International Science Index, Electrical and Information Engineering Vol:11, No:2, 2017 waset.org/Publication/10006430

Neuron-Based Control Mechanisms for a Robotic Arm and Hand

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Abstract**—**A robotic arm and hand controlled by simulated neurons is presented. The robot makes use of a biological neuron simulator using a point neural model. The neurons and synapses are organised to create a finite state automaton including neural inputs from sensors, and outputs to effectors. The robot performs a simple pick-and-place task. This work is a proof of concept study for a longer term approach. It is hoped that further work will lead to more effective and flexible robots. As another benefit, it is hoped that further work will also lead to a better understanding of human and other animal neural processing, particularly for physical motion. This is a multidisciplinary approach combining cognitive neuroscience, robotics, and psychology.

Keywords**—**Robot, neuron, cell assembly, spiking neuron, force sensitive resistor.

I. Introduction

ROBOTS are becoming increasingly effective, but they still cannot duplicate a range of human and animal behaviours, such as dynamically responding to the environment. One promising path towards duplicating that behaviour is to duplicate human neural responses. Moreover, building robots that are driven by neurons, may help the scientific community discover how the human neural system actually works.

This paper describes a robot that is driven by simulated neurons. It is a Robotis Bioloid robot platform that performs a pick-and-place task. A BeagleBone Black runs the simulation of neurons on NEST. There is a force sensitive resistor (FSR) mounted on the end effector of the robot hand to provide feedback when the object is grasped and ready to be picked.

A Python and PyNN implementation of the simulated neurons running on BeagleBone Black is presented in this paper. A finite state automaton (FSA) has been implemented in neurons to determine the state changes of the robot. The neural model is a integrate-and-fire (IAF) point model [1]. The robot has Dynamixel-12A servos that are programmed in Python and associate with the simulated neurons. The motor is activated with the simulated set of neurons and the end effectors grasp the object. Once the object is grasped, the FSR sends a feedback and the second set of neurons fire. There is a transition of state at this point, which signals the motors to lift the object and place it back at the destined position.

This paper is organized as follows: some literature review is provided in Section II; Section III describes the methodology of the work followed by the results in Section IV. Section V provides a discussion of the results obtained and Section VI concludes the paper.

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II. Literature Review

Research efforts dealing with spiking neural networks (SNNs) are attempting to gain a better understanding of the brain and are making efforts to realize the brain's electronic replicas partially to imitate brain functionalities such as learning and memory [2]-[6]. Motion is driven by neurons, both cortically and subcortically. One fundamental question in motor control is to establish to what extent the same neurons can be reused to generate a variety of related motor patterns [7].

At least in the cortex, many neurons do not function in isolation but are organized in Cell Assemblies (CAs) [8]. These are known to show asynchronous activity states. Information processing in the brain is achieved through the collective action of groups of neurons. These neurons are constituents of various CAs, which in turn are a small set of connected neurons that through neural firing can sustain activation without stimulus from outside the CA [9], [10]. It has been shown that the generalized IAF models can approximate the dynamics of classical Hodgkin-Huxley model of squid giant axon with high accuracy [11], [12]. These neuronal networks can exhibit potentially useful properties [9].

The robot, described in this paper, requires simulated neurons, and thus simulation of neurons is a crucial step. NEST is a neuron simulator that is used for simulation of large networks of spiking model neurons [13]. It has a wide range of neuron and synapse models and provides high-level commands to create spatially structured networks. It works via a Python-based interface and has support for parallel simulation. NEST supports simulation of precisely timed spikes [14] by combining the precision of event-driven simulators [15] with the efficiency of grid-based simulation. A comparative study of agents that have been implemented in simulated neurons has advocated the development of a neurorobotics platform capable of replacing virtual environments [16]. The neural model that is used in the robot is the adaptive exponential integrate-and-fire model [1].

Using physical robots abolishes the limitations of virtual environment, but adds useful constraints for understanding motor action. Implementation of brain-based studies into robotics has been promising and these studies have taken a big leap forward [17]. However, much still needs to be done in the area of neurorobotics. To effectively program robots with neurons requires a good understanding of the behaviour of neurons and their psychophysiological effects.

