The Implementation of Noradrenaline in the NeuCogAr Cognitive Architecture

Max Talanov, Mariya Zagulova, Salvatore Distefano
Boris Pinus, Alexey Leukhin

Kazan Federal Universtity
ITIS
Russia
Email: max.talanov@gmail.com, mazagulova@stud.kpfu.ru,
salvatdi@gmail.com, bvpinus@gmail.com,
alexey.panzer@gmail.com

Jordi Vallverdú

Universitat Autonoma de Barcelona, Catalonia
Spain
Email: jordi.vallverdu@uab.cat

***Abstract*—In this paper, we present a novel approach to model and re-implement the noradrenaline influence in a bio-plausible manner suitable for the modelling of emotions in a computational system. We have upgraded our previous bio-inspired architecture NEUCOGAR (Neuromodulating Cognitive Architecture) to capture a key aspect of cognitive processes: novelty detection and its evaluation. With our model, we can computationally implement a bioinspired cognitive architecture that uses neuromodulation as a mechanism to identify signals, as well as to evaluate them according to their novelty, taking into account the noradrenaline concentration dynamics. At the same time, the values thus generated are stored in the system using the same neurotransmitters model.**

Keywords–spiking neural networks; artificial emotions; affective computing.

I. INTRODUCTION

After the revolution provided by new neuroscientific tools, especially fMRI (functional magnetic resonance imaging), the studies on cognition changed drastically the understanding of the fundamental role of emotions [1]. When the sensorimotor and embodied approaches to cognition [2] were identified (even at robotic level [3]), the key functional role of emotions was still unexplored. Artificial cognitivists specializing in machine cognition started to consider the design and implementation of emotional architectures [4], as well as initiated the fields of affective computing [5] or social robotics [6]. At that point, the interest was to capture human affective modes to implement them into machines, which humans should interact with. During this process, a very important question emerged: do machines need to have emotions, if we want to make them cognitively powerful? This is the question that triggered our research some years ago [7][8] and that oriented our research towards biomimetic models [9]. The neurotransmitter architecture of human brains controls the main cognitive and emotional processes, indeed, acting as a twofold mechanism [10]. Therefore, the role of emotions and their effect (only including inborn basic emotional reactions) in the mammalian cognition is considered to be significant by several researchers [11][12][13][14][15]. Even from the evolutionary perspective, the key role of emotions in social design is of no doubt [16], and also helps to explain moral behaviour [17].

For all the reasons above, the design of artificial architectures through emotional values attracted interests, aiming at providing the key to the existence of adaptive, creative, and multiheuristic artificial architectures, by mimicking the most successful characteristics of human cognition. Several attempts to re-implement emotional aspects in artificial cognitive architectures have been performed as discussed in Section IV, but the work of [18] represents the fundamental internal approach to emotional robotics and AI (Artificial Intelligence). This way, we started with the assumption that it could be beneficial to re-implement basic emotional mechanisms in a computational system gaining the richness of emotional appraisal and behavioural strategies, as well as pain/pleasure reactions that could be used in reinforcement learning. Following Lövheim model of neurotransmitters [19], we propose a bio-inspired artificial architecture called NEUCOGAR that implements emotional-like mechanisms into machine data processing. In Section II, we point out the mismatch between computational resources available to current robotic systems and what is required for neuronal simulation, introducing our concept of a robotic system execution separated into day and night phases, in order to bridge the gap between robotic systems and supercomputers performing the simulation. In Section III, we introduce the notion of bisimulation to answer the questions of learning and mapping from realistic neural network to rules-based control system. Section IV provides the information about the actual topics in the field of affective computing, notable authors and research projects in this area. We sum up the ideas presented in the paper and discuss the arose questions in Section V.

II. THE APPROACH

The key aspect for any living system is the skill to recognize external and internal signals and to evaluate them [20]. On top of this basic feature, more complex operations can be performed, such as the identification of novel signals [21][22]. The novelty can be considered as the discrepancy between what is known and what is discovered, by which activity and exploration of the environment are elicited. Creativity is also deeply related to this process [23].

