Memristive neuron integration in digital robotic embodiment

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Abstract

In the current paper, we introduce a high-level approach for an integration of a neuromorphic memristive neuron in a real-time operating robotic system. The memristive neuron schematic, which we had presented in our earlier works, is capable of inhibitory and excitatory learning (eSTDP, iSTDP) as well as modulation via dopamine input. We discuss a possibility of integration of the analog memristive neuron into a digital robotic embodiment and present block diagram of an adapter that includes pseudo-neuronal encoder and decoder.

Keywords: artificial intelligence, robotics, spiking neural network, memristors.

1. Introduction

Previously we have demonstrated successive attempts to implement in bio-plausible manner four of eight basic emotions or affects in a computational system[1,2]. These emotional drives could be useful for the self-learning autonomous robotic systems to be used as reward-and-punishment systems. This development of our research put us in a position to answer the question of a robotic embodiment therefore we have started the project "Robot dream" [1].

The idea of proposed project is to discriminate two phases of real-time (a so-called "wake") phase and not real-time bio-inspired calculations ("dream") phase. The "wake" phase is performed via a robotic system that is synchronized periodically with the "dream" phase, which is implemented at a cluster or a supercomputer due to their high performance impact. NeuCogAr project[2] describes in details the bio-plausible neuromodulating cognitive architecture. For the purpose of implementation of the real-time operating robotic embodiment system we have selected a memristive approach that was introduced during several decades in various optional implementations including organic polyaniline[3,4] and silicon memristive devices[5] etc. One of promising features of memristive devices is spike timing dependent plasticity (STDP) characteristic of learning or self-learning of a memristive devices[5,6]. Using this feature we have implemented excitatory and inhibitory STDP and dopamine modulation of a memristive artificial neuron[7].

2. Problem

The idea to use memristive device as synapse is not new but still we have failed to find a successful implementation of bio-plausible neural network capable of neuromodulation, excitatory (eSTDP) and inhibitory (iSTDP) STDP. The listed above basic neurobiological mechanisms are crucial for mammalian emotional regulation, decision-making and behavioral strategies generation and implementation[8,9,10,11]. Even if we could create a bio-inspired memristive brain there is still a fundamental problem of its embodiment. We believe that the most promising approach for the embodiment problem solution is through a use of a robotic body. How do we integrate a spiking neural network with a digital robotic environment?

This position paper describes a high level architecture for memristive neuromorphic devices integration with a realtime or semi-realtime robotic embodiment system and is based on our previous papers on memristive neuromorphic computing solution for neuromodulating neuron with eSTDP and iSTDP[11].

3. Proposed Solution

3.1. *Memristive neuron*

Previously we have proposed an overall block diagram and the implementation of memristive neuromodulatory neuron[11]. We have demonstrated the bio-inspired learning via STDP and modulation of learning functions via dopamine input. The proposed schematic has three types of input: excitatory, inhibitory and modulatory. Excitatory and inhibitory inputs have their memristive devices that implement the learning functions of eSTDP and iSTDP. The modulating input alters the eSTDP functions increasing and decreasing its amplitude in bio-inspired manner[12]. Currently we carry on with making the schematic more bio-plausible to get easier integration option into biological environment. We have successfully demonstrated the simulation results of the Hebbian learning via levels of memristive device conductivity that was determined by series of learning impulses $\Delta w = 1/\Delta t$ where Δt is the time lag between pre-synaptic spike and post-synaptic spike or inbound and outbound impulses of the memristive neuron, and their modulation by the dopamine level. The dopamine level is identified via the setup of dopamine potentiometer that influences the learning impulses amplitude and in its turn influences the memristive device conductivity.