For humans and animals, a behaviour such as moving an arm is a process that involves several stages including perception, decision, action and monitoring the effects of the performance. Cognitive neuroscience has studied these different stages and related processes have been identified using a range of neuroscientific techniques. For example, by recording EEG from the scalp of the brain, movement activity has been established. Approximately 1000 ms prior to a movement onset, the readiness potential (RP) is observed. This gradually increasing ERP component was widely seen as a direct indicator of the neural decision to move [18]. However, later it was proved that the final decision to move now might follow up very late in the time course of RP [19]. There is a commitment associated with the production of a movement with the neural decision to actually move. This is taken care by the presence of a threshold crossing of the accumulator that underlies the decision of such response [20], a lateralization of the pre-movement potential [18], and an abrupt increase in excitability in primary motor cortex nearly 100 milliseconds before the onset of the muscle flexion [21].

The stages of performing an action include several other distinct processes. After the decision to move has been made and the action initiated, then there is typically an input from the action effect. A simple action such as grasping will generate somatosensory input, which has been measured using ERPs [22]. An action is not an isolated bottom up process, but is driven and affect by higher order cognitive processes, such as attention [22].

The above mentioned facts and factors form an integral part the idea behind simulation of neurons and the use of those neurons in performance of a neurorobotic task. The spiking behaviour of a set of neurons can be determined for simulation with its neuro-cognitive aspect. Hence, it can be suggested that biological cognitive behaviour cannot be overseen when programming and simulating neurons. The work in this paper features the application of simulated neurons as governing entities in the movement and simple task performance of a robot arm.

III. Methodology

The robot platform used in the experiments described in this paper is a Robotis Bioloid Robot. Dynamixel-12A servos are used as motors in the robot. These Dynamixel-12A actuators are serially controlled servos and are considered among the most advanced actuators that are a standard in the small scale-robotics. Speed, temperature, shaft position, voltage and load can be tracked, thus providing a wide range if scalability with their programming. Every 12A actuator has the capability of being governed individually by a control algorithm.

An FSR is used to determine if the robot is grasping something. Processing is done on a BeagleBone Black; it integrates input from the FSRs, and sends signals to the actuators. The BeagleBone Black has Cortex A-8 processor.

Python 2.7 is used for controlling the Dynamixel-12A servo-motors of robot. The neurons are programmed using PyNN 0.8 middleware [23], which invokes the NEST simulator for neural processing. All of this processing runs on the Beaglebone Black.

The present work is an initial form of the idea of using neurons in robots. As neurons are known to be the basis of cognition, using them as for all processing in robots is a promising idea and is an area that needs further exploration and effort.

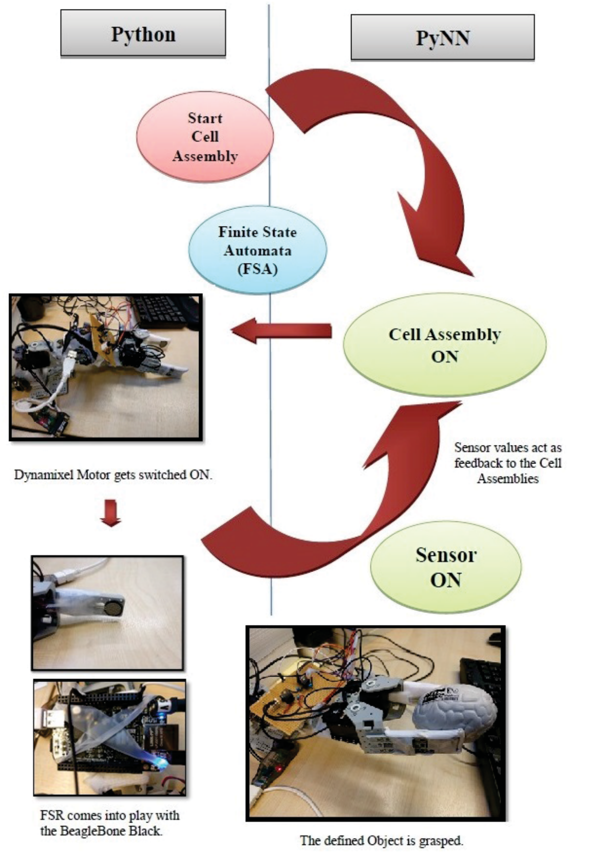

Fig. 1 Representation of the working prototype, where the robot performs a pick-and-place task with the neurons

