persistence, and I_i is the synaptic input which is computed by

$$I_i(t) = \sum_j \eta(t-1)\omega_{ij}(t-1)s_j(t-1), \quad (2)$$

j with ω_{ij} as the synaptic weight from neuron j to neuron i and $\eta(t)$ is the level of neuromodulator at synapse ij. Connections between the visuamotor area to the neuromodulatory area and to the action area are subject to synaptic plasticity modeled by

$$\Delta\omega_{ij}(t) = \begin{cases} \varepsilon\Omega_{ij}(t), & \eta(t-1) \le \eta_{Th} \\ \varepsilon\Omega_{ij}(t) + \Delta_j(t), & \eta(t-1) > \eta_{Th} \end{cases} \quad (3)$$

Here $\Omega_{ij}(t) = \omega_{ij}(0) - \omega_{ij}(t-1)$, $\Delta_j(t) = \delta(s_j(t-1) - \Theta_{BCM})$, ε is the decay rate, δ is the learning rate, η_{Th} is a threshold representing the level of neuromodulator activity at which the learning should occur, and Θ_{BCM} is given by

$$\Delta\Theta_{BCM} = 0.001(s_i^2(t) - \Theta_{BCM}) \quad (3)$$

that represents the amount of synaptic potentiation/depression.

The visuomotor area consists of subareas, each with 15×20 (height × width) neurons. These subareas have as input the response of a series of filters that responded preferentially to each one of the colors: cyan, green, magenta, and red. The simulated neuromodulatory systems are an ACh basal forebrain (BF) area, a 5-HT raphe nucleus (Raphe), and a DA ventral tegmental area (VTA). Each of these neuromodulatory areas contained 100 neurons. Action areas consist of a Find and Flee area that each contained 100 neurons. The Find action is to approach to objects of interest while the Flee action is to move away from noxious objects. The behavior driver areas are formed by a good and bad area that each contained 100 neurons. The experiments and their results employing a group of CARL-1 subjects with the neural architecture shown in Figure 4(b) are summarized in Section III-C.

III. Results

A. VNR Interaction with a Human

As proof of concept, the proposed VNR system was tested in a scenario considering a virtual robot dog interacting with a human [12], [13]. As it is shown in Figure 1, the robotic dog was projected onto the forward screen with a group of sensors that enable its simulated brain to perceive and to respond to the movements of the human actor in the context of a background scene projected onto the rear screen where a static image of a neighborhood was used for the demonstration.

The dog could respond to the movements of the actor with either of the next three behaviors

1) a cautious growl while remaining in lying position (Cautious behavior),
2) threatening bark while sitting up (Angry behavior), and 3) happy breathing and tail wagging while fully standing (Happy behavior).

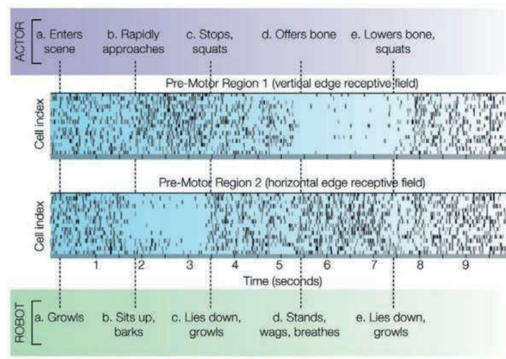


Fig. 5. Spike rasters from a 10-second behavior scenario indicating the timing of ACTOR and ROBOT events. Reproduced from [12], [13].

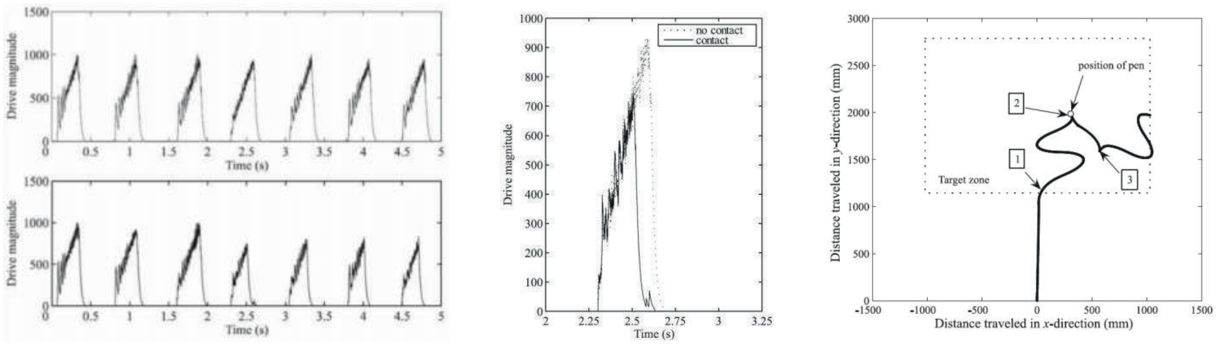
The actor was told in advance that moving vertically oriented objects posed a threat to the robot. For example, walking toward the robot or waving an arm or a bat in a striking manner would cause predominant vertical edge movements in the visual field of the dog. Meanwhile, moving horizontally objects would be perceived as friendly gestures. For instance, offering a hand or a horizontally held object like a bone triggered a horizontal edge response.

