Muscle tone control system based on LIF model neural network

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The article describes the solution to the control problem using machine learning. The article presents a model to simulate muscle tone. Based on spiking neural network control system was designed. The task of the neural network was to find a control function to maintain the muscle length. A LIF model of a spiking neural network was used. Excitatory signal was produced by muscle activity. Inhibitor signal was produced by motor neuron activity. Numerical simulations were performed and analyzed. A critical value of synapse weight was found. This value can be understood as a bifurcation parameter of the dynamic system.

Keywords—spiking neural network, control system, mathematical model, artificial neural network.

I. Introduction

Neural networks are widespread worldwide for data processing. Historically the perceptron model is one of the first mathematical models of a biological neuron. The development of such models goes on. And, spiking neural networks are currently the closest type of network to describe the neuron with regard to biological origin. Approaches based on such networks type are becoming increasingly common in stabilization and control tasks [1, 2, 3].

A number of authors apply such models to the agent control, but with the application of such models occurring at the agent macro-level. Like in [4], two control actions are defined for the agent - right and left locomotors and sensor system defined by viewing angle. In this case, the spiking network triggers each locomotor. And agent orientation is defined by velocity difference in the left and right locomotors. Similarly, in [5], a unicycle agent with a similar sensor system, and the agent control are based on the feedback, velocity, and orientation of the unicycle.

In both cases the is only one type of feedback - reaction on the environment. In fact, in real biological systems, there is a number of feedbacks in control systems. Moreover, these feedback mechanisms exist as multilevel systems in real biological organisms. It means that some feedback is carried out as a pair of sensor-motoneuron and others thru the central nervous system. This mechanism is called reflex arcs. For this reason, the study was devoted to modeling a neuro-mechanical model with feedback not only via the sensor but also via other reflex arcs.

The research of an algorithm for modeling muscle tone using a spiking neural network is presented. The simulating imply the biology-based architecture of the neural network. Muscle tone can be understood as a prolonged tension or contraction of a muscle. Muscle tone provides maintenance of a posture or a certain position of the body.

The purpose of the research is to simulate the muscle tone. The control system is based on a spiking neural network, the net topology is based on biological neuron net architecture. To simulate muscle tone external force will be applied. Hills model will be used to simulate muscle mechanics. Sensor-motoneuron feedback was used.

II. Methods

A. Lif model of neuron

Topologically the design of a spiking neural network is similar to a multilayered perceptron. The fundamental difference is a mathematical model of the perceptron. From a biological point of view, neurons are complex structures with an electrochemical mechanism of information transmission. Due to this fact, there are a number of studies describing such a mechanism. Nowadays, there are several corresponding mathematical models. In the research Leaky Integrate-and-Fire (LIF) model of a neuron was used. The LIF model can be described by an equation:

$$\tau_{mem} \cdot V' = E_{leak} - V + g_e \cdot (E_e - V) + g_i \cdot (E_i - V), \qquad (1)$$

where τ_{mem} is the membrane time constant, V is the membrane voltage, E_{leak} is the reversal potential for the leak, E_e is the reversal potential for excitatory inputs, E_i is the reversal potential for inhibitory inputs, g_e is the excitatory conductance, g_i is the inhibitory conductance.

Excitatory conduction can be described by the equation:

$$\tau_e \cdot g_e' = -g_e + w_e \cdot h(\Delta L), \qquad (2)$$

where τ_e is the time constant of postsynaptic potential, w_e is the strength of the excitatory synapse, t_s is the time of an excitatory input spike, $h(\Delta L)$ is a function of tone reflex activation.

The function of tone reflex activation was used as follows equation:

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$$h(\Delta L) = \theta(\Delta L - \Delta L_{THR}), \tag{3}$$

where $\theta(x)$ is the Heaviside step function, ΔL_{THR} is muscle length limit.

Inhibitory conduction can be described by the equation:

$$\tau_i \cdot g_i' = -g_i + w_i \cdot f(V), \tag{4}$$

where τ_i is the time constant of postsynaptic potential, w_i is the strength of the inhibitory synapse, $f(V)$ is a neuron activation function.

The neuron activation function was used as follows equation:

$$f(V) = \theta(V), \tag{5}$$

In this approach, the potential of each neuron is characterizing its value. The potential should be compared to the neuron threshold value. And if the potential exceeds the threshold value, the neuron sends an impulse to the next layer, then the potential drops to a relaxing level. Such a process calls spike. Otherwise, potential accumulation occurs. The LIF model assumes the tone reflex of the muscle. Moreover, this reflex is excitatory input. On the other side, neuron spiking triggers the inhibitory inputs on the neuron.

B. Hill's based muscle model

A three-element model based on the Hill model was chosen as a mathematical model of the muscle to simulate the mechanical response of the muscle. As described in [6, 7, 8], the model includes passive sequential and parallel nonlinear spring elements and an active contractile element. The scheme is given in Fig. 1.