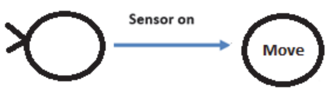

Fig. 2 The grasping action initiated with the start of the FSA: When the FSR is activated it sends feedback, the FSA changes state and the movement of the robot arm is initiated, and is completed by placing and releasing of the object

Neurons and their synapses are slowly varying structures, which in-turn perform cognition. There are a wide range of biological neural models, which range from point models to more complex compartmental models. Simulated versions of these neurons can be programmed by setting up connections between them (synapses) so that the neural firing propagates and performs the necessary computation. Simulated neural system are Turing complete given a sufficient number neurons [24].

As described above and shown in Fig. 1, there are two programming platforms; Python 2.7 controls the robot; PyNN 0.8 is used to program the neurons.

The processing in the running robot is entirely neural, though there are non-neural steps to convert sensor values to spike trains, and to translate spike trains to motor actions, and then signal those actions.

The processing itself is based on a finite state automaton (FSA) that is implemented in simulated neurons. States are represented by simple binary (on or off) CAs. In this case, the CA consists of five neurons that are well connected. If they all fire, they each send activity to the other neurons, and the state persists indefinitely.

When the system starts, spikes are sent to the initial state so that it fires persistently. The side effect of this firing neuron is to grasp. That is, the spikes are interpreted to activate this actuator. As long as they fire, the actuator will run. Similarly, a second set of five neurons fires when the FSR passes a threshold. When this happens, in collaboration with the initial state, there is a transition to the second state. The synapses from the first state in collaboration with connections from the FSR neurons are sufficient to ignite the second state's CA. This in turn inhibits the first state, and its neurons stop firing. As the first state has stopped, the robot stops grasping harder. The firing of the second state causes the left motor to lift the object. The neuron used here is adaptive exponential integrate-and-fire model 'if-cond-exp' from NEST). The code can be found at [25].

The CA is activated, which fires its neurons with the FSA. This signals back to the motors of the robot and movement of the robot arm is initiated. The motors come into action and move to grasp the object.

The appropriate motor is activated so as to lift the object and place it back at another designated location. The end-effector releases its grip and the task is completed [cf Fig. 2]. The Bioloid Robot completed the entire pick-and-place task efficiently. There were two CAs in the FSA that coordinated the movement of the various dynamixel motors of the robot and made. This work establishes that a simple task such as pick-and-place can be governed by the programmed neurons. It opens a window to further improve this area.

IV. Results

Fig. 3 shows the firing of the neurons. The first set of five neuron responds after 15 ms (milliseconds), which reflects the combined membrane and the synaptic time-constants. These spikes are driven by the forward inputs only and are quite reliable.

Subsequent neurons fire in a similar fashion. At 50 ms, there is a shift in the neuron population and this population fires simultaneously till the end of the simulation time i.e. 200 ms. This shift is caused by the external (to the neural system) activation of the middle five neurons, causing a state transition. Note the regularity of the spiking. The model is such that it spikes in regular 4 ms. intervals.

The neuron populations here attain a finite state of firing and then trigger the motor of the robot for its movement. Similarly, once the FSR returns passes the set threshold value of 0.04 Volts, the neurons that initiate the movement of the next motor are triggered. This performs the task of picking up the defined object and then the arm turns to the final position and the grasped object is released. Videos of the complete movement of robot can be viewed at the web link [25].

