Modeling Inhibitory and Excitatory Synapse Learning in the Memristive Neuron Model

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Abstract: In this paper we present the results of simulation of exitatory Hebbian and inhibitory "sombrero" learning of a hardware architecture based on organic memristive elements and operational amplifiers implementing an artificial neuron we recently proposed. This is a first step towards the deployment on robots of a bio-plausible simulation, currently developed in the neuro-biologically inspired cognitive architecture (NeuCogAr) implementing basic emotional states or affects in a computational system, in the context of our "Robot dream" project. The long term goal is to re-implement dopamine, serotonin and noradrenaline pathways of NeuCogAr in a memristive hardware.

1 INTRODUCTION

In this paper we propose a new hardware architecture to implement an artificial neuron based on organic memristive elements (Hernández-Mejía et al., 2017) and operational amplifiers (Ibrayev et al., 2014; Samsonovich and Robertson, 2014), towards a possible integration and embodiment of a (cluster based) bio-realistic simulation of a mammalian brain into a robotic system acting as an evolutionary information processing system (Rodriguez and Granger, 2016).

This work originated by the neuro-biologically inspired cognitive architecture (NeuCogAr) project, which aims at implementing basic emotional states or affects in a computational system (Talanov et al., 2016; Talanov et al., 2017), according to a three-dimensional neuromodulatory "cube of emotions" model (Lövheim, 2012). In this model, axes correspond to the levels of serotonin, dopamine and noradrenaline neuromodulators that, properly combined, can identify eight basic emotions on this 3D cube. For example, "fear" corresponds to high dopamine, low serotonin and noradrenaline, while "interest" corresponds to high noradrenaline, high serotonin and dopamine (Balkenius and Gärdenfors, 2016). However, the relationships between these neurotransmitters and the psychological emotion space is mostly unexplored and currently under investigation, therefore there is room for further development since preliminary results are promising. The Lövheim model is an interesting attempt in this direction, establishing a, so far qualitative, connection between brain mechanisms and emotions through neurotransmitters. These emotional values are not only directly related to emotional or affective moods and states, but also have great importance in the regulation of the subtle mechanisms of cognitive processes (Damasio, 1999; Fellous and Arbib, 2005; Minsky, 2007).

On this premise, we propose to integrate dopamine, serotonin and noradrenaline pathways previously developed in NeuCogAr (Talanov et al., 2016; Talanov et al., 2017) into embodiment hardware memristors schemes suitable for the implementation of basic emotional states or affects on a "thinking" machine, and specifically on a bio-inspired, cognitive robotic system (Khusainov et al., 2015; Magid et al., 2011).

From the high-level perspective the focus of this work is the idea and implementation of inhibitory

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memristive neuron schematic. Currently among works dedicated to memristive biomimetic implementation of STDP we could not find the implpmentation of an inhibitory processes and learning (Prezioso et al., 2016; Strukov et al., 2008; Serb et al., 2016; Egorov et al., 2015; Matveyev et al., 2015). According to current understanding of emotional and neuromodulatory processes the inhibition plays important role in balancing a mammalian brain in dopamine, serotonin, noradrenaline pathways (Vogels et al., 2013). This way we have to start from most basic and important mechanism of a mammalian neuron the inhibition including inhibitory learning and excitatory/inhibitory sub-threshold balancing.

This lays at the intersection between bio-inspired and cognitive robotics, implementing a new way of controlling and acting on robots driven by emotions, sort of *affective robotics*.

2 PROBLEM RATIONALE

2.1 Robot Dream

As starting point for our work we identified the embodiment problem for bio-plausible simulation (Tchitchigin et al., 2016b; Tchitchigin et al., 2016a), approached by using the neuro-simulator NEST (Potjans W., 2010) on the Hodkin-Huxley and Izhikevich models of neurons (Izhikevich, 2006) to simulate dopamine, serotonin and noradrenaline pathways in the NeuCogAr project (Talanov et al., 2016; Talanov et al., 2017). The simulation of one second of dopamine neuromodulation took 1 hour of computing, not compatible with real-time requirements and operations. Since the robotic system that we want to use for embodiment must operate in (quasi) real-time, we have proposed the "Robot dream" two phases approach represented in the Figure 1. The real-time cognitive robotic system should provide proper performance and should be able to act independently, periodically synchronizing with simulated brain structures.

