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Conditioned behavior in a robot controlled by a spiking neural network*

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***Abstract*— Insects show a rich repertoire of goal-directed and adaptive behaviors that are still beyond the capabilities of today's artificial systems. Fast progress in our comprehension of the underlying neural computations make the insect a favorable model system for neurally inspired computing paradigms in autonomous robots. Here, we present a robotic platform designed for implementing and testing spiking neural network control architectures. We demonstrate a neuromorphic real-time approach to sensory processing, reward-based associative plasticity and behavioral control. This is inspired by the biological mechanisms underlying rapid associative learning and the formation of distributed memories in the insect.**

I. INTRODUCTION

The nervous systems of animals employ efficient stochastic computations to obtain fast and reliable estimates of the world state and to predict consequences of their potential actions. Neural computation bears a number of interesting features such as parallel processing, sparse codes, adaptation and plasticity on multiple time scales and distributed memories. Developing neuromorphic computing paradigms that mimic nervous system function is an emerging field of research that fosters our model understanding of the biological system and targets technical applications in artificial systems.

Insects provide favorable and well-studied model systems for neurally inspired computations. Despite their limited neuronal resources they exhibit surprisingly complex behaviors. Their capabilities of exploration, reliable navigation, pattern learning, and social interactions are desirable features in autonomous robots.

Our focus here is on computations that underlie learning and memory formation in the insect. Classical conditioning has been heavily studied in various insect models, notably in the fruit fly and in the honeybee. Investigation at the behavioral and the neural circuit level is improving our model understanding at different levels of abstraction [1], [2], [3], [4], [5], [6], [7].

Spiking neural networks (SNNs) provide biologically realistic models of neural computation. They allow us to test our theories of nervous system function. Concomitantly, computing with SNNs bears a number of interesting key features that are lacking in conventional computing paradigms. These comprise inherent parallel processing, distributed cellular mechanisms of adaptation and robustness, distributed memory, and low energy consumption. These factors make SNNs attractive for a number of potential applications, including artificial mini-brains for autonomous robots.

To date, the number of studies on autonomous robots that have employed SNNs is still very limited and have primarily focused on peripheral stages of sensory processing or on pattern generation for peripheral motor control [8], [9]. Our goal is to design SNNs that perform sensory-to-motor transformations including the central control of behavioral states and the ability to learn and adapt in complex environments. In order to test biological realistic neural network models with a robotic approach we here developed a platform that supports interfacing real-time SNN simulations with the robotic hardware sensors and actuators. We tested our platform with a simple SNN model that is able to form associations between visual sensory input and reward by a mechanism of synaptic plasticity.

II. PLATFORM

A. Robotic platform and sensors

Figure 1 gives an overview of the robotic platform and sensors. We used a DfRobotShop Rover V. 1.5 [10] (Rover) which is a versatile mobile tank using the Arduino Uno [11] prototyping platform equipped with a ATMEGA328p microcontroller. It uses two tank tracks, each connected to a DC gear motor for which speed and direction can be controlled. The Rover also features an analog light sensor and a temperature sensor.

For visual processing we used a HaViMo-a vision processing module v. 2.0 [12]. It is equipped with a CMOS camera chip and a ATMEGA8 microcontroller that performs image processing. The module supports two color-based image processing methods: online region growing and gridding. The color values are calibrated and then stored in a built-in look-up table.

The communication between the Arduino platform and `iqr`, the SNN simulator (see II-B), was done via WiFi. A DfRobot WiFi shield for Arduino [13] was used and connected to a virtual serial port on our PC. The SNN simulator read sensory data from the virtual serial port and sent back motor commands.

B. Simulation environment

To control the Rover we use `iqr` [14], a free open-source SNN simulator (released under the Gnu Public License). It

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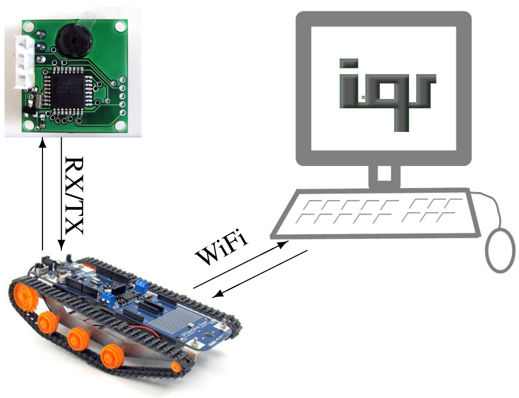

Fig. 1: Robotic platform overview as described in II-A.

