Emotional social robot "Emotico"

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***Abstract*—This work presents high level design and preliminary results of the implementation of an psycho-emotional system based on DA and 5-HT subsystems implementing 4 basic emotions.**

***Index Terms*—emotional robot, social robotics, human-robot interaction, dopamine, serotonin**

I. Introduction

Just a few decades ago, developers only discussed the issue of creating social robots and the option to include them in the everyday practices of ordinary people [1]. Today we know a lot of different service robots that perform social functions under various scenarios: promoter [2], waiters/hostesses [3], [4], security guards [5], therapeutic support [6], teacher/nanny [7], [8] etc. One of the well-known mass-selling platform is the Pepper robot, entertaining people in shopping malls [9], helping in airports and a companion for the elderly [10]. There are several platforms available for purchase and are used in various social spaces: Nao, Paro, Promobot, Aibo, Thespian etc. Researchers actively explore user experience of interaction with social robots in public spaces [11] and at interpersonal communication [12]. A lot of attention is focused on what social interaction elements should be implemented to make the user experience as comfortable as possible. In early works, Terry Fong outlined human social characteristics. Ability to express and/or perceive emotions is one among them [13]. The significance of the emotional component in social interaction has been confirmed by many further studies. Currently, the affective human-robot communication is actively explored in the field of social robotics. Turns out that people assess the "humanity" of a robot by its ability to express and recognize emotions [14], [15]. It happens because the most part of human communication is encoded by facial expressions and body movements [16]. So consumer acceptance of service robots highly depends not only on how well the robots can meet the functional needs of the user but also on additional user interactions possibilities (status interaction, politeness, verbal and non-verbal emotional communication establishment, etc.) [17].

II. Problem

Technologies and ways of emotion expression and recognition are key tasks in the study of social robotics. The emotion recognition is mainly based on the analysis of facial expressions, rarely supplemented by psycho-physiological data.

The majority of works use Ekman [18] and Russell [19] models, while few of them exploit alternative theories, like Plutchik's model [20]. Usually a robot expresses emotions via imitation of facial expressions [21], non-verbal behavior [8], [22], [23] or through semiotic indicators: color, sound, vibration, temperature [24]. Developers often strive to simulate multimodal ways to express a robot's emotions to improve a user experience.

We can indicate the limited variance of emotional responses in the majority of the platforms currently used (Fig. 1.1). The link between the stimulus and the reaction is fixed and straight-forward: in response to a specific action, the robot always provides the same reaction. At first, users are curious and enthusiastic with the robot interaction, but soon, as noted by researchers [25], the novelty effect vanishes and interaction becomes too predictable and boring. Users usually try to find out robot's hidden communicative capabilities, its personality-specific features, but the lack of individual reactions to a particular person adversely affects the ability to maintain long-term relationships. The development of the behavioural emotional variability that makes robot's social behavior more individualized towards the user [26] is a challenge for robotic systems designers today. In this work we propose the model that recreates the human's emotional low-level reactions as a possible solution to these challenges. Based on the role of emotions we hope that this model will make a robot's behavioral system more variable, teachable and less predictable.

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III. Solution

In this work we present a novel approach for affective self-learning, adaptable behavioral reaction, emotional expression and emotional involvement of a robot (Fig. 1.2). We also develop the emotional social robot "Emotico" using this approach. It interacts with humans by begging for coins. This type of human-robot interaction implies the expression of "emotions" and adaptive emotional behavior. We use Hugo Lövheim's "cube of emotions" [28] as basic emotional model for our robot based on three monoamines: dopamine (DA), nor-adrenaline (NA) and serotonin (5-HT). These neuromodulators play a central role in psycho-emotional states and drives [29].

At the initial stage, we decided to incorporate only DA and 5-HT into our system. The robot can experience four different emotions: joy, sadness, disgust and interest (Tab. I). "Emotico" has different sensors, which project their signals to different groups of neurons.

TABLE I: Robot's four emotions based on Hugo Lövheim's model [28]. Each emotion has a corresponding behavioral reaction.

Emotion	**DA**	**5-HT**	**Robot's behavior**
Joy	High	High	Dance
Sadness	Low	Low	Look for people
Disgust	Low	High	Spit out/swallow
Interest	High	Low	Drive up

The emotional expression plays the important role in human-robot interaction. Thus, robot should not only experience "emotions", but also express them. Tab. I presents the robot's behavioral responses to the emotional state. The interaction of our robot with humans has a certain goal – getting coins from them that creates special feature of the "Emotico" – manipulative behavior. Initially, low levels of DA and 5-HT make the robot "feel sad" which drives "Emotico" to find a source of coins.

