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Neuromusculoskeletal Modeling of Elbow Flexion/Extension – Aided by OpenSim

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Abstract

Neuromusculoskeletal (NMSK) models are recently exploited as a non-invasive approach for advanced predictive simulations and subject-specific modeling to enhance clinical applications. A cerebellar model, in addition to a musculoskeletal model, is fundamental to this idea. In this paper, we aim to establish an integrated framework to simulate the role of the cerebellum in producing the motor control commands of flexor/extensor muscles of the elbow. The model of cerebellum is abstracted to a Spiking Neural Network (SNN) that receives sensory information from the musculoskeletal and delivers the motor actions. The Izhikevich model is utilized to capture neuron activity function due to its balance between biological accuracy and computational efficiency. The learning is based on the strategy of Spike Timing-Dependent Plasticity (STDP) modulated by Dopamine (DA). Accordingly, firing of a presynaptic neuron immediately before a postsynaptic neuron results in Long-Term Potentiation (LTP) of synaptic transmission, and the reverse order of firing results in Long-Term Depression (LTD). The trained network provides flexor and extensor command signals to move the elbow for reaching the hand to a target position. By using the OpenSim API in MATLAB, we investigate our neuromusculoskeletal model in a closed-loop procedure in which the elbow muscles in forward dynamics receive the neural excitations and feedback the motion information. This framework highlights the potential of SNN-based cerebellar models in improving motor function rehabilitation through personalized, precise neuromuscular simulations, advancing computational neuroscience, and benefiting both healthy and impaired conditions in clinical settings.

Introduction

Neuromusculoskeletal (NMSK) models are exploited as a computational non-invasive approach for advanced predictive simulations and multi-scale modeling to enhance clinical applications. NMSK models are powerful tools to estimate the complex interactions between neural control, muscle dynamics, and skeletal movement, enabling personalized treatment plans and improved rehabilitation outcomes, for example in human-in-the-loop control of assistive robots [1,2]. These models must be adapted for real-world environments, requiring the integration of high-fidelity simulation data to compensate for lower resolution measurements in settings like fields, gyms, and clinics [1]. Recent research emphasizes the importance of subject-specific modeling and the potential for advanced predictive simulations and multi-scale modeling to enhance clinical applications [3,4].

Neuromusculoskeletal modeling is a complex and interdisciplinary field that has significant implications for both artificial and biological systems. These models are essential for understanding motor control mechanism, designing experiments, and optimizing motor performance. However, current models are not able to fully capture the complexities of the neuromusculoskeletal control system, especially the nonlinear dynamics of skeletal muscle, suggesting a more realistic approach to modeling. Implementation of such models according to brain structures (e.g., the cerebellum) and functions (e.g., spiking activity) could significantly enhance the fidelity of simulations and provide deeper insights into motor control mechanisms [3,4].

The cerebellum plays a crucial role in motor control, prediction, and learning. It processes sensory input and coordinates voluntary movements, ensuring smooth and precise actions. Pathologies affecting the cerebellum can lead to significant motor impairments. For instance, Geminiani et al. (2018) developed a detailed computational model of the cerebellum embedded in a sensorimotor circuit to study cerebellar pathologies [5]. Moreover, Bruel et al. (2023) addressed to spinal cord (SC) influence on motor learning in the cerebellum to find that dose the SC facilitate or hinder cerebellar motor learning [3].

Research has shown that artificial neural networks (ANNs), particularly spiking neural networks (SNNs), are effective in simulating realistic human body movements, e.g. elbow flexion/extension, for various applications, including assistive technology and rehabilitation systems [1,3,6]. These networks can generate inverse dynamics transformations of arm and hand movements with low torque errors, providing subject-specific parameterization and precise predictions of limb dynamics [7]. They have also been integrated into closed-loop models for human activities of daily living (ADL) movements, accurately predicting angular trajectories during tasks like eating and drinking with high target access rates and minimal error rates.

Recent advancements in spiking neural networks (SNNs) have revolutionized the simulation of biological neural behavior, particularly in motor control tasks like elbow rotational movement. SNNs, inspired by the brain's neural processes, excel in replicating precise spike timing and communication dynamics of biological neurons, offering valuable insights into temporal processing and learning mechanisms [8-9]. Moreover, by incorporating Spike Timing-Dependent Plasticity (STDP), SNNs provide a biologically plausible framework for motor control tasks, making them ideal for controlling robotic systems and modeling biological processes [10]. The utilization of cerebellar-inspired learning rules in SNNs enhances their capability to simulate and control complex movements, such as robotic arm manipulation, showcasing their potential in realistic simulations of motor tasks [11-13].

The objectives of this study are to synthesize current research on SNNs and their application in motor control, elucidate the significance of STDP in learning, and explore the role of cerebellar learning in motor function and pathology. By integrating evidence-based information from neuroscience, robotics, and computational modeling, we aim to provide a comprehensive overview that is accessible to a broad audience, including researchers, engineers, and clinicians.

