The Memristive Artificial Neuron High Level Architecture for Biologically Inspired Robotic Systems

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Abstract—**In this paper we propose a new hardware architecture for the implementation of an artificial neuron based on organic memristive elements and operational amplifiers. This architecture is proposed as a possible solution for the integration and deployment of the cluster based bio-realistic simulation of a mammalian brain into a robotic system. Originally, this simulation has been developed through a neuro-biologically inspired cognitive architecture (NeuCogAr) re-implementing basic emotional states or affects in a computational system. This way, the dopamine, serotonin and noradrenaline pathways developed in NeuCogAr are synthesized through hardware memristors suitable for the implementation of basic emotional states or affects on a biologically inspired robotic system.**

Keywords—**Cognitive architecture, memristive elements, circuits, artificial neuron, affects, biologically inspired robotic system.**

I. Introduction

The implementation of emotional states in a machine is a challenging and quite explored topic [1], [2] since it can be considered as the cornerstone for the implementation of human-like consciousness and possibly cognition. From a different perspective, the computational model of human emotions could be the key for the emotional profiling of groups of people and in its turn could be of interest from an economical and marketing viewpoint. To this purpose, three years ago we have started the NeuCogAr project [3] to re-implement mammalian bio-realistic affects (here inborn emotional reactions) in a computational system.

In the NeuCogAr project we have proposed a neurobiologically plausible approach for the re-implementation of affects in a computational system. We adopted the neuropsychological model called “cube of emotions” created by Hugo Lövheim [4]. This model creates the correlation between affects and monoamine neuromodulators: noradrenaline, serotonin, dopamine. Taking into account the role of neuromodulators we assumed that re-implemented neuronal pathways of a mammalian brain should influence the computational system processes of the host system in a similar way they influence the mental processes of the “host” animal. Based on this assumption, we have currently managed to re-implement fear-like and disgust-like states in a machine.

We consider as fundamental a so called *embodiment problem*. We understand the embodiment problem as integration of the simulated brain with the real world. We wanted to remove the borderline on a simulated brain allowing interaction with the real world. In the NeuCogAr project, the simulations are calculated on a cluster composed of up to 10 nodes and they are rather time consuming, while a real robotic system has strong real-time or quasi real-time requirements for the calculations. Unfortunately, robotic systems complexity and on-board computation abilities are currently much lower than it is required for the bio-realistic simulations of a mammalian brain, even such as a mouse or a rat. For example, if we closely examine biologically inspired humanoid robotic systems, obviously the computational system parameters are far away from the required for bio-realistic ones:

- AR-601 [5] is equipped with Intel Core i7-4700EQ with 8 GB;
- REEM-C [6] - Intel Core i7 2710QE x 2;
- Nao [7] - Intel Atom at 1.6 GHz;
- iCub [8] - Intel Core 2 Duo with 2 GB;

Moreover, most computational power is intensively used by humanoids for sensing and supporting path planning calculations, which target for achieving static and dynamic balance of a walking system [9]; the later require significant computations even at a simulation level due to a large number of systems' degrees of freedom [10].

To provide bio-realistic simulation integration with a robotic embodiment and partly remove a borderline between the simulated brain in spiking neural network (sNN) and real world, we proposed the "Robot dream" architecture [11], [12] with two-phase calculations. The first phase involves lightweight real time calculations, while at the second phase the bio-realistic based on sNN calculations are performed within a simulated "sleeping brain". This way, a possible approach for the robotic system control system could be based on memristors application. With memristors being perceived as close to bio-realistic implementation of synapses [13], we currently see them as especially organic implementation with low energy consuming candidates for the artificial neuron basic elements. While implementations of memristors or memristive elements could be realized in silicon with STDP [14], the other way around the problem is to generate the bio-realistic action potential or the spike [15].