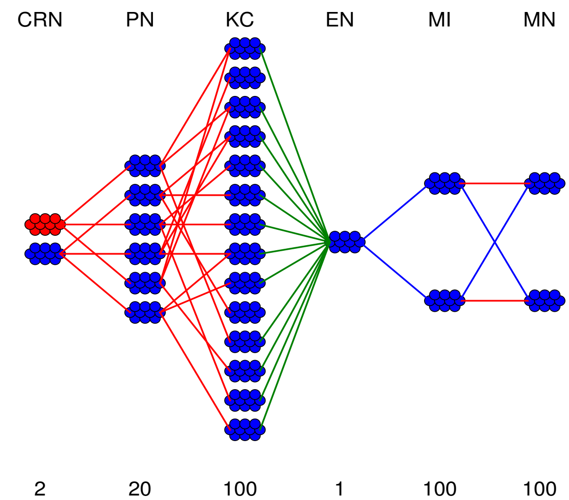

Fig. 2: The neural network architecture from sensory input to motor output. Red(blue) connections indicate excitatory(inhibitory) synapses, green connections indicate modulatory synapses, that are adjusted during reinforcement. Numbers under each group indicate the number of neurons. Detailed description of the network in section III-A.

has a graphical interface for designing neural networks and comes with tools for online visualization for analysis of data. Simulations can be controlled in real-time and it is possible to adjust most of the parameters of a model at run-time. More importantly, it has an open architecture, which makes extensions possible.

We added a neural module which simulates an adaptive integrate and fire neuron, and a modulatory synapse module. We extended the existing Arduino module in order to be able to read and write values with pulse width modulation as well as analog values.

Conversion of the sensory data into spike trains depends on whether sensory data is read from the analog sensors or the camera. The camera output is processed on the Arduino board and is sent to the simulator as 1 or 0, depending on whether or not a colored region was found. It is then translated into spike trains in `iqr` by generating regular distributed spike times as long as the value remains 1 and no spikes during epochs of value 0. Creating a spike train for the analog sensor input is done inside the `iqr` Arduino module. There, the values read from the sensor have to reach a predefined threshold to stimulate spiking of the sensory neuron.

III. Neural Network Model

A. Network architecture

Figure 2 gives an overview of the neural network architecture used to control the Rover. Each population consists of a number of adaptive integrate and fire neurons. The architecture of the learning network is inspired by the model of olfactory learning in the fruit fly [15] and the honeybee [18]. Here, color is used instead of odors. The color receptor neurons (CRN), one tuned to red and one tuned to blue, project to a group of projection neurons (PN) that excite the Kenyon cells (KC) in the mushroom body. The KC output converges onto a single extrinsic neuron (EN). The KC-EN synapses are plastic and form the basis for the association between the conditioned stimuli and the unconditioned stimulus.

The camera output serves as sensory input (either blue or red) to the network. The reinforcement signal is a short flash of light sensed by the light sensor. The output of the learning network is fed to a simple motor network consisting of four neuron groups. Two of them (MN) directly control the motors. Additionally, they each project onto a group of neurons (MI) that inhibit the opposing motor neuron group. Thus, only one motor is running at any given moment, creating a search behavior by spontaneous changes in rotational direction. Once the network has learned to associate a visual sensory input with the reinforcement through strengthened KC-EN synapses, the EN inhibits the mutual inhibition of the motor network upon presentation of the reinforced conditioned stimuli (CS+), making the Rover move forward (both motors are active).