For this demonstration, a simple neuromorphic brain was considered. It had 64-single-compartment neuron divided into 4 columns representing pre-motor regions, *i.e.*, precursors to coordinated behavioral sequences. Each of these regions was connected to one of the visual field preferences, vertical or horizontal. According to the probability vector from BRAINSTEM, the BRAIN simulator, NCS, injected short step current pulses (1 ms with amplitude of 3 nA) sufficient to reach the threshold of -50 mV and generated a single spike. Membrane voltages updated at a frequency of 1 kHz.

The results for the ACTOR-BRAIN-ROBOT interplay are shown in Figure 5. The ACTOR was free to choose any sequence of movements. For instance, when the robotic dog responded with an Angry behavior in response to threatening, *i.e.*, vertical, movements, the human actor must decide whether to freeze, to move back or to move toward the robot doing a friendly, *i.e.*, horizontal, movement to get a Happy behavior from the dog. It was found that no consistent movements for more than 50 ms triggered a Cautious response from the robot. In the cell rasters depicted in Figure 5, each row represents the timing action potentials of a single neuron where darker markers indicate clustered burst of spikes.

B. Whiskerbot/SCRATCHbot experiments

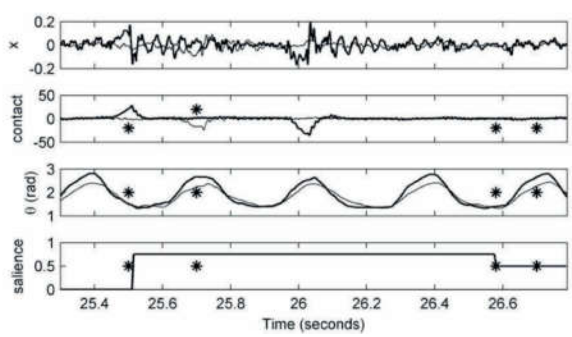
The first goal of the Whiskerbot platform was to demonstrate that the embedded computational neuroscience models could adequately perform the active vibrissal sensing [14]. In other



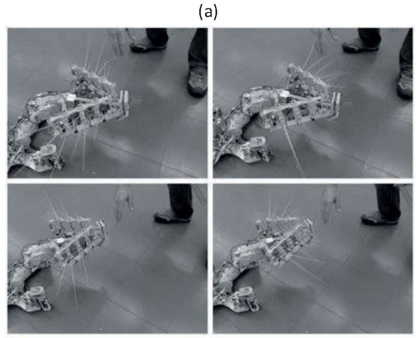
(a) (b) (c)

Fig. 6. (a) Drive signals derived from the WPG during 5 seconds, top plot: no contact case, and lower plot: contact case. (b) Comparison of the fourth pulse taken from the top and lower plots of the previous part. (c) Trajectory followed by the Whiskerbot in a 30-s run. Adapted from [14].

words, the first task was to test the functionality of the WPG. As it was explained in Section II-B, this generator was implemented using leaky-integrate-and-fire neuron models updated in real-time using an FPGA. An active drive signal was derived from the WPG by integrating the spike response. Afterwards, it was used to set the duty cycle of the PWM that drives the artificial whiskers. An example of a typical drive signal derived from the WPG for the no contact case is shown in the top plot of Figure 6(a). Meanwhile, the drive signal for the contact case is shown in the lower plot of the same figure. These signals were recorded during a 5-second experiment. An object was moved into the whiskers on the fourth cycle and remained for the duration of the experiment. Figure 6(b) illustrates a more focused comparison of these signals during the fourth whisk cycle highlighting the strong attenuation of the drive signal.