In the current paper we are focused on the robotics embodiment system. A possible alternative to this two step solution could be to adopt a hardware approach, e.g. based on memristors. This way memristors should be used as the electronic analogue for synapse and paly important role in training/learning an electronic neuron. The first block, the elementary and main functional unit of this cognitive robotic embodiment system with a "robotic brain" is the artificial/electronic neuron. Based on artificial/electronic memristive neurons, in a longer term we will build

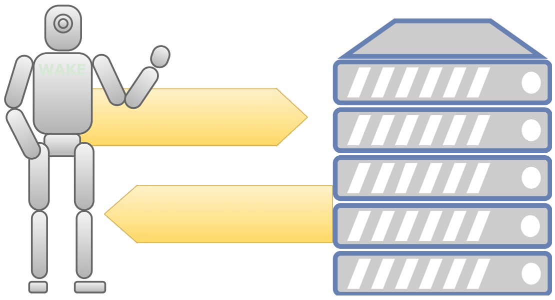

Figure 1: The "Robot dream" two phase architecture: during the wake phase robotic embodiment system operates real-time and stores inbound information and actuators activation in form of pseudo-neuronal activity; during the "dream" phase stored experience is "played back" through direct translation via simulated neuronal structures of the "dreaming brain" and after several cycles is transferred back to the robotic system via synchronization of synaptic weights of the memristive schema.

the robot brain as a bio-mimetic neural network structure similar to a rat brain This way, we will be able to recreate the emotional subsystems and behaviors of a rat through dopamine, serotonin and noradrenaline pathways. as described in (Talanov et al., 2016; Talanov et al., 2017).

The overall schema of a memristive neuron could be described as follows:

1) approximately 10^4 input channels are connected to other excitatory and inhibitory memristors;

2) the threshold adder and generator plays the role of axon hillock accumulating inbound excitatory and inhibitory signals and triggering outbound signal or "spike";

3) two integrators and the inverting adder implements the inhibitory learning feedback by taking in account Δt variations of inbound and outbound signals to generate the "sombrero"-shaped learning signal to inhibitory memristors;

4) the inverting adder via monostable multivibrator, relay and slave inverter transforms the outbound signal flipping the left part of "sombrero" along Y axis to produce similar to $\frac{1}{x}$ graph and then forwards it to excitatory memristors.

The aim of the present work is to study the feasibility of the implementation of complex systems, including a large number of memristive devices, allowing mimicking a mammalian brain learning, in particular, Hebbian learning (reinforcement of outbound signals) and "sombrero" learning (inhibition of outbound signals).

2.2 Memristive Approach to a "Robot Brain"

After the first work on the physical implementation of memristors (Strukov et al., 2008), hypothetical devices, varying the resistance as a function of the passed charge (Chua, 1971), the activity in the field was explosively increased due to possible applications in new types of non-volatile memory arrays. Currently, these elements are widely considered also for neuromorphic applications. Organic memristive device (Erokhin et al., 2005; Erokhin and Fontana, 2011) was developed exactly for mimicking some synaptic properties in electronic circuits. As a benchmark, mnemotrix was taken the other hypothetical element, used by Valentino Britenberg in his mental experiment, explaining learning process (Braitenberg, 1984). Thus, these elements were supposed to be used as electronic analogs of nervous system elements, as shown by direct comparison of essential features (Erokhin et al., 2010)

The synapse mimicking properties of the polyaniline organic memristive device were demonstrated by the electronic circuit with architecture and properties similar to the part of the nervous system of pond snail, responsible for learning of the animal during feeding (Erokhin et al., 2011). Recently, these elements were used for the hardware realization of artificial neural networks (elementary (Demin et al., 2015) and double layer (Emelyanov et al., 2016) perceptrons). These works have directly demonstrated the capability of memristive devices to be used as elements, varying their weight functions during learning essential characteristics for neuromorphic networks organization.