One of our long-term research goals within the current project targets to integrate organic memristor based system into a biologically-inspired robotic system. This will allow for a significant technological breakthrough in robotics and will affect multiple fields within robotics research, ranging from natural emotion generation and human-robot interaction to path planning and heterogeneous team interaction of robots [16] for various critical and real time missions, including such complicated domains as planetary research and urban search and rescue activities [17]. Organic memristor based approach will provide mechanisms for non-completely deterministic behavior of autonomous robots, which may be crucial for operation and decision making in various uncertain and highly dynamic environments.

The rest of the paper is organized as follows. Section 2 describes memristor-based approach, introducing organic memristors and memristive artificial neuron. Section 3 demonstrates our first approximation of architecture implementation of the system. Finally, we conclude in Section 4.

II. Memristor-Based Approach

A. Organic Memristors

In our long-term research project, we concentrate on applying memristors as key elements. It has been already demonstrated the possibility to realize neuron [18] and synapse [19] mimicking elements on these compounds. Organic memristive device has specific properties with respect to those based on inorganic materials [20]. Its working principle is based on redox reactions occurring in polyaniline layer [21]. For purposes of this work, we must mention its two important characteristics: hysteresis loop and strong conductivity anisotropy according to the bias polarity. The ON/OFF conductivity ratio can reach 5 orders of magnitude [22]. Other advantages of the element are low operation voltage (within 1 V), low energy consumption and possibility of the flexible realization.

Main applications of these devices were in adaptive networks [23] and in circuits with synapse mimicking properties [24]. Direct demonstration of the last statement was done by the realization of electronic elements with architecture and properties of the part of the pound snail nervous system [13], where organic memristive devices played a role of synapses. Recently, these devices were used for elementary perceptron hardware and as a first step toward a hardware realization of a double-layer perceptron.

As it was mentioned above, organic memristors were mainly used for synapse properties mimicking. The present work outlines how they could be used for the neuron mimicking. Further, organic memristors based system architecture will be integrated into emotion generation component [3] of human robot interaction [25] and further extended for a classical sense-think-act robotics paradigm [26] of navigation architecture [27].

B. Memristive Artificial Neuron

Fig. 1 presents a high level block diagram of artificial memristive neuron and contains inputs as green color circles 1, ..n, ..$n + m$, where n is the number of excitatory synapses and m is number of inhibitory synapses per one cell. The scale of the n+m is 10^4. Excitatory and inhibitory memristive elements are depicted with pink and blue color rectangles and are marked as "Ex" and "Inh" respectively. Excitatory memristive elements are trained via *Hebbian training* while inhibitory memristive elements are trained to via one of the inhibitory learning rules known as "sombrero" [28]. All excitatory and inhibitory memristive element outputs are transferred to threshold adder and integrator 2. The adder implements balancing of excitatory and inhibitory impact of memristive elements (synapses), and its output starts the output impulse (spike) generator. The rest of the diagram refers to complex feedback and training of memristive elements. Integrator 1 represents integrated output of the neuron and its output is been processed by inverting adder to be compared with integrated input of the neuron provided and extended via integrator 1. The inverting adder output is transmitted to inhibitory memristive elements and implements "sombrero" shaped training (the blue rectangular graph). The monostable multivibrator is activated via positive signal of the inverting adder triggering a relay that grounds the slave invertor crating the positive half of Δt axis of the train function graph (shown to the right of the pink rectangular graph). The negative (right) half of the graph is formed via the slave invertor in the non-grounded mode. The output of the feedback: $1/x$ or "Hebbian training" is broadcasted to all excitatory memristive elements.

The proposed schema implements two possible algorithms of training or STDP for excitatory and inhibitory memristive elements along with "integrate and fire" algorithm of output spikes generation.