(a)



(b)

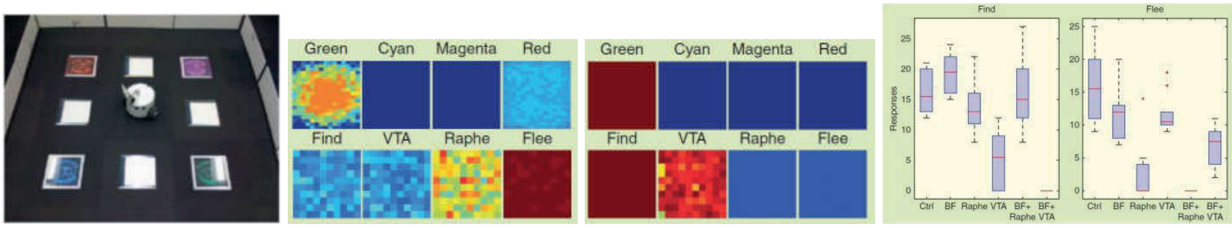
Fig. 7. (a) Data from SCRATCHbot during an orient to stimulus behavior. (b) Frames showing specific instants during the experiment. Reproduced from [16].

The next step was to test Whiskerbot in an open environment. It was programmed with three possible actions: dead reckoning, explore environment and orient to 6timulus. Dead reckoning was employed to navigate the robot to a desired position. Explore environment drove the robot to generate a slow sinusoidal searching pattern loosely based on an idealized rat exploratory strategy. Orient to stimulus modeled the observed orient response of rats towards contacts made by their vibrissae. The Whiskerbot was placed into an open environment and a 30-s experiment was performed, see Figure 6©. Here, the dead reckoning action was set to have the highest salience at the beginning, so the robot could enter to a target zone. Then, the salience to continue this action would decline rapidly once the neurorobot entered to the target zone, point 1 in Figure 6©, resulting in an action change to the explore behavior. This behavior was seen as the default behavior of the robot, so its salience was constant. When a vibrissa made contact with an object, *e.g.*, a pen in the case of point 2 in Figure 6©, the salience to orient towards this stimulus increased rapidly due to the rise in activity within the superior colliculus. Thus, the BG inhibits exploration and activates the orient to stimulus behavior. The robot then brought its nose to the source of contact. After a pre-defined period of time, the robot reversed away from the source of contact, point 2 to point 3 in Figure 6(c), and then it returned to the default explore behavior.

For the case of the SCRATCHbot, a video of one of the performed experiments can be seen in [28]. The results during the orient to stimulus behavior for one of the experiments are reproduced in Figure 7 from [16]. The upper three plots of Figure 7(a) show data from the fifth whisker, thick line, and from the seventh whisker, thick line. The lower plot on this figure is the salience of the orient behavior. A series of frames during the orient to stimulus behavior are presented in Figure 7(b). The timing of the frames is indicated in the plots of Figure 7(a) by the stars. Contact on whisker 5, see frame 1, is followed by an increment in the orient salience. Additional contacts on whisker 7, see frame 2, during the orient to stimulus behavior are ignored. Snout arrives at the point of initial whisker contact completing the orientation, see frame 3. A second phase of orientation is shown in frame 4 where the micro-vibrissae gets closer for fine inspection.

C. CARL-1 Behavioral Results

The following explanation is based on the results presented in [17]. The experimental setup made of eight light panels in an area of 10 x 10 ft is shown in Figure 8(a). The neural architecture, Figure 4(b), was run on a 2 x Quad-Core 2.8 GHz Intel Xeon Mac Pro Workstation. The step time was fixed at



(a) (b) (c) (d)

Fig. 8. (a) Experimental setup for CARL-1. (b),(c) Neural activity just before and during Find behavior. Each pixel denotes a neuron where the activity is color coded from quiescent, dark blue, to maximally active, bright red. (d) Behavioral response for the ten neurorobots for the experiment simulating lesions (on each box in the plot, the central mark is the median, the edges of the box are the 25th and 75th percentiles, the whiskers extend to the most extreme data points not considering outliers, and outliers are plotted individually with the plus signs). Reproduced from [17].

100 ms. The experiments consisted of a first phase of training to associate the color green with the Find behavior and the red with the Flee behavior. Then, a group of ten different CARL-1 neurorobots were tested under various conditions. The differences among the neurorobots were at the level of synaptic connections, *e.g.*, probability distributions of connectivity between neurons and variations of initial strength of those connections.

A video showing one of the neurorobots during training can be found in [27]. In this phase, a CARL-1 subject explored the environment getting closer to the light panels. Once it is close to one of the panels, an operator turned the light panel to green activating maximally the good area or turned the light panel to red activating maximally the bad area. The training continued in this manner until the subject had experienced ten good and ten bad events. After training, all the ten subjects responded to a green light with Find behavior and to a red light with Flee behavior. The neural activity right before and during the Find behavior are reproduced from [17] in Figures 8(b) and 8(c), respectively. The Raphe and Flee neural areas were still active when the light panel switched from red to green, see Figure 8(b). Then, a burst of VTA activity amplified Green and Find activity causing a suppression of the other areas, Figure 8(c).