The simulation results are presented in Figure 1. The top graph depicts the dopamine (DA) level and identifies the level of modulation of learning impulses that is visible as the increment of green graph amplitude (the bottom graph), that in its turn influences the memristive device conductivity, described below. In Figure 1 (in the middle) the lilac graph represents the result of the memristive device learning the overall conductivity. It is set by modulated learning impulses that are formed as Hebbian learning. For the simplification of the simulation purposes we used two different generators with phase shift to simulate different Δt. This way we could depict the entire Hebbian learning in one graph. Simulation methods were used to calculate required nominal values of the electronic components and to validate the quality of the

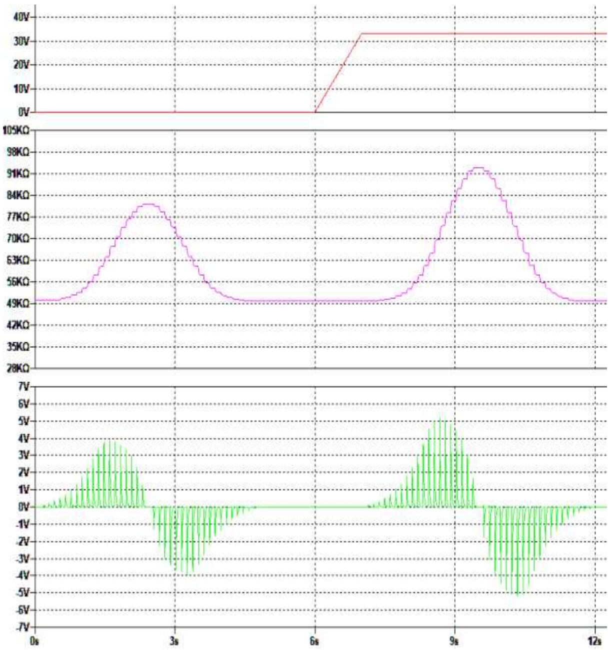

Fig. 1. The simulation results of learning STDP: (top) level of DA influence or setup of DA potentiometer, (middle) graph of memristive device conductivity, (bottom) learning impulses

proposed model. We used integrated schematic editor and mixed analog/digital simulator LTspice. Figure 2 represents the wiring schematic, where excitatory and inhibitory learning impulses are transmitted to memristive elements. Two different sources generate signals with different phase to gain the effect of viable Δw. Temporal and amplitude characteristics of impulses have been simulated. Impulses have been investigated in the time range from 1 to 800 milliseconds. The excitatory and inhibitory impulses replicate the Hebbian and "sombrero" learning functions according to the theoretically predicated forms.