Material and Method

We utilized the Izhikevich model for its balance between biological accuracy and computational efficiency designing a spiking neural network to simulate cerebellar function in motor control tasks, specifically elbow flexion and extension. The SNN architecture was inspired by previous successful applications, consisting of neurons representing the cerebellar, receiving proprioceptive input and delivering motor commands, see Fig. 1. Spike Timing-Dependent Plasticity (STDP), modulated by dopamine, served as the primary learning mechanism, adjusting synaptic weights based on the temporal correlation of neuronal activity. Structural synaptic plasticity further enhanced network adaptability by allowing the formation and elimination of synaptic connections. Moreover, in a larger time scale, dopamine as the reward of approaching to the target modulates the strength of the synaptic connections. This architecture is, in fact the, inspiration of reinforcement learning in which rewards obtained through interaction of an agent with environment conducts the system towards an optimal policy.

The network underwent a motor babbling phase, generating random motor commands to map sensory inputs to motor commands. The commands serve as activations of the biceps (BIC) and triceps (TRC) muscles to move the musculoskeletal model of the elbow established under OpenSim API in MATLAB [14]. This closed-loop system involved the SNN, as cerebellum model, generating motor commands, applying them to the musculoskeletal model, and receiving proprioceptive feedback. The simulation evaluates the accuracy and efficiency of the control system via performance metrics including target-reaching ability, movement smoothness, and response to perturbations. The Pipeline of the learning algorithm based on STDP and DA modulation is illustrated in Fig. 2.

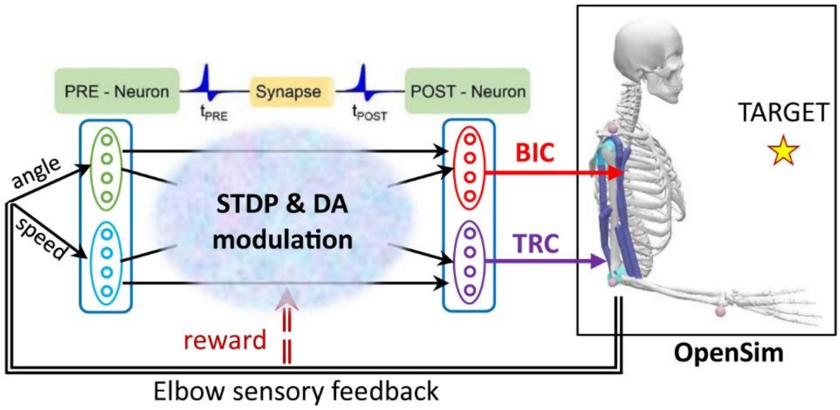

Figure 1. The neuromusculoskeletal model including a SNN architecture trained via STDP & DA modulation.

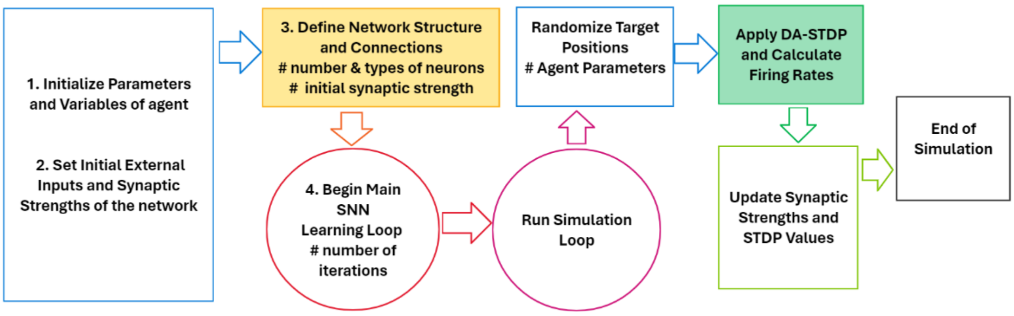

Figure 2. Pipeline and information flow in the neuromusculoskeletal model.

Conclusion

Spiking neural networks, leveraging mechanisms such as STDP and structural plasticity, offer powerful tools for modeling and controlling motor behaviors. The detailed study of cerebellar functions and pathologies through computational models provides valuable insights into the neural basis of motor control and learning. These advancements pave the way for innovative applications in robotics and neuroprosthetics, enhancing the quality of life for individuals with motor impairments. The integration of SNNs with STDP and cerebellar learning models holds promise for developing advanced neuroprosthetics and rehabilitation devices. By mimicking the biological processes underlying motor control, these networks can provide more natural and efficient control mechanisms for robotic limbs and assistive technologies.

Future research should focus on enhancing the scalability and robustness of SNNs, integrating multimodal sensory inputs, and exploring the co-adaptation of neural networks and users in brain-computer interface (BCI) applications. Additionally, further studies on the interplay between different forms of synaptic plasticity and their impact on learning and memory will deepen our understanding of both artificial and biological neural systems.

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