The DA and the 5-HT neuromodulator levels increase when the robot gets a coin. In contrast only the 5-HT level increases when the robot gets another object (so called fake coin). High levels of the DA and the 5-HT make the robot "feel joy" and it demonstrates pleasure and dances. The low level of the DA and high level of the 5-HT make the robot "feel disgust" and it spits out coins and other objects provided in the coin acceptor of the robot. In absence of an external decreases DA and 5-HT levels during some time thus making the robot "sad". These behavioral reactions, as well as expression of interest and sadness, let the robot influence people attracting attention to itself.

Fig. 1.2 presents the high-level design of the proposed social robot that perceives the environment via coin acceptor and camera. The digital-to-spikes (DSA) adapter interface (Sec. IV-A) converts data from both sensors into the neuronal subsystem representation, a sequence of spikes. DSA-generated spikes affect the activity of neuromodulatory nuclei (DA, 5-HT) in the neuronal subsystem (Sec. IV-D). Tab. I identifies the behavioural response implemented via the corresponding motor cortex activity based on psycho-emotional state that is identified according to the levels of DA and 5-HT. The spikes-to-digital adapter (SDA) converts outputs of the motor cortex into the sequence of commands to robot chassis actuators and coin acceptor drives. This way, our robot is able to "make decisions" and move through the environment based on its psycho-emotional state. The neuronal subsystem is implemented as a spiking neural network based on Izhikevich model (Sec. IV-D).

Fig. 1.3 shows the appearance of the PMB-2 platform with "Emotico" system installed. The robot lower part is represented by PMB-2 PAL Robotics mobile platform [27], [30]. Camera with its pedestal and coin acceptor are located on the top of the robot's head.

IV. Preliminary Results

A. Spikes Adapter

The information in SNN is represented and transmitted by means of spikes. The interface of digital input sensors to the SNN is organized via DSA, for the output from SNN to digital actuators we use the SDA. In the DSA, we map digital input into spiking frequencies, or *firing rate* [Hz], and employ a Poisson stochastic process for modelling arbitrary spike firing events using the formula $P(X_i) \approx r_i \cdot \delta t$, where $P(X_i)$ – the probability of spike firing at i^{th} simulation step, r_i – the firing rate and δt – the simulation time sampling step [31]. In each simulation step a uniformly distributed random number $x_i \in [0; 1]$ is generated, if $x_i \leq r_i \cdot \delta t$ a spike is initiated. SDA has not been implemented yet.

B. Coin Acceptor

The coin acceptor distinguishes between real coins and coin-like objects, or fake coins (e.g. buttons and plastic tokens). There are two types of sensors inside the coin acceptor: the first one determines the presence and size of an item, the second one determines whether the item is made of metal or not. Two built-in actuators allow to transfer coins to the moneybox (this process represents the act of digestion), and throw fake coins back when the robot "feels disgust" (spitting mechanism).

When one puts a coin in the coin acceptor the DSA activates the corresponding DA and 5-HT nuclei (proportionally to the value of the coin) or only 5-HT in case of fake coins (Fig. 1.2). Neuronal subsystem makes the coin acceptor to "swallow" or "spit out" the coin activating the corresponding behaviour. Parts *a* and *b* (Fig. 2.1) are constructive elements of a catapult for "spiting out" fake coins. Part *a* is attached to the motor shaft that rotates triggering the catapult to "spit out" a fake coin, while the part *d* is attached to the servo shaft and when it turns, the coin falls into the moneybox "swallowing it".