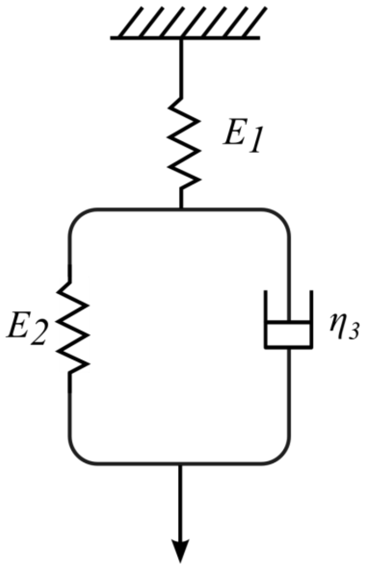

Fig. 1. Modified Hill muscle model. E_1 - stiffness coefficient of the series element, E_2 - stiffness coefficient of the parallel element, η_3 - contractile coefficient.

The forces of the series (F_1), parallel (F_2), and contractile (F_3) elements satisfy the equation:

$$F = F_2 + F_3,\ F = F_1, \tag{6}$$

where F is a total force in a muscle.

The total muscle displacement (ΔL) and the displacement of corresponding elements (ΔL_1, ΔL_2, and ΔL_3) satisfy the equation:

$$\Delta L = \Delta L_1 + \Delta L_2,\ \Delta L_2 = \Delta L_3, \tag{7}$$

In the research linear model was used. The muscle elastic element is under a tension of an external force. Since the length of the muscle must be constant the stretching of the series element can only take place with equal contraction of the contractile element. Thus, the contraction of the muscle triggers the contractile element, so the control (neuron spike) will be applied to it.

C. Network architecturel

The task of a neural network is to determine the control function to realize the muscle tone. In this case, the muscle maintains a given lengthening. To design the topology of the neural network the biological ones were used. The topology of the proposed network was based on architecture from [9, 10, 11] and presented in Fig. 2. The network consists of one motor neuron with inhibitory feedback, and one excitatory sensor neuron.

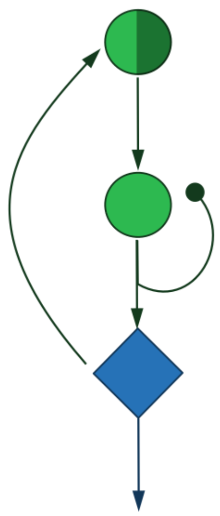

Fig. 2. The topology of the proposed network: the semigreen circle is sensor, the green motor neuron, the blue rhombus is muscle; excitatory feedbacks marked by arrows, inhibitory marked by circles.

The sensory neuron receives information about the muscle stretch. When it reaches a threshold value, the sensor neuron generates excitatory signals that come to the motor neuron, which is described by the LIF model. The motor neuron generates an activation signal to the contractile element and an inhibitory signal on himself. Via activation of the contractile element the muscle contract and the muscle length change. The scheme of the control system is shown in Fig .3.

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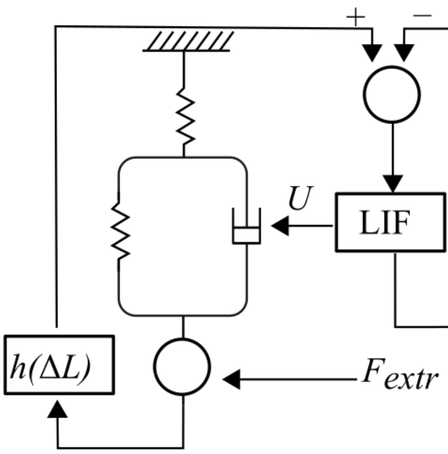

Fig. 3. The scheme of the control system: F_{extr} - external tensile force, ΔL – muscle displacement, LIF – motor neuron (LIF-model), U - muscle contract activation signal.

III. Results

The following values of macro parameters were used in simulation:

$F_{extr} = 0.2$ N, $U = \{0; 0.08\}$ N, $\Delta L_{THR} = -0.05$ m.

In Hill's based model the following parameters were used:

$E_1 = 10$ N/m, $E_2 = 5$ N/m, $\eta_3 = 3$ N s/m.

The following synaptic weights for excitatory signal were used:

$w_1 = 6.3$, $w_2 = 7.5$.

Fig. 4 shows the muscle elongation under the only external force without the control system. It is casual oscillation with damping. The results of applying the control system are shown in Fig. 5. The muscle elongation maintains a given value ΔL_{THR}.

As elongation flatten the curve the spikes triggers with a constant frequency. It can be concluded that a tone neuro pattern appears. However, by changing the value of the synaptic weight the behavior of muscle elongation fundamentally changes. An oscillation occurs (see Fig. 6). Such behavior can be explained by hyperactive reflex. In this case, the control system reacts rapidly to little changes in the dynamic system.