Based on this consideration, we propose to implement emotional mechanisms to manage processes such as attention, resource allocation, goal setting, into our biomimetic architecture NEUCOGAR. These mechanisms seem to be beneficial for dealing with informational systems in general (such as living entities) and for AI and robotic systems in particular. Indeed, classical approaches tend to be computationally demanding, as well as current cognitive-based ones, while the

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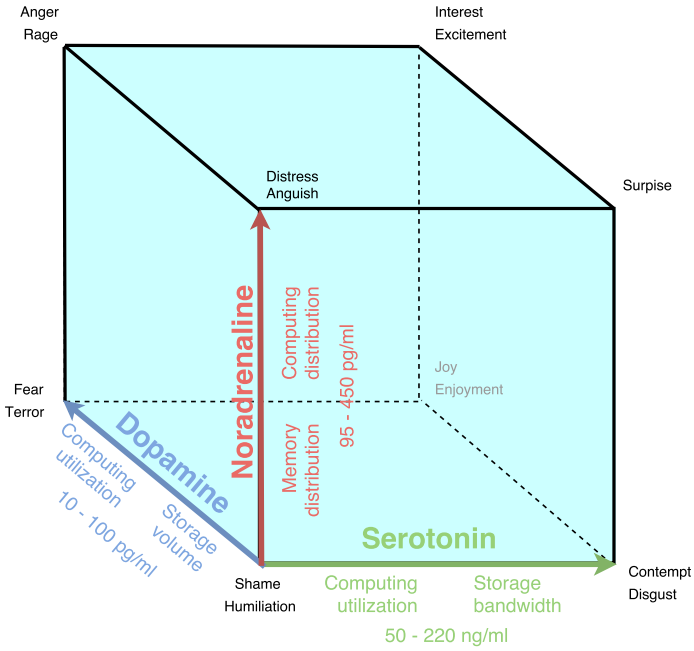

Figure 1. A three-dimensional space of three basic neuromodulators encapsulating basic emotions, mapped to computational system parameters.

proposed solution, NEUCOGAR, is quite promising, since it adopts a higher level, mammalian neurotransmitter-like model to implement a cognitive architecture for machine novelty-detection and evaluation. This way, to implement the phenomena related to emotions, we simulate the neurobiological processes underlying emotional reactions, basically through three neurotransmitters, which are active during brain cognitive processes: noradrenaline (NA), dopamine (DA) and serotonin (5HT). It is important to remark that several works identify the noradrenaline as the main driver of neural response to novelty, while this response is dampened by cholinergic transmission. Later responses to novelty emanating from the frontal cortex seem to be under the influence of the cholinergic system [24].

The selection of the neuro-plausible approach is based on the assumption that the main mechanisms of neuro-computations are similar to those of cellular level bio-chemical reactions. We do not limit our approach to neuro-plausible modelling, we established a link between psychological phenomena, neuro-biological mechanisms and computational processes. We started from the "cube of emotions" by Hugo Lövheim [19], bridging psychological phenomena of "affects" with neuro-biological phenomena of monoamines neuromodulation, i.e., using NA, DA and 5HT, see Figure 1. We have thus built a bio-plausible emulation of the dopamine pathways and managed to emulate the "fear-like" state of the computational system in [25][26]. Further developments include the emulation of serotonin and noradrenaline. This paper is focused on emulating the noradrenaline mechanisms through the neurobiological simulator NEST [27] to reproduce in a bio-plausible manner the psycho-emotional states identified by dopamine and noradrenaline.

As the neuropsychological base for our cognitive architecture, we used a three dimensional monoamines neuromodulators model called "Cube of emotions" created by Hugo Lövheim [19]. Three-dimensional space of three basic neuromodulators: noradrenaline (NA), serotonin (5HT) and dopamine (DA) encapsulates basic emotions or affects inherited from work by Silvian Tomkins [28]. We have extended it with mapping to computational system parameters: computing utilization, computing redistribution, memory redistribution, storage volume and storage, utilization.