Fig. 2.2 shows the block diagram of the coin acceptor sensors and motors. It is controlled by the Arduino Nano [32] microcontroller. The pair of LEDs (Fig. 2.2c) and four photoresistors (Fig. 2.2b) identify the presence of a coin or

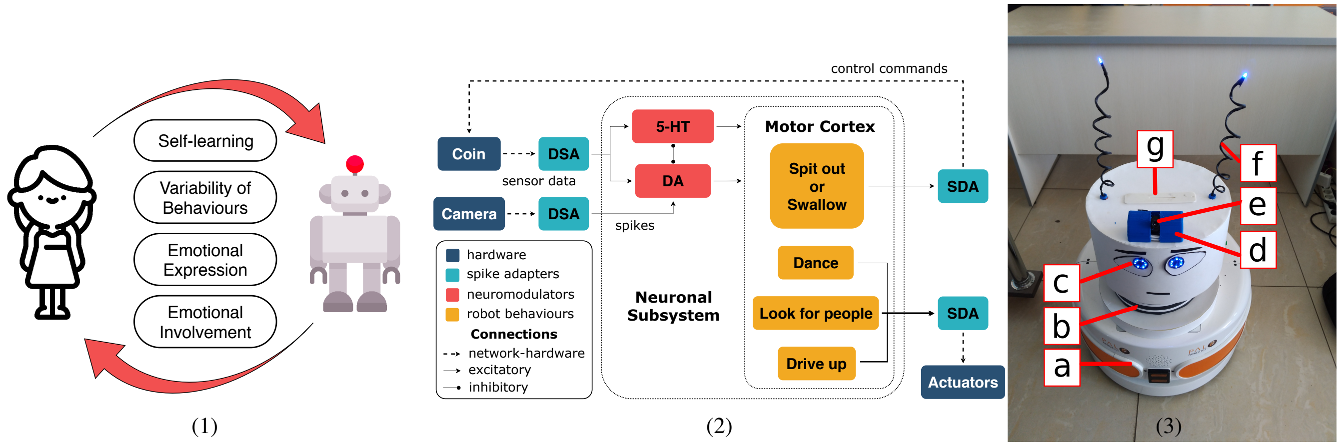

Fig. 1: (**1**) Interaction issues between humans and robots. (**2**) High level design of the proposed system: coin – coin acceptor, camera – robotic camera, DSA – digital-to-spikes adapter, 5-HT and DA – serotonin and dopamine nuclei, SDA – spikes-to-digital adapter, motor cortex – robot behavioral reaction neurons, actuators – robot control drives. (**3**) "Emotico" design: (a) PMB-2 platform [27], (b) neck, (c) eyes, (d) camera box, (e) camera, (f) decorative antennas, (g) coin acceptor.

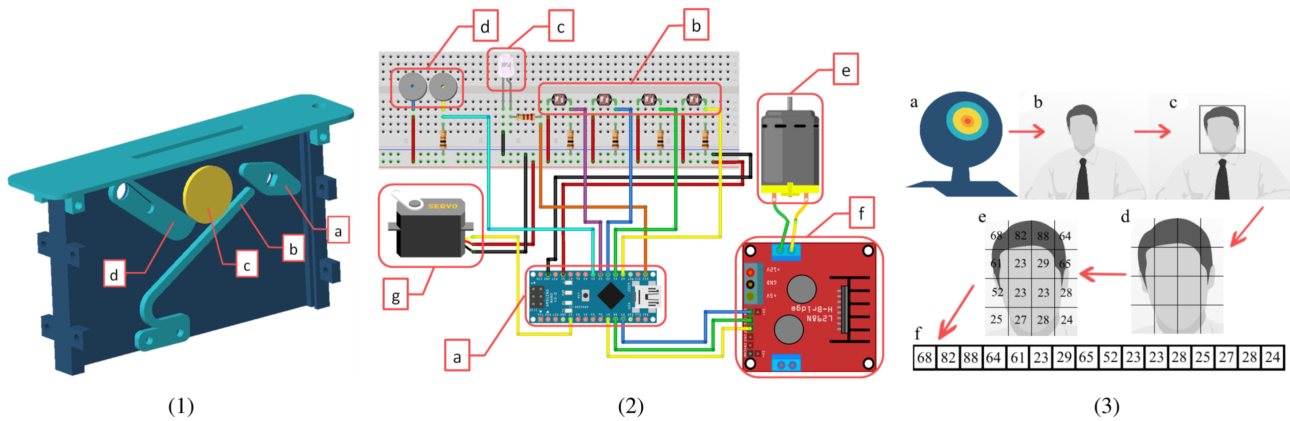

Fig. 2: (**1**) The mechanism of the coin acceptor: (a) torque arm, (b) catapult, (c) coin, (d) servo arm. (**2**) The block diagram of the coin acceptor sensors and motors: (a) Arduino Nano, (b) photoresistors, (c) LED, (d) metal contacts, (e) DC motor, (f) DC motor driver, (g) servomotor. (**3**) Major steps of vision subsystem algorithm: (a) image acquisition from USB-camera, (b) converting image to gray-scale, (c) face detection, (d) face region split into sub-regions, (e) average intensity of each sub-region identification, (f) scaled intensity values 1D array.

other object in the coin acceptor and its size. We also use two contacts (Fig. 2.2d) to determine a fake coin.