A further test was conducted by simulation of lesions in all the neurorobots and comparing their behavior with the one from a control group, *i.e.*, assuming no lesions. The lesions considered were in the Raphe area, in the VTA area, in the BF area, and in multiple areas, BF + Raphe and BF + VTA. A lesion was simulated by zero activity of the neurons in the damaged area. The results are reproduced from [17] in Figure 8(d). The lesion of the VTA significantly reduced the number of Find responses but not the Flee responses. On the other hand, the Raphe lesion significantly reduced the number of Flee response but not the Find response. The lesion of the BF alone did not have a significant effect on the behavior. However, the lesion of BF + VTA completely eliminate the Find behavior and the BF + Raphe lesion entirely cancel the Flee behavior.

IV. Discussion

In this work, we provide an introduction to Neurorobotics by focusing on three projects as examples of two main advantages of embodying models of the brain on robotic platforms. The first one is the possibility of test and study a neural function model in a more realistic environment without assuming a model for noisy sensors. For instance, the three projects worked under noisy conditions of the sensors and actuators and the brain-based control architectures for each case showed its robustness capability which is not the case, in general, for traditional control schemes. The second important benefit is to study the interaction between the brain, the body and the environment and how it affects the behavior of a cognitive agent. Currently, simulations of real-world interactions are not capable of adequately capturing all its dynamical properties. Maybe robotic platforms are one of the most cost-effective ways of studying these interactions. Even that a virtual robotic dog is used in the VNR system, its interplay with a human actor allowed to study more spontaneous intelligent responses. For the whisker robots, the interaction of the artificial vibrissal system with moving or irregular surfaces helped to improve its mechanisms as it can be seen on the difference between the SCRATCHbot and the Whiskerbot. In the case of the cognitive robot CARL-1, it was possible to test how the neuromodulatory system can drive attention and select action according in a controlled real environment.

Also, the three projects point out the engineering practicalities on the designing of a bio-inspired mechanism. The clearest example is the VNR system where a virtual robot is incorporated instead of using a real one. The demanding time of designing and implementing a robot is reduced in this approach without giving any direct benefit to the engineering aspect of Neurorobotics that is to build intelligent bio-inspired robots. Because of this, in our opinion, the VNR framework can be as a step where a simulated neurorobot can be tested before proceeding to the redesign and implementation of real mechanisms. On the other hand, the project on the whisker robots developed a useful tactile mechanism that can be adopted by other autonomous platforms. Even though the whisker mechanism does not fully mimics the properties of natural whiskers, we think it can be used as an alternative or complement for vision sensors in situations where smoke is present on the environment.

The amount of processing for employing neural-based controllers on the neurorobots is demanding, as it is clear from the explored projects. For example, the NeoCortical Simulator for the cases of the VNR system ran in a supercomputer, a PC-104 single-board computer together with FPGA expansion modules was the based for the implementation of the brain of the whisker robots, and the neural architecture was run on an external workstation for the case of CARL-1. Unfortunately, these computing requirements limit the power and capabilities of the robotic platforms. Notice that in two of the three projects, the VNR and CARL-1, the robot's main controller is outside of the platform and in the other one, Whiskerbot/SCRATCHbot, a heavy power supply should be added as part of the robot. We believe that new power-efficient embedded computers would alleviate this problem making possible to embody completely the neuro-based controller on the robot.

V. Conclusion

Traditional robots have become important tools for increasing industry productivity and our quality of life in the last decades. They are generally confined to specific assignments without fully exploiting their ability to sense the environment. Therefore, they fail in adapting their behavior to dynamic environments. If these autonomous systems are equipped with a control architecture inspired on the nervous system of animals or insects, they might display the flexibility and adaptability capabilities that are present in biological organisms. This is the inspiration for the exciting and emerging research field of Neurorobotics. This relative nascent field pursues to develop better autonomous systems by embodying models of the brain on robotic platforms, and to learn new hypotheses of how the nervous system works by experimenting with brainbased robots. We give an introduction to Neurorobotics by summarizing the achievements of three projects in this area.

These projects are examples of the interdisciplinary nature of Neurorobotics which can be seen as a link between natural and engineering sciences. Furthermore, it is clear that this field carries the potential for expanding our understanding of the way sensory information is processed in the brain and for the construction of innovative autonomous systems. Promoting the collaboration between the disciplines of neuroscience and robotics will lead to a major advancement for the development of truly intelligent autonomous agents.

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VII. Bibliography

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