The Potential of Reinforcement Learning for Lumbar Load Prediction in Multi Body Models of the Spine

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Introduction

Multi body models (MBS) of the spine are an integral part of clinical and biomechanical research. Their non-invasive and adaptive character makes them a promising tool to address a large variety of questions regarding spinal loading, its causes, and consequences for the healthy and pathological spine. Thus, we can gain valuable insights to support injury prevention, personalized medicine, treatment and rehabilitation planning, implant design, and even sports performance.

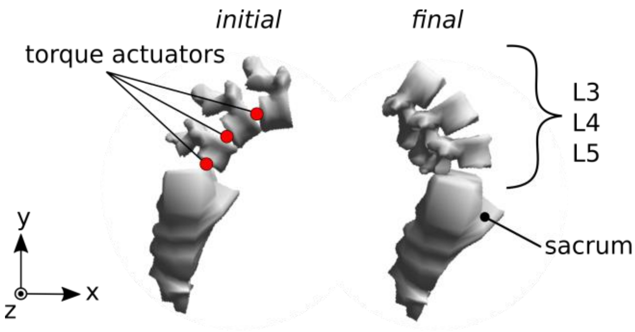

Figure 1: The MBS model of the lumbar spine.

Most studies including MBS of the spine use a combination of inverse kinematics and optimization for muscle force and lumbar load estimation. However, these approaches either use generic assumptions for loading tasks of low complexity or require kinematic data from experimental studies. In this study, we address the following question: *What is the potential of the Reinforcement Learning (RL) algorithms [1] for predicting existing optimal torques?*

Methods

Model of the lumbar spine. We built an MBS of the lumbar spine (Figure 1) in OpenSim [2] to investigate the robustness of the RL algorithms concerning the movements that the model can perform while being limited by its degrees of freedom. At the same time, this model will allow us to study the scalability of the RL algorithms with respect to the dimensionality of the data, which the model produces, and the algorithms must process. Accordingly, before attempting to predict the lumbar spine's joint torques by using a detailed MBS, we must validate that the RL algorithms can predict realistic torques using a simple MBS. The first version of our model featured three joints with one rotational degree of freedom in the sagittal plane.

Trajectory optimization. We used OpenSim Moco, the trajectory optimization tool for musculoskeletal optimal control, to generate the optimal torques and trajectory of a lumbar extension. Considering the extension's duration (2 seconds) and its initial and final joint configurations, OpenSim Moco applies direct collocation to minimize the joint torques and computes the extension's optimal trajectory. The optimal torques (Figure 2, in orange), and trajectory are used as ground truth for the RL algorithms.

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Reinforcement Learning. RL is a machine learning paradigm rooted in behavioral psychology. It involves training an agent to make progressively improved decisions within an environment while aiming to maximize a cumulative reward. In our context, the OpenSim simulator represents the environment, a deep neural network (DNN) represents the agent, and the reward is computed relative to the kinematics of the extension's optimal trajectory. The DNN takes the joint states of the MBS model as input and forecasts the (next) torques to be applied in OpenSim's (forward) simulation. To train the agent, we used the Behavioral Cloning (BC) [3] RL algorithm. As BC strives to replicate the kinematics of the extension's optimal trajectory, the DNN that it trains inherently learns to predict the extension's optimal torques.