C. Vision Subsystem

The vision subsystem is a DSA that performs mapping of information derived from video frames to spikes activity thus affecting robot's psycho-emotional state. It is written in C++ using machine learning library OpenCV [33]. Major steps of the algorithm behind the DSA are presented in Fig 2.3 where red arrows indicate the sequence of steps. The subsystem reads an image from the USB-camera (Fig. 2.3a), converts it into grayscale (Fig. 2.3b), applies histogram equalization and performs face detection by Haar feature-based cascade classifier [34] (Fig. 2.3c). Detected face region is then resized to the number of neurons N allocated for visual cortex of the robot and is split into N sub-regions (Fig. 2.3d). The average value of pixel lightness is normalized in the range $[0 \ldots 100]$ for each sub-region (Fig. 2.3e). These values are used as spiking frequencies arranged into one-dimensional array (Fig. 2.3f) which is published to the neuronal subsystem. If no face is detected an empty array is published.

D. Neuronal Subsystem

The neuronal subsystem is a spiking neural network (SNN) (Fig. 1.2) based on Izhikevich neuron model [35] written in C++ with the Boost Graph Library [36]. We provide the API to: (1) create groups of neurons with certain properties, (2) connect groups of neurons in one-to-one or many-to-many modes, (3) attach groups of neurons to spike generators (4) simulate neuronal activity with a predefined resolution. Each simulation step we keep track of neuronal activity and update the state of neurons considering input stimuli coming from adjacent neurons and spike generators. We run two types of simulations to demonstrate the capabilities of the implemented SNN (Fig. 3):

1) simulation of one neuron network configuration for the $200\,\mathrm{ms}$ with sampling $0.5\,\mathrm{ms}$, where one neuron is attached to a $500\,\mathrm{Hz}$ Poisson spike generator producing the current $372\,\mathrm{pA} \pm 10\,\mathrm{pA}$.
2) simulation of two groups of neurons SNN, *Input* and *Output* groups with 10 neurons in each. The *Input* is attached to the $400\,\mathrm{pA} \pm 10\,\mathrm{pA}$ spike generator and connected to the *Output* in 1-to-1 mode with weights of $320\,\mathrm{pA} \pm 10\,\mathrm{pA}$ and axonal delays of $10\,\mathrm{ms} \pm 2\,\mathrm{ms}$ (Fig. 3.3). Generated spikes directly stimulate the *Input* triggering spiking activity in the adjacent *Output* group neurons.

The first simulation starts with a neuron in the resting state $V_{rest} = -72\mathrm{mV}$. The spike generator produces current (Fig. 3.1) that increases the membrane potential up to the threshold value $V_{th} = -55\mathrm{mV}$, where an action potential is initiated, i.e. the potential goes up to the $V_{peak} = +35\mathrm{mV}$ and drops down to $-80\mathrm{mV}$. The membrane recovers to the resting state in $5\,\mathrm{ms}$ during the so-called refractory period. Frequent consecutive input stimuli (see Fig. 3.1 around $50\,\mathrm{ms}$) results in a higher neuronal spiking activity.

In case of the second simulation the spike generator operates in three modes: (1) low external stimuli for the first $50\,\mathrm{ms}$, the firing rate is $40\,\mathrm{Hz}$; (2) high stimuli for the next $100\,\mathrm{ms}$ with the firing rate of $500\,\mathrm{Hz}$; (3) low stimuli with the firing rate of $40\,\mathrm{Hz}$. *Input* and *Output* spikes raster plots (Fig. 3.4 and 3.7) exhibit the spiking activity of corresponding neuron groups. Relatively low firing activity on both of groups is presented in the first mode with the maximum mean current in *Input* (Fig. 3.5) $\sim 150\,\mathrm{pA}$ and *Output* (Fig. 3.8) $\sim 50\,\mathrm{pA}$ respectively. In the second mode, during the 50-150 ms, the spiking activity in the *Input* increases (Fig. 3.5) with the maximum mean current in the *Input* $\sim 600\,\mathrm{pA}$ which causes more dense spikes distribution in the *Output* (Fig. 3.7) - the maximum mean current increases to $\sim$100-150 pA (Fig. 3.8). In the third mode, the spiking activity on the *Input* goes back to the initial one (see the 150-200 ms interval). The mean current decreases for the *Input* while the *Output* preserve delayed synaptic currents.