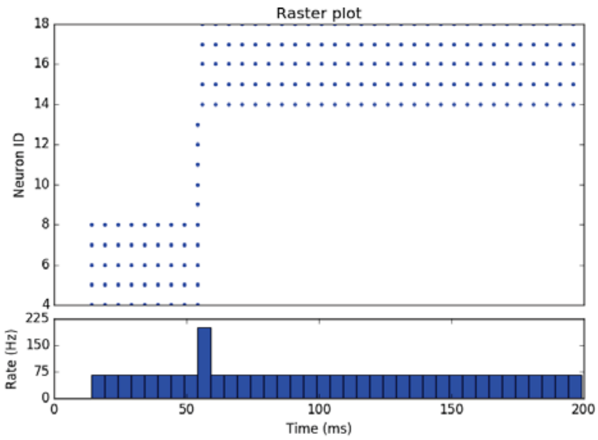

Fig. 3 Raster plot for the simulated neurons: Firing of five neurons occurs after 15 ms and the next neuron population fires after 50 ms; the persistent responses of two neuron populations are shown here

V. Discussion

The robotic arm and hand, controlled by simulated neurons, is quite simple. None the less, at a basic level, the simulated neurons and synapses mimic the neurons and synapses in the brain. Under a given set of conditions, a neuron overcomes its threshold and creates a spike that is sent to the synaptically connected neuron. All processing is done in the neurons, and this organization is simple yet efficient.

The idea of programming a robot with simulated neurons is based on an effort to understand and make use of a neural network that is more effective than existing methods for controlling robots. There is an incredible variability in the size, shape and connectivity of neurons in the brain but this diversity allows an individual human to do interesting things. These neurons organize themselves, in response to the environment, for the execution of a vast array of tasks.

There are studies of virtual robots have been driven by simulated with neurons. Virtual neurorobotics (VNR) makes use of cognitive control, which incorporates realistic neural dynamics with the time constants that reflect synaptic and neuronal activation along with established membrane and circuit properties [26]. Such studies have certain advantages including the ease of testing of the neurons and synapses. As the environment is virtual, it can run at any speed avoiding the difficulties of working on a particular hardware structure. However, in real-time such advantages may also pose a practical limitation. The robot architecture itself is complex, and the neural system must respond to real time demands. Unlike biological neurons, these simulated neural systems can be relatively easily engineered. The approach of engineering a robot controller in simulated neurons will hopefully lead to better robotic systems by mimicking the biological system. This approach may also help improve the community's understanding of how the human neural system works. More and more, complex robots are functioning in a range of domains. The state of the art in managing complex multi-domain systems is the cognitive architecture. For example, ACT-R [27] and Soar [28] are basic architectures with particular programs written for performance of particular tasks. Different tasks can be readily supported in the same architecture. Despite some effort in building neural cognitive architectures (e.g. [29], [30]), these systems fall short of symbolic cognitive architectures. Similarly, understanding of how biological neurons generate motion is far from complete.

One way forward is to align the underlying neural behaviour to known human neural behaviour. To this end, an experiment where a robot, based on simulated neurons, could make a timed decision could duplicate existing human ERP studies.

Simulated neurons can be programmed for the performance of activities. Programming of neurons is achieved by setting up connections between the synapses such that the neural firing propagates and completes the required computation. Provided there are sufficient neurons, such a system anything can be programmed. Biological neural models can be programmed and the intelligence emerges on the basis of the models developed. Hence, a cognitive architecture developed from biological neural models could viably perform a range of real world tasks. Agents in virtual environments governed by neurons have been targeted and made use of for some time now. There is a need for work on actual physical robots to both develop more effective robots, and to better understand the biological neural processes. This paper reports an initial work that has been done that will pave the way for further research with physical robots and simulated neurons.

VI. Conclusion

This work has been carried out as a pilot study to realize the working of a robot with simulated neurons. The movement of a robot arm with simulated neurons takes the initial steps required for further enhancement and improvement of the idea. The robot arm makes the required movement for the performance of pick-and-place task with the simulated neurons and the feedback. This work provides a basis for further research in this area and more complex biological neural agents. It provides a platform for the exploration of simulated neural systems driving physical robots.

Given a new and a higher level task the robot could determine the demand for a higher level of cognitive neural system. Continued development of neural robots would lead to better robots in future with better understanding of a larger scale of neural dynamics along with a better understanding of the neural cognitive architectures.

VII. Conflict of Interest Statement

The authors declare that this research was conducted without commercial or financial relationships that could bring up any potential conflict of interest.

Acknowledgment

The authors would like to thank School of Science and Technology, Middlesex University, London for funding this study. This work is partially supported by the Human Brain Project.

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