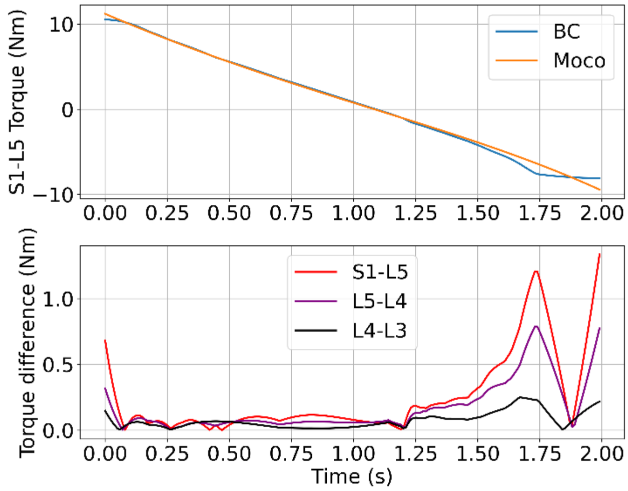

Figure 2: On top: the optimal (orange) and predicted (blue) torques for the joint between S1 and L5 vertebrae. At the bottom: the absolute differences per joint for all three joints.

Results

We evaluated how precisely the BC algorithm predicted the optimal torques. In Figure 2, except for the trajectory's beginning and end, the predicted torques (in blue) closely resemble the optimal ones (in orange). The absolute offsets between the optimal and predicted torques are depicted at the bottom of Figure 2. BC's precision represents solid evidence that the RL algorithms can predict existing optimal torques of a lumbar spine extension, and encourage us to address follow-up questions.

Ongoing research

Our in-progress experiments address the question: *Can the RL algorithms predict the optimal torques of a new lumbar extension in changed boundary conditions and without kinematic data?* and show promise in answering it affirmatively. While the BC algorithm uses the optimal torques during its training, more advanced algorithms like Deep Deterministic Policy Gradient, Proximal Policy Optimization, or Soft Actor Critic can predict the lumbar spine's joint torques without relying on optimal torques.

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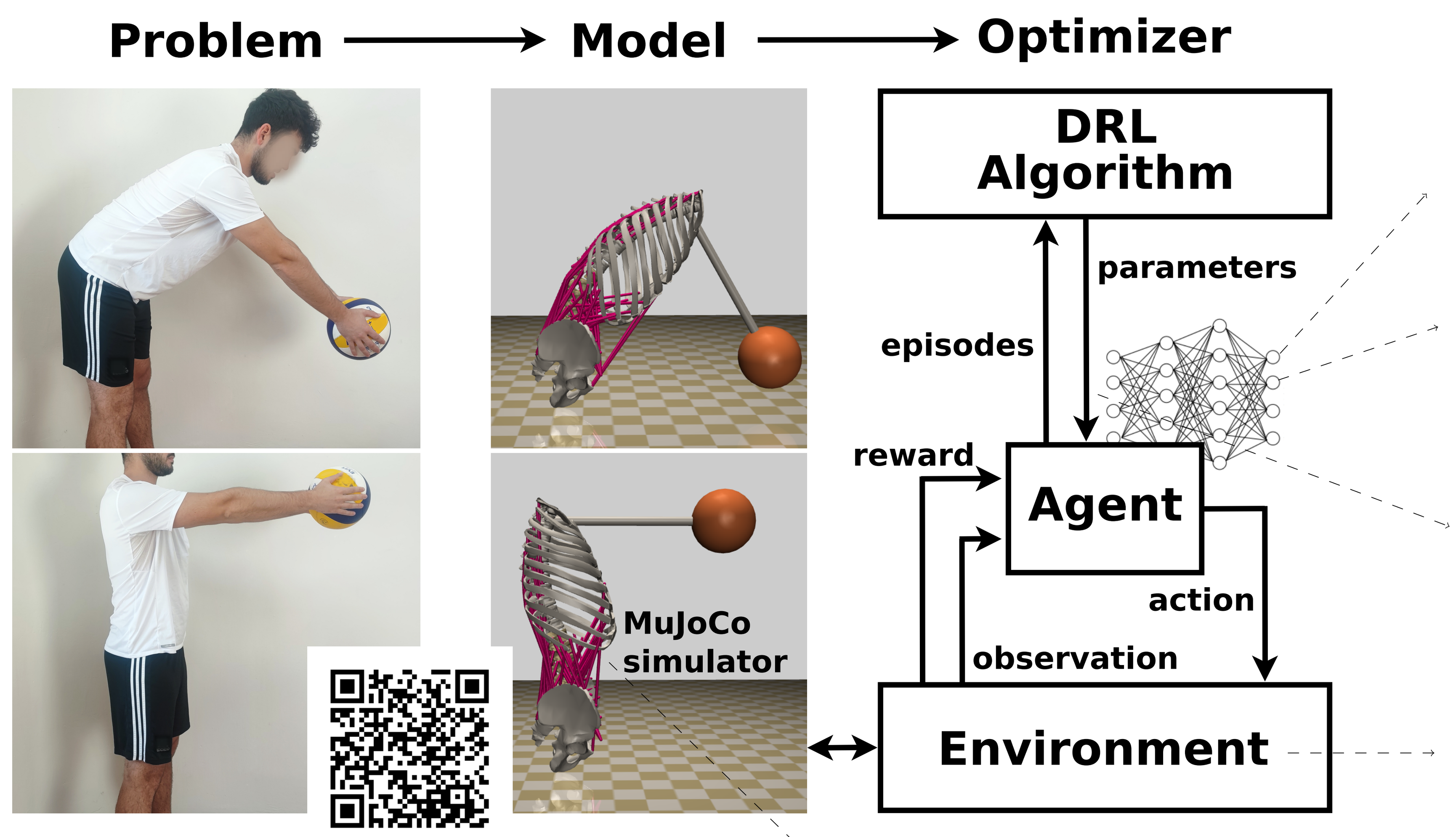

