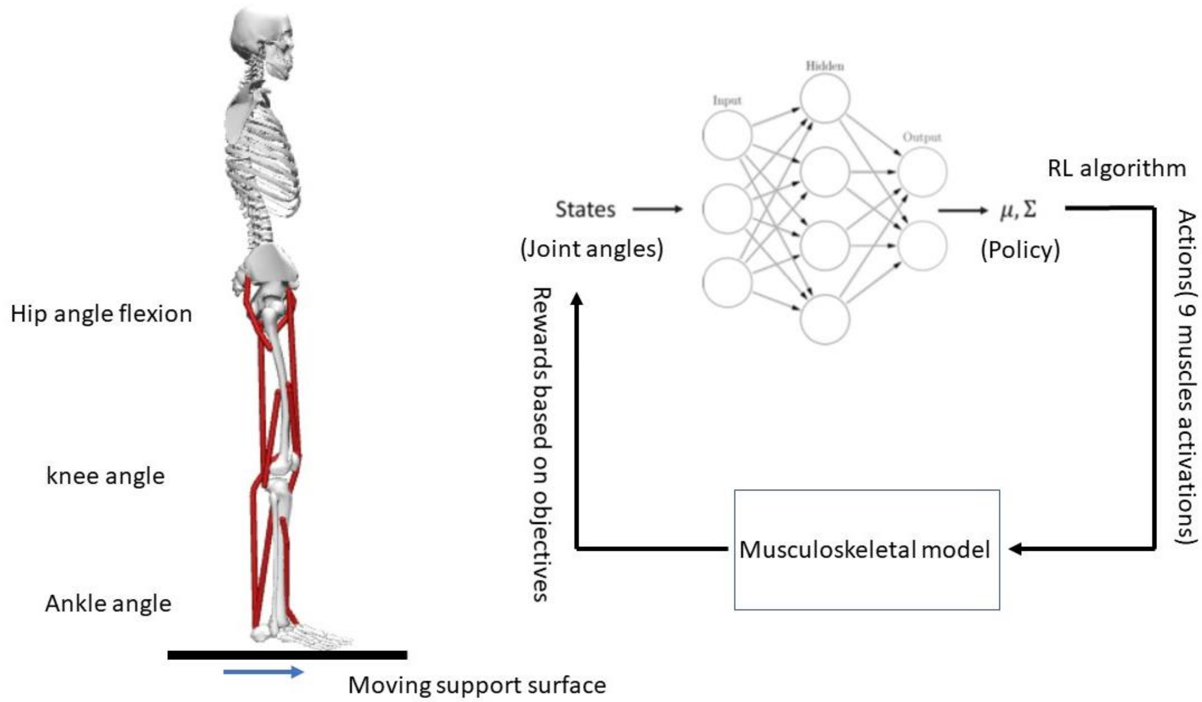
RL model of standing perturbation

Reinforcement learning (RL) is an advanced machine learning method that has been applied to deal with many challenging applications, such as control sophisticated robotics [1-3] training agents outperforming top human players in decision-making games [4]. Compared to other data-driven approaches such as supervised learning and unsupervised learning that passively learn from the input data, the RL inherently reflects how humans and other animals learn in real-world environments by actively exploring the given environment[5]. Additionally, in the RL algorithm the decision at each timestep depends on previous decisions, while the outputs of supervised and unsupervised learnings are independent. This trait exists in the level of each muscle activation which is also dependent on the level of activation of that muscle in previous time steps [6] which makes RL a beneficial candidate to tackle such fields. Furthermore, RL is able to find solutions without requiring predefined knowledge if the agent can sufficiently explore the input domain of the environment [7]. Due to these advantages, there has been an increasing number of RL applications in the field of human biomechanics for MSK model simulation, such as training a rigid-body MSK model to run and avoid obstacles [8-10], and assistive device control to change joint dynamics, such as learning optimal control of prosthetic legs [11,12]. However, the number of studies that use RL to estimate joint moments via kinematics or EMG signals to assist human biomechanics study has been quite limited[13].

In this study, we aim to implement an RL based algorithm to study human response to the external disturbance in stance. Maintaining standing balance is achieved by keeping the ground projection of the body center of mass (COM) within the base of support(BOS) [14]. The goal of the simulation is to find the muscle activation patterns allowing effective and efficient balance recovery from forward-inclined initial velocity induced by support surface. This study will build the ground for further investigation on traits of human response to a standing perturbation that cannot be studied experimentally such as muscle short-range stiffness[15]. These neuromuscular models also provide an effective mechanism to support robust robotic control in addressing the uncertainty led by the environment [16].

To this purpose analyses of perturbed standing balance during forward translations of the support surface using an Open Sim lower-limb musculoskeletal model consisting of 3 degrees of freedom and 9 muscles per leg are conducted. The foot of the model is fixed to the ground assuming there would be no hill lifting with the no-slip assumption during the perturbation (ankle joint is fixed to the ground). The response of the model is also assumed to be symmetrical in the sagittal plane. This model is illustrated in the figure below. We aim to find a response of the model to the external disturbance which is a combination of those 9 muscle activation patterns across all time-steps of the simulation so COM horizontal position will be minimized from reference point and be within the base of support, muscles squared torques around the joint and joint squared speeds, and the total time will be optimized. Total time is also one of the variables to be optimized because it would vary with different joint activation patterns and the optimization became an open final time problem.



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