III. The Experiments

The proposed noradrenaline concentration dynamics model is based on Izhikevich model for dopamine [29]. The state of each synapse is described by two variables: synaptic weight w and synaptic tag c, also called "eligibility trace". The eligibility trace is a parameter used to control the "memory" of the algorithm, associated with a given state, enabling the assignment of some values to the data under analysis [30][31]. From a biological perspective, it is either some enzyme activation, or another relatively slow process that happens in the synapse, if pre-synaptic and post-synaptic neurons fire by the spike-timing-dependent plasticity (STDP) rule. The eligibility trace can modify the synaptic weight, but only in the presence of extracellular neurotransmitter (noradrenaline), and only during the timeframe of a few seconds. During that time interval, the eligibility trace decays to zero. In a nutshell: the eligibility trace controls the data evaluation in learning processes and is directly involved in novelty detection, something that manages temporal difference learning [32][33]. In this process, the predictive role of dopamine is fundamental [34].

Consequently, we extend the Izhikevich equations for dopamine [29], referring to interesting approaches such as [35] or [36], to describe some governing equations and features in the model of a neural network by noradrenaline. The key aspect of this approach is that we are not just using some kind of existing neural network, but the one implementing a fundamental biomimetic model. Our approach allows to consider classic neural networks adding a biomimetic meaning and semantics to implement the mechanistic regulation operated by neurotransmitters, especially dopamine as a modulator of novelty detection and management [37].

We begin this process considering spiking network of quadratic leaky integrate-and-fire neurons [38]. The neuron ratio is distributed as follows: a) 80% excitatory neurons, and b) 20% inhibitory. The dynamics of each neuron is such that the membrane potential v of each neuron at each moment (new current potential $\dot{v}$) depends on abstract membrane recovery variable u (new current value $\dot{u}$) [39]:

$$\dot{v} = k(v - v_{rest})(v - v_{thresh}) - u + I \quad (1)$$

$$\dot{u} = a * b * (v - v_{rest}) - u \quad (2)$$

$$if(v >= 30[mV]) : \{v = -65[mV], u = u + 2[mV]\} \quad (3)$$

In our model, membrane voltage threshold v_{thresh} and resting potential v_{rest} are constant, and the synaptic current input I (the current flowing in a neuron) has an exponential shape. The spike occurs when the membrane potential is higher than -50 mV, and then the membrane potential recovers: v decreases to -65 mV, u increases by 2 mV. We set a to 0.02, b to 0.2, k to 1.

Following Izhikevich, the STDP model [40] does not change the synaptic weights directly, but instead it modulates weights through a temporal eligibility trace (as it will be shown in 6. The variation of the eligibility trace c (new current eligibility trace $\dot{c}$) is described as follows:

$$\dot{c} = -\frac{c}{\tau_c} + A^+ e^{\frac{(t_{pre}-t_{post})}{\tau^+}} \delta(t-t_{post}) - A^- e^{\frac{(t_{pre}-t_{post})}{\tau^-}} \delta(t-t_{pre}) \quad (4)$$

where t_{pre} and t_{post} are the times of a pre- or post-synaptic spike, A^+ and A^- are the amplitudes of the weight change, τ_+ and τ_- are constant rates, $\delta(t)$ is the Dirac delta function that step-increases the variable c. The eligibility trace decays at the rate of τ_c.

The concentration of noradrenaline also impacts the modulation of synaptic weights [41][42], as shown in (6).

The noradrenaline concentration n decreases exponentially with time (natural fade rate is τ_n), and increases depending on salient, novel events:

$$\dot{n} = -\frac{n}{\tau_n} + p_{nov} n(\delta(t-t_n)p_{rew} + \delta(t-t_n)p_{pun}) \quad (5)$$

where p_{punish} is a punishment (stressor) event, p_{rew} is a reward event, p_{nov} is the probability of the event being novel and unexpected (salient). The noradrenaline concentration cannot go below zero: it increases with stressors, if p_{nov} is bigger than zero (a sudden stress), as well as with rewards, if p_{rew} is bigger than zero (a surprise reward).