3 MEMRISTIVE NEURON MODEL

We have described the electronic system that provides two types of learning: excitatory and inhibitory, and it has been developed through memristors. The Figure 2 represents the wiring diagram, where excitatory and inhibitory impulses are transmitted to memristive elements Xj, with $j = 1..n+m$ where n is the number of excitatory synapses or memristors and m is the number of inhibitory memristors. When the accumulated voltage on the memristive elements exceeds the threshold, the one-shot multivibrator on the operational amplifier OA1 provides a single short pulse, with the duration that is determined by

$$T1 = C2 \cdot R2 \cdot ln(1 + R3/R4) \tag{1}$$

Signals from "Out" and OA1 output are then transmitted to integrators on op-amps OA2 and OA3, which set the impulse descending edge of the learning function.

The pulse-rise time constant of the integrating circuit is

$$t = R5 \cdot C3 = R7 \cdot C4 \tag{2}$$

Output signals from integrators are transmitted to the inverting adder on op-amp OA4. The output signal (the turned upside down "sombrero") is applied to inhibitory "Inh" memristive elements. The monostable multivibrator on the op-amp OA4 is triggered by a positive pulse of the signal Out. The pulse duration is determined by the circuit elements via:

$$T2 = C6 \cdot R13 \cdot ln(1 + R14/R15) \tag{3}$$

and equals T1. Output positive pulse is applied to the MOSFET key M1, that controls a state of not inverting input of the controlled inverter of op-amp OA6. When the non-inverting input of the operational amplifier on op-amp OA6 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 OA4. From the output of op-amp OA6 the signal is transmitted to excitatory memristive elements "Ex" i, where $i = 1..n$.

4 RESULTS

Simulation methods were used to calculate needed nominal values of the electronic components and to validate the quality of the proposed model. We've used integrated schematic editor and mixed analog/digital simulator Micro-Cap. 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.

We have created the schema represented in the Figure 3 for the simulation and validation of our idea wiring schematic represented in the Figure 2. The goal of the validation is to indicate the correlation of the inhibitory and excitatory learning impulses to Δt in form of "sombrero" and flipped along Y axcis "sombrero" similar to $\frac{1}{x}$. Where the inhibitory out is $G_SOMBRERO and excitatory is $G_HEBB. The input signals, are generated by voltage sources V5 and V6, their graphs are displayed in the Figure 4, and tagged: $G_INPUT and $G_INPUT1. The vertical axis represent voltage, relative to ground, while time