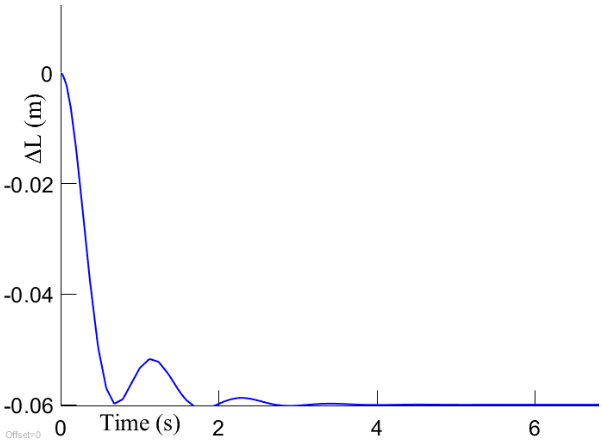

Fig. 4. The elongation of the muscle without a control system.

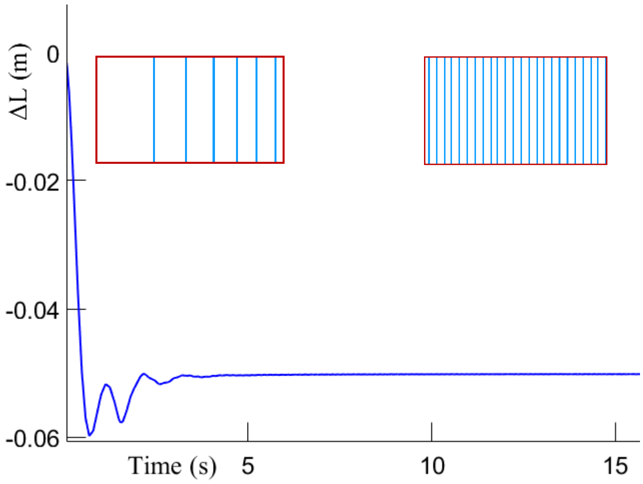

Fig. 5. The elongation of the muscle with the control system: muscle activation spikes are shown in red boxes. Case of muscle tone.

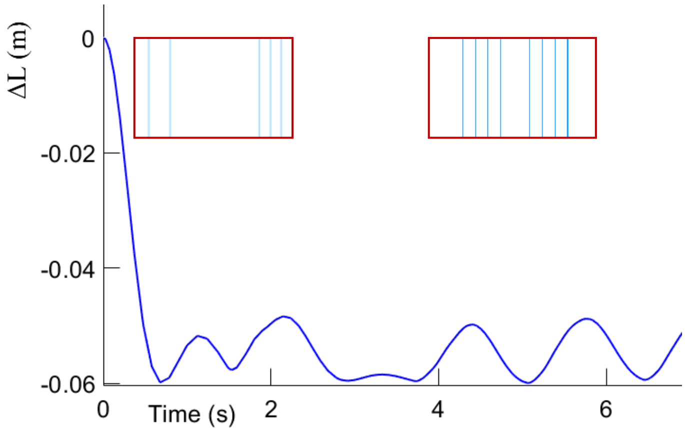

Fig. 6. The elongation of the muscle with the control system: muscle activation spikes are shown in red boxes. Case of hyperactive reflex.

IV. Discussion

Simulation shows that the control system is sensitive to parameters changes. So critical value of w_{crit} was found ($w_{crit} = w_1$). In the case of w_e is equal to w_{crit} the muscle tone appears and the muscle length became constant after some time. Also, neuron pattern appears with constant frequency. In the case of w_e is less than w_{crit} the muscle tone appears, but the given ΔL_{THR} elongation does not reach. The neuron pattern behavior is the same. In the case of w_e is more than w_{crit} the muscle's tone has an oscillation behavior. Meanwhile, neuron pattern appears as a signal with superposition of frequencies.

The critical value can be understood as a bifurcation parameter of the dynamic system. This value can be found by analyzing the dynamic system. In this approach, Hill's based muscle model can be understood as a dynamic system with some frequent signal outupt and inputs. LIF model can be treated as a nonlinear frequency changer.

Contrariwise from a biological point of view the dynamic system should adapt to the environment and respond to it. It means that superstructure should be added to the proposed control system. And the purpose of the superstructure is to analyze the quality of the dynamic response and change the

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given list of the system macroparameters. This superstructure can be understood as part of the central neuron system, which manages the motion patterns. Since the same muscle can produce different types of functions: contraction, excitation-contraction coupling, muscle movement, proprioception; it can be concluded that different patterns exist. Potentially, they can be described by one topology with a list of system macroparameters or by a topologically complex system with a number of inputs activating different muscle functions.

V. Conclusion

The article presents a model to simulate muscle tone. The task of maintaining the muscle at a given length under the influence of an external tensile force was considered. The control system was designed. A LIF model of a spiking neural network was used. Excitatory signal was produced by muscle activity. Inhibitor signal was produced by motor neuron activity. Numerical simulations were performed and analyzed. A critical value of synapse weight was found. This value can be understood as a bifurcation parameter of the dynamic system.

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