Deep reinforcement learning for controlling musculoskeletal spine models

Background Human movement requires controlling a high-dimensional, redundantly actuated musculoskeletal (MSK) system. Based on delayed multisensory feedback and internal motor programs, the central nervous system sends neural control signals to drive our muscles to produce motion. Using detailed and physiologically accurate MSK models, we can use simulation to understand aspects on how humans control and move their MSK system that are difficult or impossible to obtain experimentally. Traditionally, biomechanical simulation has relied on inverse analyses of measured movement, such as OpenSim[1–3].

More recently, the Myosuite/Mujoco framework enables forward-dynamic simulation of muscle-actuated MSK models, with control policies trained using deep reinforcement learning (RL) [4]. Such forward simulations open the door to a wide range of applications: investigating and probing neural control strategies and muscle synergies, in-silico testing of orthoses, exoskeletons and surgical interventions, and generating synthetic training data for wearable sensing and clinical biomarkers.

Realizing this potential, however, requires MSK models whose parameters and emergent behaviour have been validated. To date, spinal modeling in Myosuite has received comparatively little attention, despite the spine's central role in nearly all human movement and postural control.

To address this, this master thesis aims to refine and validate the current Myosuite/Mujoco MSK spine model[5,6], improve the associated deep RL environment, and validate trained control policies, with the goal of producing neuromechanically plausible behaviour suitable for future research applications.

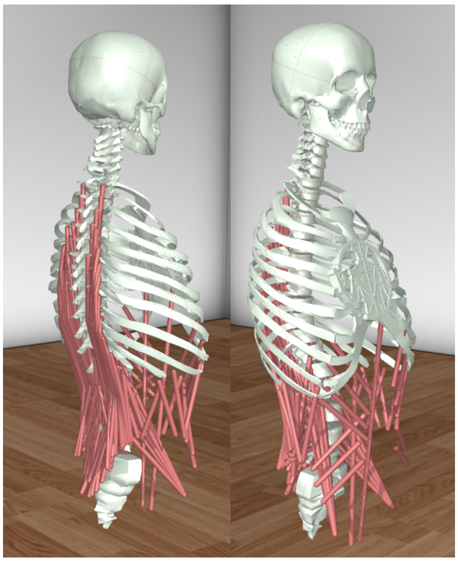

Figure 1. Musculoskeletal spine model as implemented in Myosuite (Mujoco).

Materials and Methods You will 1) use a previously developed MSK spine model implemented in Myosuite (Mujoco) and refine its muscle paths, moment arms using OpenSim spine model data and literature values; 2) use deep RL (e.g., PPO) to train policies to maintain upright posture and improve the neuromechanical accuracy of the reinforcement learning environment, and 3) use already available literature and lab data collected on human participants to validate kinematic and neural control outcomes resulting from trained policies.

References

1 Christophy, M. *et al. Biomech. Model. Mechanobiol.* 11, 19–34 (2012)
2 Beaucage-Gauvreau, E. *et al. Comput Methods Biomech Biomed Engin* 22, 451–464 (2019)
3 Bruno, A. G. *et al. J Biomech Eng* 137, 81003 (2015)
4 Caggiano, V. *et al.* (2022) arXivpreprintarXiv:2205.13600
5 Wang, H. *et al.* (2025) doi:10.1101/2025.06.05.656344
6 Walia, R. *et al.* (2025) doi:10.1101/2025.03.13.643057

Nature of the Thesis:
Literature reviews: 10%
MSK model manipulation: 30%
Deep RL manipulation and training policies: 30%
Validation generated simulations: 20%
Documentation: 10%

Requirements:

- Interest in biomechanics, deep learning/reinforcement learning, and computational modeling
- Programming skills in Python, experience with OpenSim is an advantage

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