E. Benchmarks

In this work we employ the PMB-2 mobile robot with the following hardware parameters: (1) CPU Intel Core i7-4790S (4 cores @3.2 GHz); (2) Intel HD Graphics (no dedicated GPU); (3) RAM 16 GB (DDR3). To estimate the PMB-2 operation in real-time, we computed real time factor (RTF) for different SNN configurations. We used 5 neuron groups with a static number of neurons in each group connected in 1-to-1 mode (Fig. 3.2), forming a graph with $2 \cdot \binom{5}{2} \cdot n^2$ edges, where n is the number of neurons in a group. The simulation time was divided into sub-intervals with steps of 0.1, 0.25 and $0.5\mathrm{ms}$. The $500\,\mathrm{Hz}$ Poisson spike generator was attached to one of the neuron groups.

Benchmark results (Tab. II) indicate that near real-time performance is possible only in case of SNN with groups of 5-10 neurons and simulation time sub-intervals $0.5\mathrm{ms}$. We observe CPU throttling – the temperature reached $86 - 89°\mathrm{C}$ and CPU started to drop down core frequencies at $0.1\mathrm{ms}$ steps.

TABLE II: Performance measures for 5 groups of neurons

Neurons in group	Simulation step (ms)	Real time factor
5	0.1	4.5
	0.25	1.8
	0.5	0.9
10	0.1	16.9
	0.25	6.7
	0.5	3.3

V. Related Work

The problem of developing emotional robots was considered by various authors. One of the first emotional robots is the Kismet robot [37], where the Russell model [19] was used. The Kismet descendant – the Leonardo robot [38] is able to emotionally interact with human agents using facial expressions and gestures. The emotional robot Nexi is used in experiments to study the effect of non-verbal signals in the interaction between human and robot [39]. Authors of the the paper [40] describe Nexi's learning via approval and disapproval signals generated by human trainers.

Possibly one of the famous examples of a social emotional robots is the Pepper [41]. Pepper is able to recognize the emotions of humans, as well as to express her emotions verbally and non-verbally via gestures.

VI. Discussion

We see two main prospects for this work. First the study of users reaction to a robot emotions expression. In the current platform, emotions are expressed via motion, light indicators and facial expression, but we exclude the verbal component (language methods of expressing emotions require additional research). All of these components have a complex effect on the interaction, however, some of them may turn out to be more significant for the user experience.

The topic of human user obedience to the robot today is in the focus of great interest. New social roles of a robot, for example, a teacher, a doctor, a security guard, a trainer, a police officer, a boss, etc., make its possible status higher than a user. In some sense, the social role of a robot gives its power over user. From this perspective we face a lot of questions that has to be answered, since this field has been studied very little [42]. How can social robots demand obedience from users? What are the consequences of user obedience to the leadership of the robot? How does obedience to a human differ from obedience to a robot? How does a person resist the influence of a robot? Is obedience to a robot based on trust, fear, inspiration or something else? The discourse of power is often associated with emotions. The proposed robot is designed to use the communicative scenario of requesting money from the user. This discourse allows to explore various influence strategies that a robot can apply to the user: request, manipulation, threat, appeal to sympathy/pity, blackmail, negotiations, etc.

