Reinforcement Learning project 2025

Introduction

The generation of human motion via machine learning is challenging, involving principles from neuroscience, biomechanics, and control theory. In this project, the main objective is to develop a machine learning-based system that allows the agent to perform a reaching task toward dynamic targets. In this case, we will employ musculoskeletal models. This document outlines concepts of musculoskeletal modeling and control objectives, describes the project goals, and provides a comprehensive guide to formulating the problem as an MDP problem and solving it using reinforcement learning (RL) approaches.

Musculoskeletal Models

Musculoskeletal models involve simulating the dynamics of the human body by representing the muscles, tendons, and skeleton. Here is where the movement is generated mainly by muscle activation. Muscle activation not only produces forces but also has to deal with other physiological constraints (gravity, friction, inertia, internal structure of the muscle's dynamics). Hill's model is probably the most famous model used to define muscle dynamics; it presents the muscle-force and muscle-length relationship and provides information on how muscular forces might alter when a muscle contracts or extends for movement control.

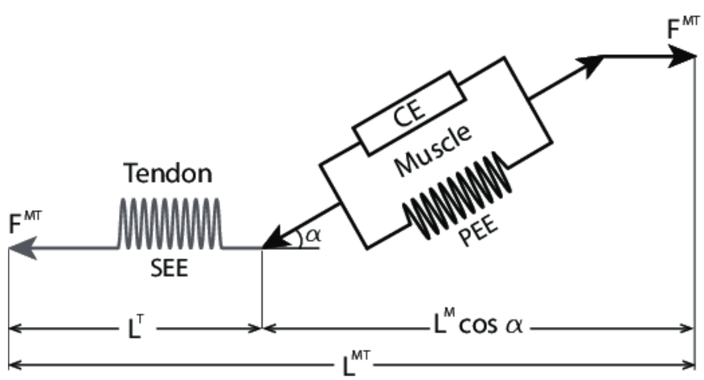

Figure 1: Hill's elastic muscle model

So, controlling such a system can be difficult due to the complex interaction among neural commands, muscle dynamics, and external physical forces. To address these complexities, specialized simulation tools such as MyoSim have been created, which support fully interactive contact rich simulation. MyoSim includes models for different parts of the human body such as the finger, elbow, hand, leg, arm, and a hybrid musculoskeletal-exoskeletal model.

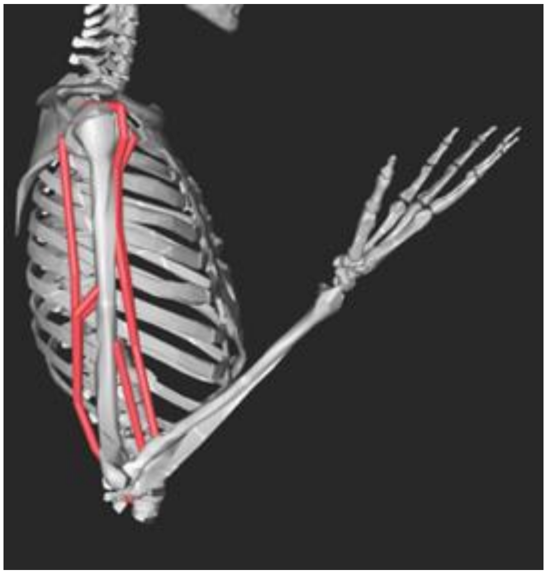

Figure 2: Example of MyoSuite's model (myoElbow)

Problem Statement

The ultimate objective of this project is to create a machine learning-based control system that can address the problem of executing a reaching task with moving targets. This requires the design of a reinforcement learning algorithm that can learn a policy to control the dynamics of a system made up of six muscles under some physical constraints (gravity, friction, inertia) and muscle dynamics described by Hill's model.

This is formalized as a sequential decision-making task. At each time step, the agent has to choose how to modulate muscle activations to achieve a smooth and coordinated movement, adapting to continuously changing target positions. Ultimately, the performance of the agent will be evaluated by how well it is able to successfully and efficiently reach these moving targets.

To sum up everything that has been stated, the primary challenge is to reach moving targets using RL algorithms. Specifically, a control policy that manages a system of six muscles, taking into account muscle activations, physical constraints such as gravity and friction, and the intrinsic muscle dynamics modeled by Hill’s model.

So, you will first need to define one or more Markov Decision Processes tailored to the problem. This includes outlining the definition of state and reward function and providing justification of your choices. Subsequently, you are to study and select proper RL approaches to solve the formulated MDPs. This, too, requires justification for choice and description of essential technical considerations of the algorithms that one has selected. Lastly, you have to evaluate the proposed policies for their success in providing smooth, coordinated movement toward the moving targets.

- **Deliverables** for this assignment are a report (20 pages maximum) and the complete code.
- The **deadline** for submission is Friday, March 7th.

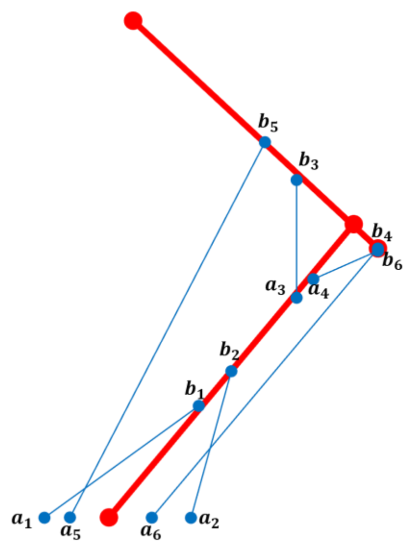

Figure 3: Diagram of the simplified arm model with two DoFs and six muscles, some of them being bi-articular. The muscle origins are labeled as a_i and the muscle insertions as b_i

References

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