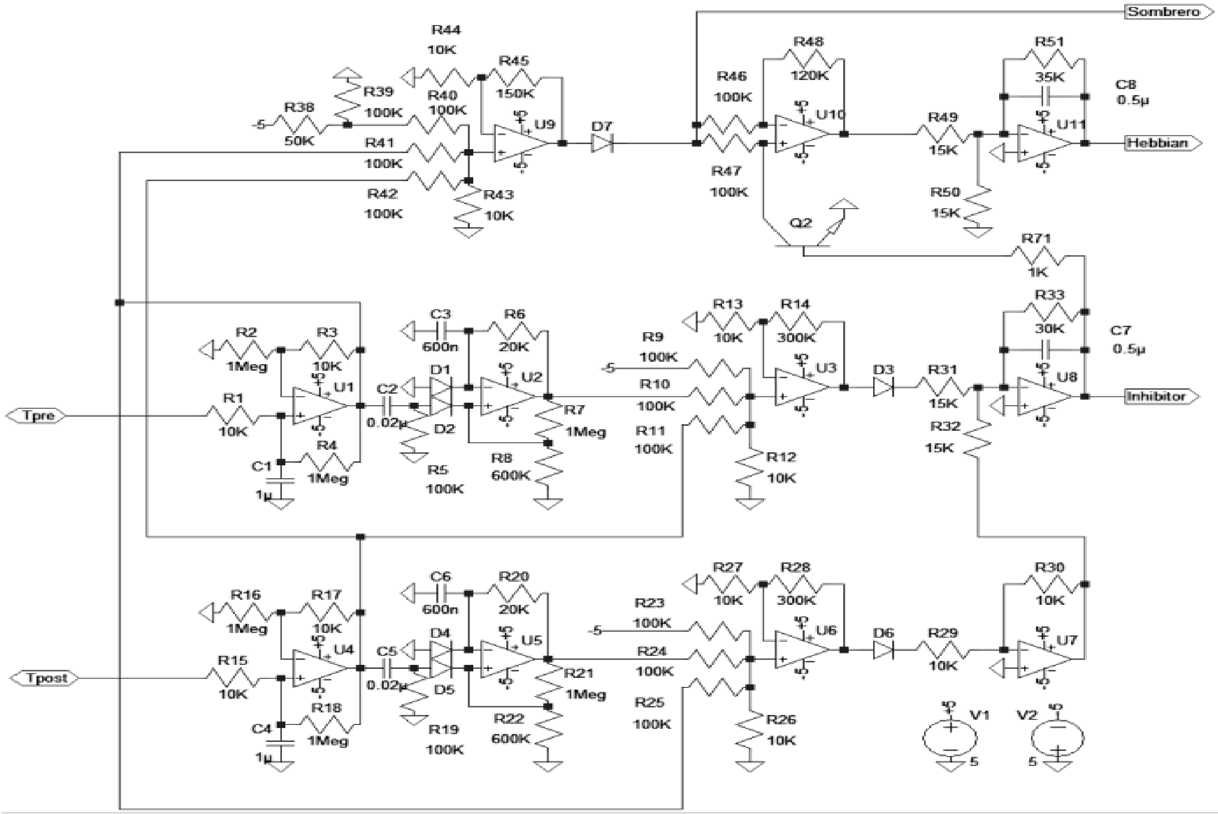

Fig. 2. Wiring schematic of modulatory, excitatory and inhibitory memristive neuron device.

3.2. *Integration*

The other interesting goal is the integration into digital robotic embodiment system, which could be the anthropomorphic[13] or non-anthropomorphic[12] system. The presented in the Figure 3 high-level architecture includes: memristive neuron presented above. The neuron has three types of inputs: sensory, inhibitory and modulatory.

Sensory is usually excitatory and is the input from different sensors that are connected via controllers and digital-to-neuronal converters (DNC) or encoders that translate the digital input in form of pseudo-neuronal activity via, for example inverse rate encoding. The pseudo-neuronal activity is similar to neuronal but is generated by artificial for example memristive neuronal devices. The inhibitory input is usually the input that comes from different neurons; for example, for reciprocally inhibition, this is frequent pattern in spinal cord. This could be considered as a blocking system for unwanted behavior.

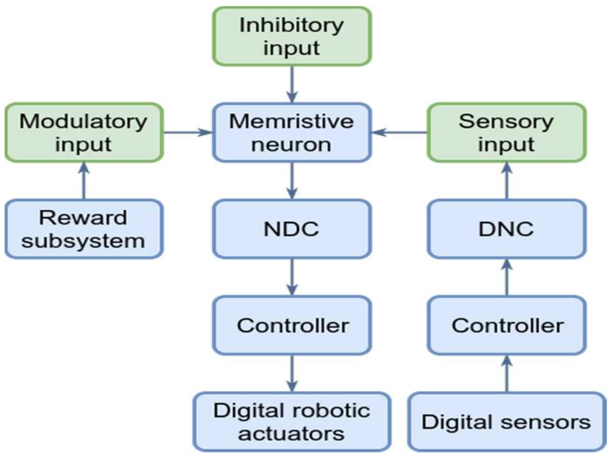

Fig. 3. The basic integration high-level architecture to integrate spiking memristive neuron with digital environment.

The modulatory input balances the neuron towards spiking or generating output impulses. It could represent a reward subsystem of a robotic system embodiment. This way we could “naturally implement the rewarding associations with, e.g., power supply.

The output of the memristive neuron schematic is processed via NDC (neuronal activity to digital converter) that converts pseudo neuronal activity into digital output activating more intensively robot actuators with higher firing rate of memristive artificial neuron. This way in the boundaries of one neuron and several sensors, we could associate modulating reward with power supply and then train a robotic embodiment system to look for the energy supply autonomously.

4. Discussion

In this position paper we proposed the overall architecture for the integration of memristive neuromodulating neuron introduced earlier.

To the best of our knowledge, there is no existing memristive schematic that successfully implements neuromodulation, though it plays important role in emotional regulation of mammals. Therefore, it seems fruitful to implement these mechanisms in a robotic environment in order to solve the integration problem.

We have proposed the overall integration approach of memristive analog devices with digital robotic environment. This approach could be used to implement "natural" reward system. The reward system could use the dopamine modulating input of proposed earlier memristive modulating device. Hopefully using pain/pleasure stimulus we could train proper associations in a real-time robotic embodiment similar to mammalian training.

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