The excitatory synaptic weight w (new current value $\dot{w}$) is not changed directly in the model. Instead, it is modulated proportionally to relative concentration of noradrenaline n (to its baseline level b_n), multiplied by eligibility trace c:

$$\dot{w} = c(n - b_n) \quad (6)$$

The model was tested on MATLAB with the following parameters:

- Network of 1000 leaky neurons with STDP;
- 100 synapses per neuron;
- Maximal synaptic strength = 5;
- Initial synaptic strength (w) = 0;
- Conduction delay = 1 [ms];
- Membrane ground potential (v) = -65 [mV];
- Coincidence interval for pre- and post-synaptic neurons = 20 [ms];
- Current level of NA concentration (n) = 0, as well as 5-HT and DA concentration;
- Initial eligibility trace (c) = 0;

The results thus obtained from simulation, shown in Fig. 2, demonstrate that:

1) Noradrenaline concentration was not affected whatsoever by predictable rewards with the novelty of zero. Meanwhile, serotonin and dopamine concentration were increased by reward - each of the three times in the interval of first 100 ms;
2) Noradrenaline concentration was almost not affected by predictable punishment with zero novelty while serotonin fade rate was vastly increased by it, which led to the serotonin concentration drop at the 90th ms of the simulation run;
3) Noradrenaline concentration was increased by every unpredictable event, proportionally to the level of the event's saliency - it went much higher at the 180th ms, when the reward's novelty was 0.75, than at 380th ms, when the reward's novelty was only 0.6. Same reaction was demonstrated for the punishments of different novelty, at the moments of 230 ms and 380 ms. However, dopamine and serotonin reaction to reward and punishment events did not depend on how unpredictable the events were: dopamine concentration was proportional to the frequency of the rewards (of whatever novelty), serotonin concentration - to both reward and punishment event frequency.

IV. Related work

Since the last decade of 20th Century the interest towards emotions and emotional representations in computational systems has been exponentially growing [43][44]. At the same time, the industrial applications that could relate humans and machines have required increased investments into Human-Robot Interaction (HRI) studies, covering a big array of topics [45][46][47], even ethical ones [48][49]. This rise of activity was based on understanding of the role of emotions in human intelligence and consciousness that was indicated by several neuroscientists [50][51].

Starting from the seminal ideas of bioinspired neural networks of Stephen Grossberg in the 1970's [8], in the following decade a new vision on computational emotional architectures was investigated by Aaron Sloman [52]. A few years later, affective computing was born thanks to the book by Rosalind Picard [5]. Social robotics was the natural evoluton of these new trends, also at MIT by Cynthia Breazeal [6].

We could identify two main directions in the new research field of affective computing: emotion recognition and re-implementation of emotions in a computational system, mostly for HRI purposes. There are several cognitive architectures that are capable of the re-implementation of emotional phenomena, starting from ACT-R [53] to modern BICA [54], among others. The interest in implementation of emotional mechanisms is based on the fundamental role of emotions in basic cognitive processes: colouring in appraisal, decision making mechanisms, and emotional behaviour, as Damasio showed in [1].

Our approach takes a step further on the road for neurobiologically plausible model of emotions [26]: Arbib and Fellous [55][56] created the neurobiological background for the direction to neurobiologically inspired cognitive architectures; appraisal aspects were analyzed by Marsella and Gratch researches [14][15], as well as in Lowe and Ziemke works [13][57], or temporal and reinforcement learning [58][59].

As it was mentioned earlier in this paper, the processing of the simulation took 4 hours of supercomputer's processing time to calculate 1000 milliseconds [60].

V. Conclusion and future work

In our paper, we have described a new approach for augmentation of autonomous robotic systems with mechanisms of emotional revision and feedback. We have modelled novelty