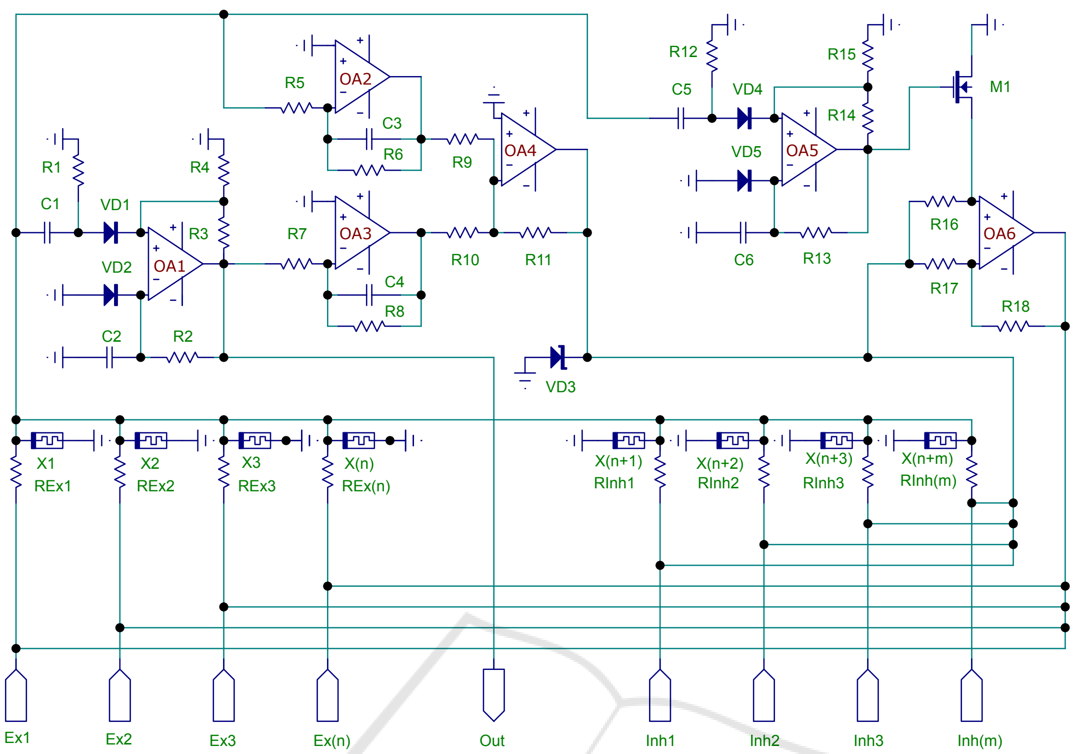

Figure 2: The wiring schematic of memristive artificial neuron.

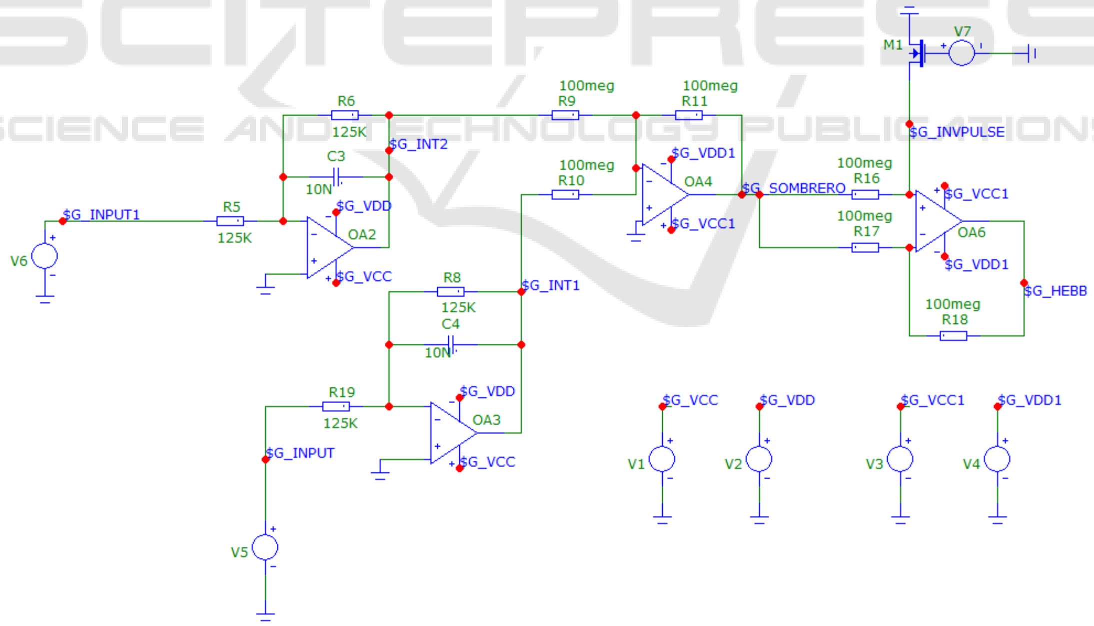

Figure 3: Experimental schematic for the inhibitory and excitatory simulation.