B. Adaptive integrate and fire neuron

The best known model of spiking neurons is the integrate and fire neuron. We implemented an adaptive integrate and fire neuron module in `iqr` that adds spike-rate adaptation to the model and is described by:

$$\tau_m \frac{dV}{dt} = E_L - V - r_m g_{sfa}(V - E_{sfa}) + R_m I_e. \qquad (1)$$

Equation 1 is equipped with an adaptation conductance g_{sfa} which is incremented with every spike the neuron fires. This introduces an outward current that drives the membrane potential V towards the reversal potential E_{sfa}. When no spikes are fired, g_{sfa} decreases exponentially. R_m is the specific membrane resistance, τ_m is the membrane time constant, r_m is the specific membrane resistance, E_L is the reversal potential and I_e is the stimulating current.

C. Local plasticity rule

The modulated synapse module implements a conditionally reward-modulated Hebbian plasticity [16] where the weights of the synapses are changed according to the following equations:

$$\Delta w = e(t) \cdot OCT \cdot \alpha \tag{2}$$

$$w(t+1) = w(t) + (1 - w(t)) \cdot \Delta w. \tag{3}$$

In equation 2 OCT is the octopaminergic signal, that is either 0 or 1, depending on whether the reward is presented or not, and α is the learning rate. We used the input from the light sensor as the reward signal. The eligibility trace $e(t)$ serves as a memory state variable.

$$e(t+1) = e(t) + (1 - e(t)) \cdot \alpha_e \tag{4}$$

It increases with each presynaptic spike by α_e and decreases exponentially when there is no presynaptic activity.

IV. Conditioning Experiments

A. Experimental Setup

In a 110x100 cm arena two red and two blue targets were placed in the corners (Figure 3). The camera was configured to detect regions with red and blue colors, and the intensity of the flash-light was calibrated. All experiments were recorded using a webcam connected to a PC. At the start of an experiment the Rover was placed in the middle of the arena and started rotating as described in III-A. Before learning took place, sensory inputs from the camera did not have any effect on the motor network. After the Rover had detected at least two targets, the experimenter selected the CS+. When the Rover was pointing towards the selected target, a flash-light was briefly turned on. This lead to spiking in the reward sensor neurons and triggered an increase in the synaptic weights (Eq. 2). After learning the association, the Rover would search and approach a target of the same color.

B. Results

Figure 3 shows the paths the Rover took in two trials, where red (Figure 3a) or blue (Figure 3b) were the CS+, respectively. Figure 4 shows the spiking of the motor neuron groups corresponding to the path taken in Figure 3a. Figure 4 shows, before the reinforcement the motors mutually inhibit each other causing only one motor group to be active at a time. After pairing the CS+ with the reward, the mutual inhibition was inhibited whenever the CS+ was detected, causing both motors to run in parallel.

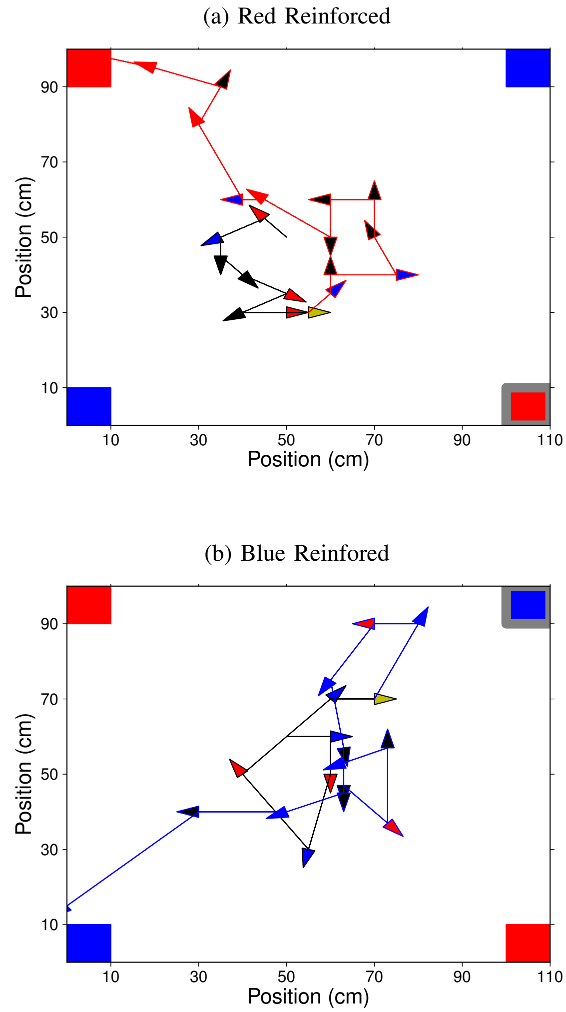

Fig. 3: The path of the Rover when the red (a) and the blue (b) color is reinforced. Arrowheads indicate camera direction and detected color along the path. Yellow arrowheads indicate reinforcement. Red and blue boxes indicate targets. Gray boxes indicate reinforced targets.