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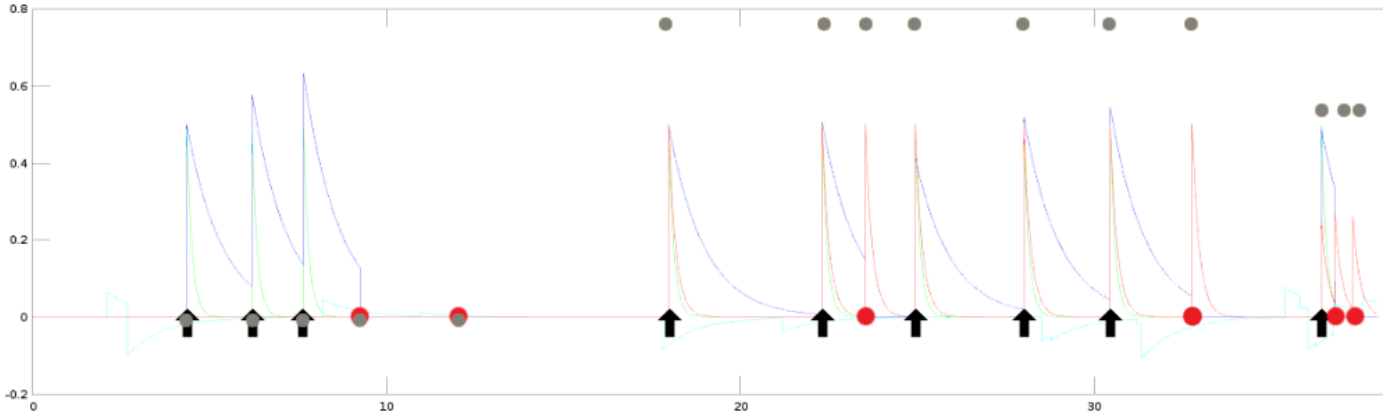

Figure 2. Transient evolution of eligibility trace c (cyan) and concentration of NA n (red), 5-HT (blue), DA (green), being exposed to reward (arrow) and punishment (red circle) events with different levels of saliency (grey circles).

recognition and evaluation skills, which are useful for a broad range of implementations: cognitive architectures, self-learning models, HRI, among other possibilities. The implementation of a biomimetic cognitive architecture that captures the basic neutrotransmitters roles (noradrenaline, dopamine and serotonin), as well the noradrenaline concentration dynamics model based on Izhikevich model for dopamine has made it possible for our NEUCOGAR model to build reliable ways to deal with cognitive novelty. This feature, novelty, is of the outmost importance for a cognitive system, because it selects and manages attention, modifies memory resources and data, stimulates responses, among other functions [61][62].

Despite of the good preliminary results, this research offers also some important questions: a) first of all, to define clearly the input formats for realistic neural network; b) secondly, the necessity of establishing reliable emotional revision thresholds; c) finally, the clarification of the way by which we capture and reproduce emotional equalizing (homeostasis) in a biomimetic way (for ”average human” inspired architectures, as well as for bioinspired but open ones).

On the one hand, different answers to these questions allow us to adapt our model to a range of possible architectures of robots' control systems. These robotic architectures can follow several scenario-demanding conditions (responses optimized by velocity, approximation, low computing demand, etc.), which can be managed through the neurotransmitters biomimetic model. The fundamental aspect of our model is that it can follow human-like standard neurotransmitting mechanisms; or the mechanisms can be modified, in order to optimize other cognitive heuristics adapted to the real demands at that specific time. On the other hand, we consider that the best way to implement our model would be a software framework with several pluggable adapters to accommodate the most popular choices for robots' ”brains”. This can be achieved using an accepted programming language, at least for academics (the barriers that create diverse manufactures employing own languages are well known: ABB (Asea Brown Boveri Ltd.) has its RAPID language, KUKA (Keller und Knappich Augsburg) has KRL (Kuka Robot Language), Comau uses PDL2 (Process Design Language 2), Yaskawa Electric Corporation uses INFORM language, FANUC (Factory Automation NUmerical Control) uses Karel language, etc.) [63][64]. Our idea is that the power and simplicity of our model, as well as its accessibility (offering all our data at free repositories), can help to unify the field. The benefits of our bioinspired architecture are evident: it allows to connect and manage modular systems with a main but not dominant emotional architecture (like our NEUCOGAR model). It can be seen as a cognitive net that increases and empowers managing systems without the necessity of reprogramming the whole architecture: it is a thin global layer that coordinates sub-layers/modules activations, allowing even a multi-heuristic system adapt to fast changing demands.

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