(seconds) is reported in the horizontal axis. Two different sources generate signals with different phase to gain the effect of viable Δt where $Deltat$ is time difference between inbound signal and outbound signal of the memristive neuron in similar way to pre-synaptic and post-synaptic spikes. The V5 source output signal is same as the monostable multivibrator signal, built on operational amplifier OA1 at Fig.2. Period of input signal was set to 5 ms. The voltage source V6 output signal imitating input signal with different period to

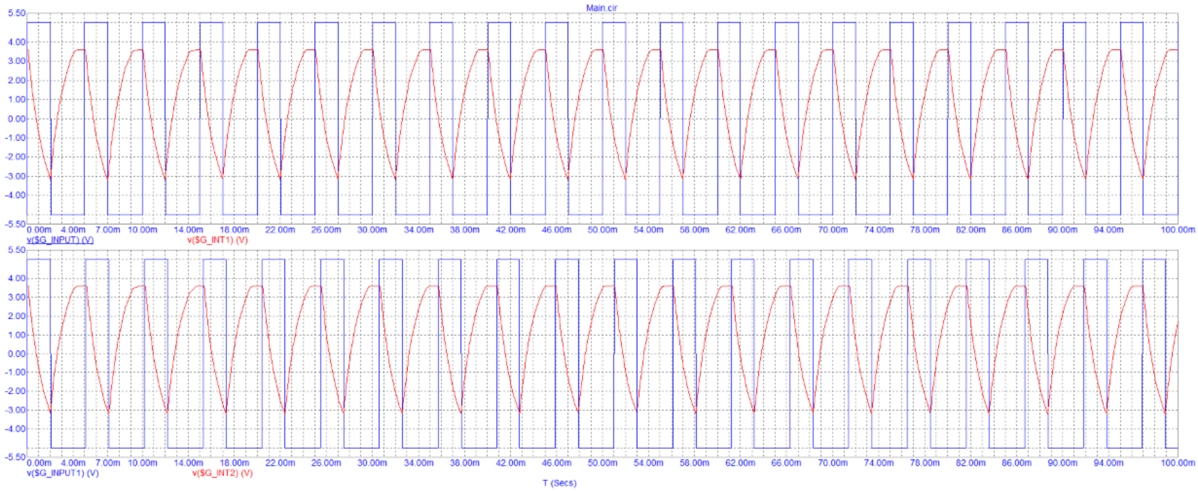

Figure 4: Service signals, used for controlling and debugging the system.

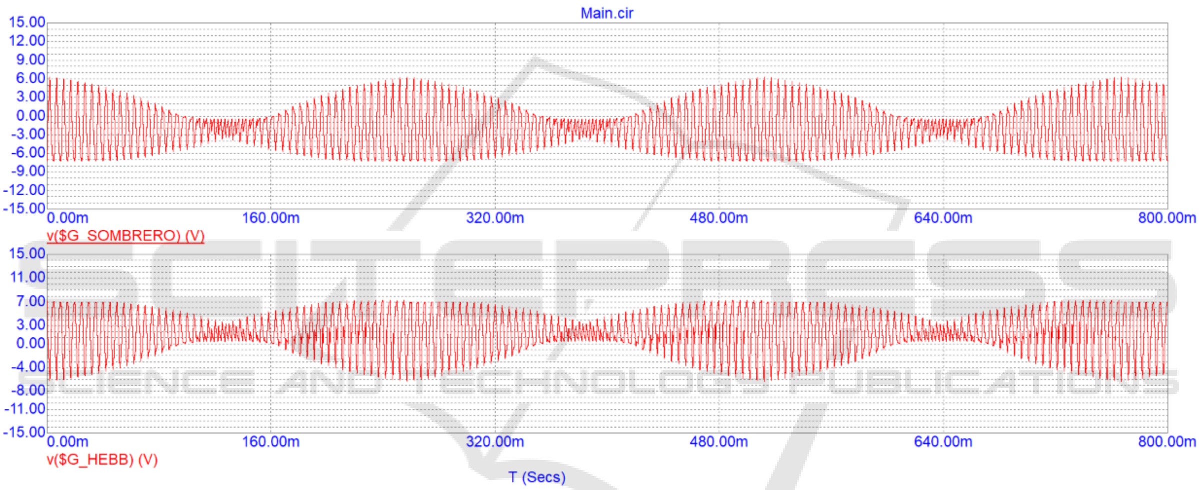

Figure 5: Experimental results of the inhibitory learning feedback.

create phase shift. Period of V6 output signal was set to 5.1 ms.