V. Conclusion and Outlook

We developed a low-cost platform for real-time interfacing a SNN simulator with sensors and actuators in order to test biomimetic closed-loop robot control. We implemented a simplified model of the insect sensory-to-motor network combined with a biologically inspired synaptic learning rule as a simple test case of our platform. This lead to a rapid association of the object color with reward, reproducing the experimental observation of rapid learning during a single association trial in individual honeybees [4]. The ongoing research in our lab aims at the implementation of more sophisticated SNN models [15], [17], [18], which combine elaborate sensory processing, reward-based learning and behavioral control in complex artificial scenes. We are planning parallel experiments with insects and robots together with our experimental partners.

The solution for the neural network simulation employed here imposes two severe restrictions. Firstly, computational power limits network complexity for real-time applications. This might be overcome by new solutions for real-time GPU simulation [19]. Secondly, wireless communication and high energy consumption prevent application in a truly autonomous system. On a longer perspective, matured neuromorphic hardware technology [20], [21], [22], [23], [24] will offer a compact and energy-efficient approach for autonomous robot control by artificial minibrains.

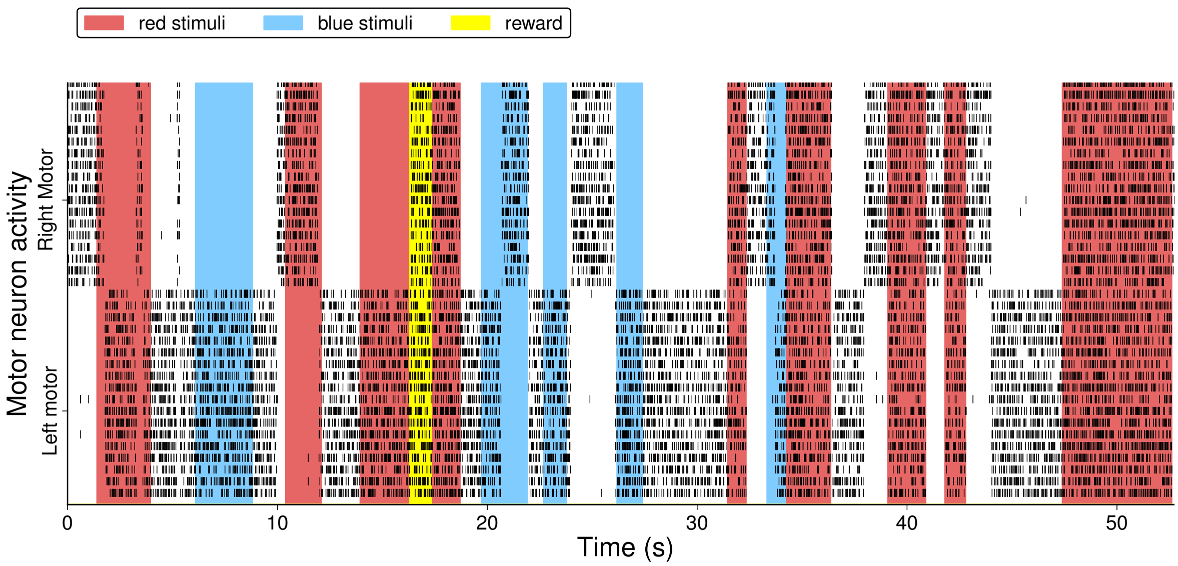

Fig. 4: Spiking activity of motor neuron groups when red was CS+. Black ticks mark the spike output of selected neurons. Detailed description in IV-B

SUPPLEMENTARY MATERIAL

Video: `http://youtu.be/Qb_R_E4DPYs`
`iqr` extensions package can be found at:
`github.com/loairpa/iqrextensions.git`

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