Figure 1: Modeling a spine extension and learning its corresponding muscle activation and muscle forces using DRL algorithms.

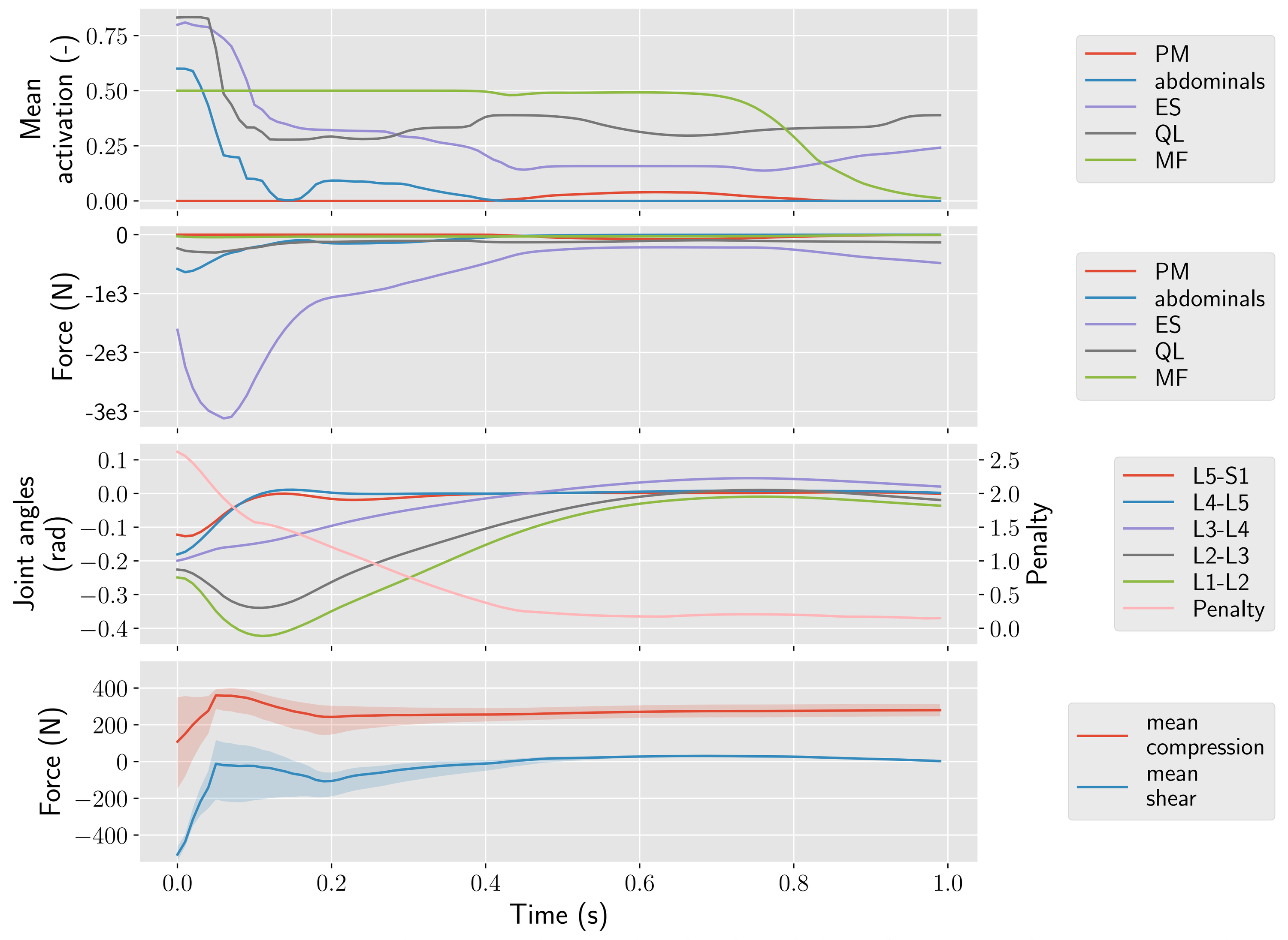

Figure 2: The forces and activation which