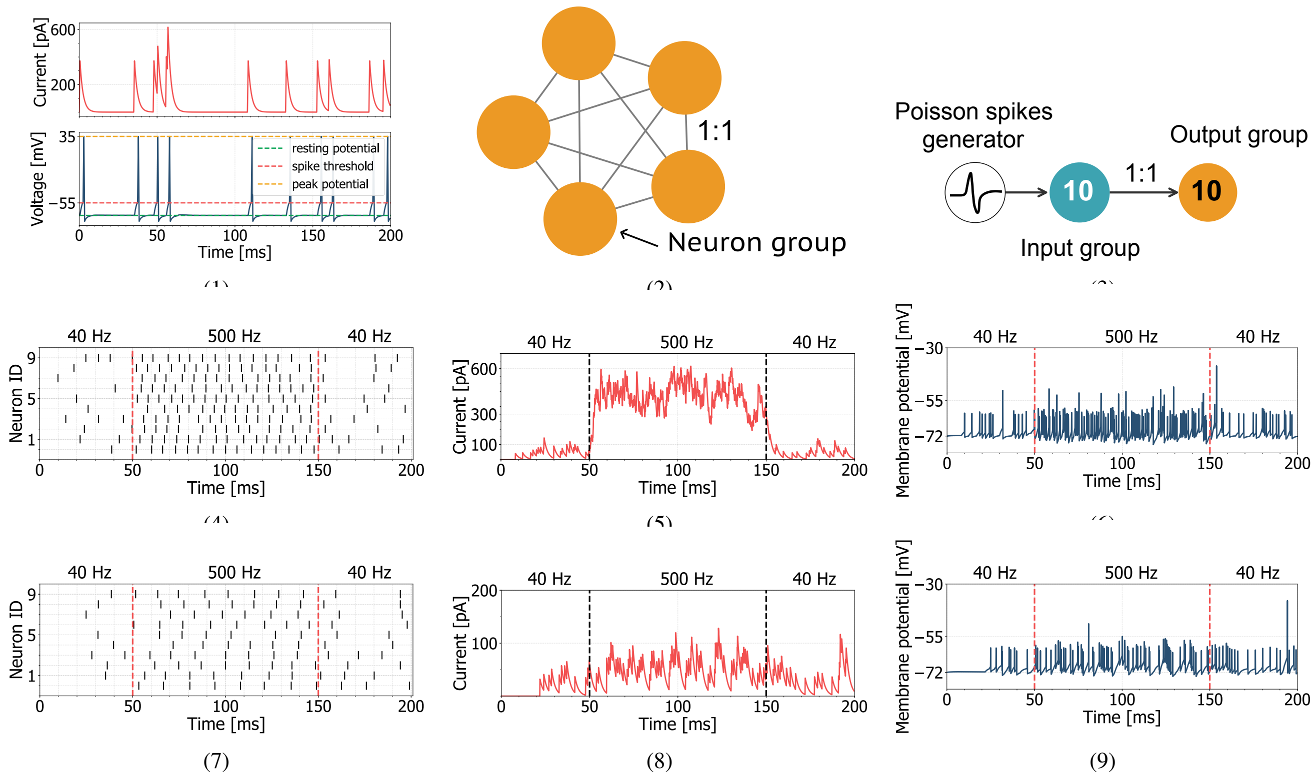

Fig. 3: (**1**) One neuron simulation results: neuronal current (top) and membrane potential (bottom) graphs. (**2**) Benchmark neuron network topology. Five neuron groups connected one-to-one. (**3**) Two groups of 10 neurons SNN topology. Spike generator connected to the *Input* group that is connected to the *Output* group one-to-one. (**4-6**) Simulation results for the *Input* in two groups SNN configuration: spikes raster plot, mean current and voltage diagrams. (**7-9**) *Output* simulation results.

The second direction of the project development is low-level reactions model implementation. We suppose this could be the key to building long-term human-robot interaction. Further development of the robot includes evolution of almost each system. Moreover, most of the following ideas are already put into work. Two additional sensors are to be implemented in the system - ultrasonic sensor and gyroscope to provide new input data for robot's neuronal system allowing robot's psycho-emotional state to be influenced by different external factors. Vision system will be based on deep learning frameworks like convolutional neural network to enable user's facial features to affect robot's psycho-emotional state based on their previous interactions. We plan to extend our subcortical areas model with additional NA subsystem and further develop DA and 5-HT subsystems.

Main concerns and limitations for the current implementation of bio-inspired neural network are the issues with robotic embedded system performance. We plan to carry on with searching for the extension of the current computational system and further less computational power consuming solution for our model of the neural network. The crucial and really strict factor for the system is the operation of the neuronal subsystem in the real-time that does not really fits nicely in the current widely used von Neumann architecture.

Behavioral patterns will be developed in a robotic system to apply them depending on its psycho-emotional state. Current robot's facial features are planned to be substituted with mechanical ones. This way robot will be able to change its facial expression according to psycho-emotional state thus establishing more effective interaction with humans.

As a part of our future work we also plan to make use of the developed system in USAR domain. It can help to maintain psycho-emotional state of the victim in a stressful situation while waiting for the rescue team.

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