Nominal values of passive elements for two integrating circuits OA2 and OA3, are selected in the way, that rising and falling times of impulses in $G_INT1 and $G_INT2 are close to 2 ms and are indicated in the Figure 4 in lines 2 and 3 and labeled as $G_INT1 and $G_INT2. Results of these integrating circuits with corresponding input signals are indicated in the Figure 4, labeled: $G_INT1 and $G_INT2. These two signals are then provided to inverting adder OA4. All passive components values selected in the way that there no amplification of any signal. The learning pulses are represented by $G_SOMBRERO graph in the Figure 5.

To generate Hebbian learning signal, we have inverted the left half of “sombrero” signals. We have used the inverter circuit built on OA6. In order to invert only half of the signal, we have used the additional voltage source V7, simulating monostable multivibrator, based on OA5 in the Fig.2. The learning pulses are represented as $G_HEBB in the Figure 5.

The Figure 6 represents the correlation of the amplitude of the learning pulse $G_SOMBRERO to Δt: the phase shift of output pulse ($G_PULSE Figure 4) to the phase shift of the input pulse ($G_INPUT1 Figure 4). The graph has the shape of “sombrero”, with maximum of this function at the point, when phase shift or Δt has minimal value. The excitatory learing function is represented in the Figure 7 we have used “sombrero” as base function and flipped along the Y axis to replicate the basic form of the $\frac{1}{x}$ function.

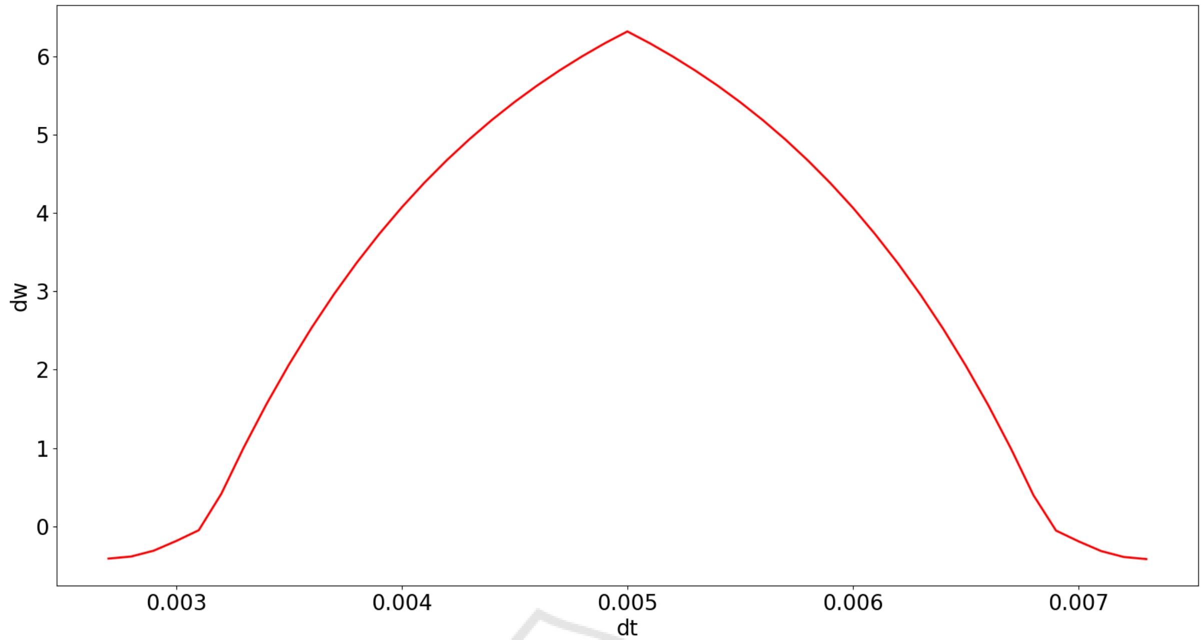

Figure 6: The inhibitory "sombrero" learning function or amplitude of learning pulse Δw to Δt.