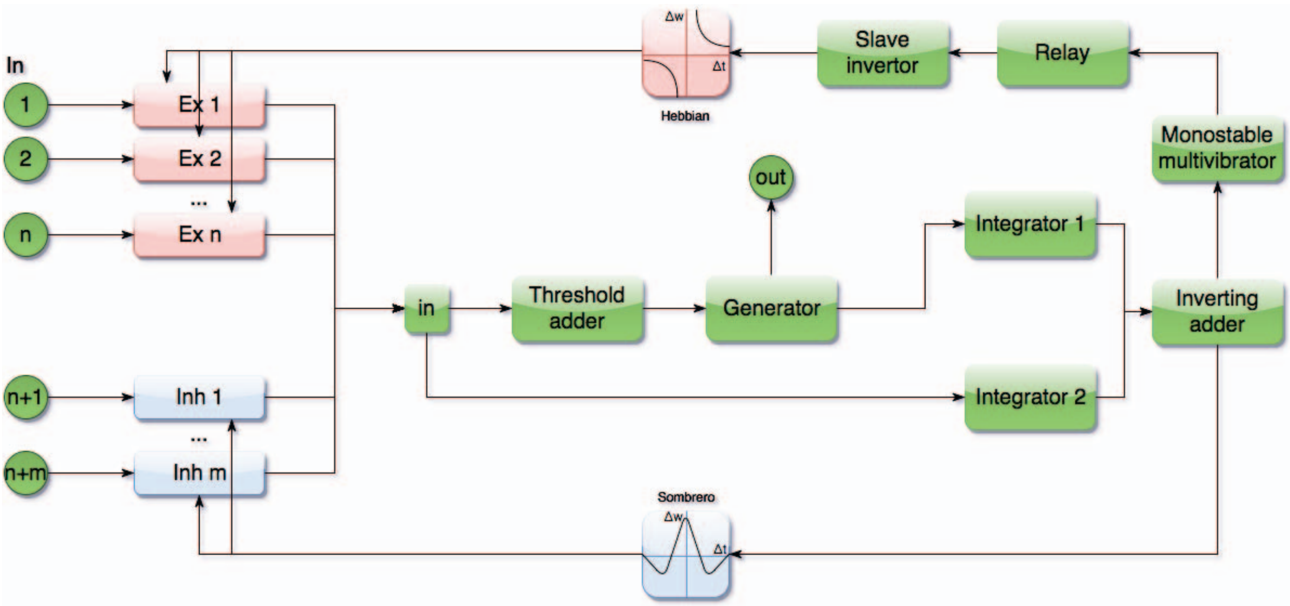

Figure 1. The block diagram of memristive artificial neuron. Inputs are depicted as green circles 1, ..n, ..n + m, "Ex.." and "Inh.." are excitatory and inhibitory memristive elements "in" is meta-element that represents all integrated inputs, "out" the output of the device