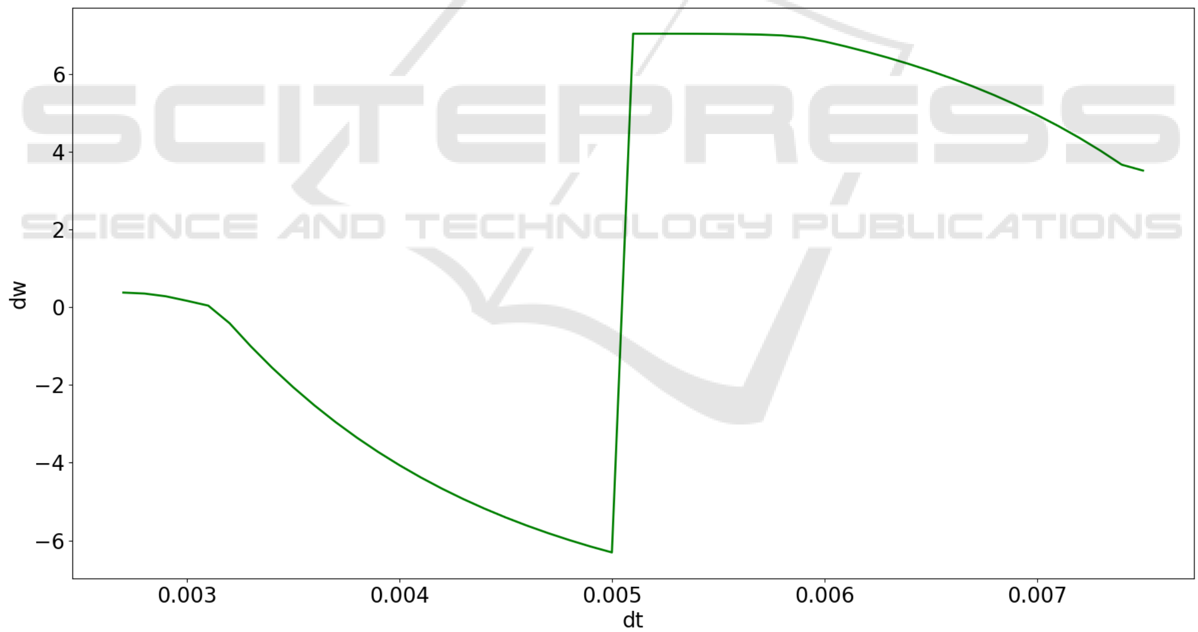

Figure 7: The excitatory learning function or amplitude of learning pulse Δw to Δt.

5 CONCLUSIONS

In this paper we have discussed on our implementation of the excitatory or Hebbian and inhibitory or "sombrero" learning mechanisms for the memristive architecture of electronic-artificial neurons. The corresponding architecture contains two feedback loops for two learning functions: similar to $\frac{1}{x}$ and "sombrero" where the learning impulse amplitude depends from Δt, i.e. the correlation of inbound and outbound impulses or "spikes". We have successfully demonstrated that the amplitude of the learning impulse matches the learning functions depending from the Δt parameter. To the best of our knowledge, this is the first attempt on implemementing the inhibitory "sombrero" learning for the memristive architecture of neurons to represent the natural inhibitory synapse learning (Vogels et al., 2013).

This way, preliminary results obtained from simulations have demonstrated the feasibility of the idea enabling the implementation of complex deterministic networks, based on organic memristive devices, with two types of learning: Hebbian (excitatory) and "sombrero" (inhibitory) ones. This finding opens new perspectives for the better understanding of processes in nervous system and for the implementation of a "Robot brain", allowing learning and decision making on thinking machines and robots as well.

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