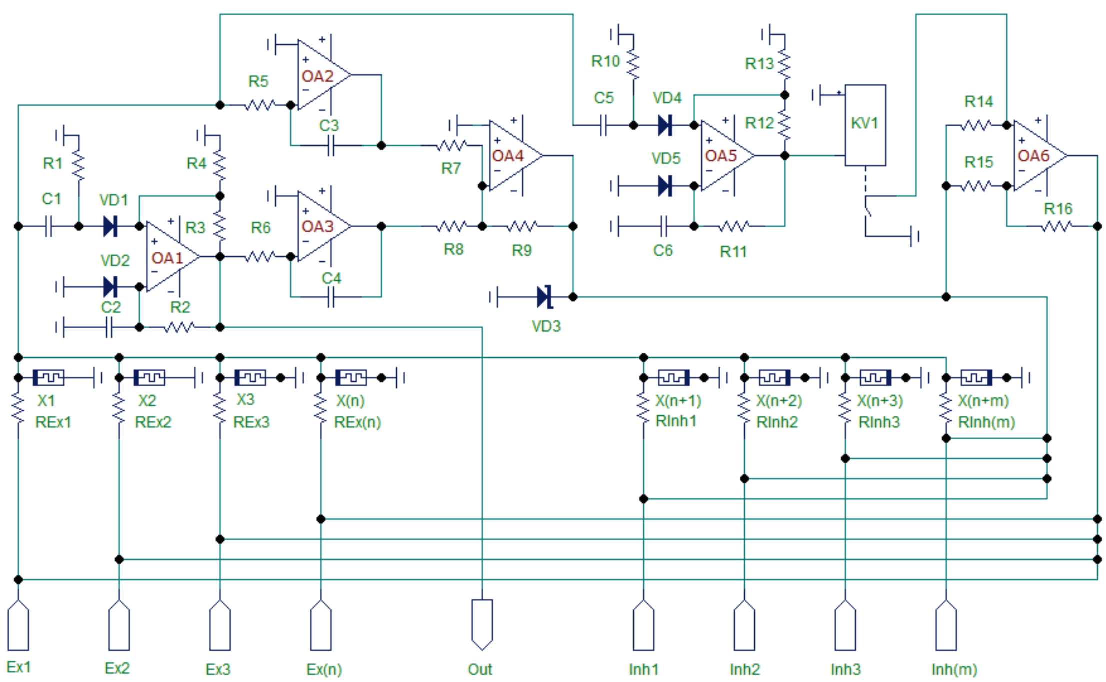

Figure 2. The wiring schematic of memristive artificial neuron

III. IMPLEMENTATION

Figure 2 represents the wiring diagram, where excitatory and inhibitory impulses are transmitted to memristive elements X_j, where j=1..n+m. When the accumulated voltage on the memristive elements exceeds the threshold, the one short multivibrator on the operational amplifier OA_1 provides a single short pulse, which duration is determined by $T_1 = C_2 \times R_2 \times \ln(1 + R_3/R_4)$. Signals from "Out" and OA_1 output are transmitted to integrators on op-amps OA_2 and OA_3, which set the impulse descending edge of the training function. The pulse-rise time constant of the integrating circuit is $t = R_5 \times C_3 = R_6 \times C_4$. Output signals from integrators are transmitted to the inverting adder on op-amp OA_4. The output signal (the turned upside down "bell") is applied to inhibitory "Inh" memristive elements. The monostable multivibrator on the op-amp OA_4 is triggered by a positive pulse of the signal Out. The pulse duration is determined by the circuit elements via: $T_2 = C_6 \times R_{11} \times \ln(1 + R_{12}/R_{13})$ and equals T_1. Output positive pulse is applied to the key KV_1 (implemented via a relay), that controls a state of not inverting input of the controlled inverter of op-amp OA_6. We used the electromechanical relay instead of transistor key for descriptive reasons. When the non-inverting input of the operational amplifier on op-amp OA_6 is shorted to the ground, the operational amplifier works as an inverter; otherwise, it acts as a normal amplifier of the signal from inverting adder op-amp OA_4. From the output of op-amp OA_6 the signal is transmitted to excitatory memristive elements Ex_i, where i=1..n.

IV. CONCLUSIONS

We have presented the high-level architecture of organic memristive based neuron hardware implementation. Current schematic contains n+m memristive elements, where n is number of excitatory synapses and m is number of inhibitory synapses; generator of action potential impulses and two complex feedback loops for inhibitor and excitatory training. In case of excitatory synapses: memristive elements are trained using *Hebbian learning* rule of STDP; in case of inhibitory synapses memristive elements are trained using "sombrero" STDP rule. This work is a position paper with the goal to implement bio-plausible hardware neuron architecture, based on which we hope to implement complex structures of a mammalian brain: for example the dopamine pathways of a rat brain. Further, organic memristor based system will be integrated into a biologically-inspired robotic system, which will allow for a significant technological breakthrough in robotics and will affect such fields of robotics as natural emotion generation, human-robot interaction, reinforced learning of non-deterministic decision making, and many others.

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