the DDPG algorithm learned. They correspond to the muscles described in Fig. 4. Penalty is reward without bonus.

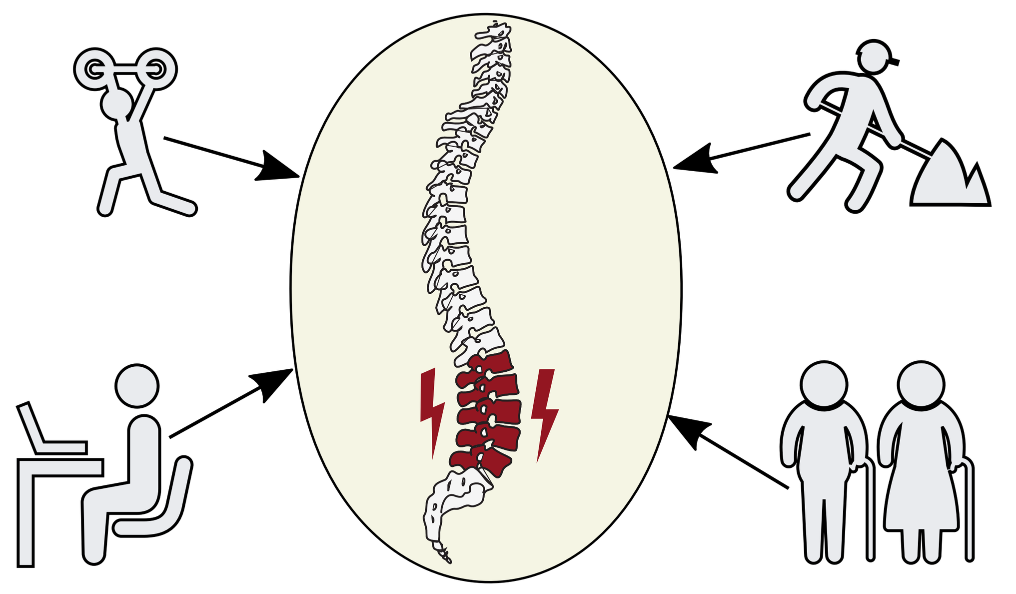

Figure 3: The most frequent causes of spine injuries.

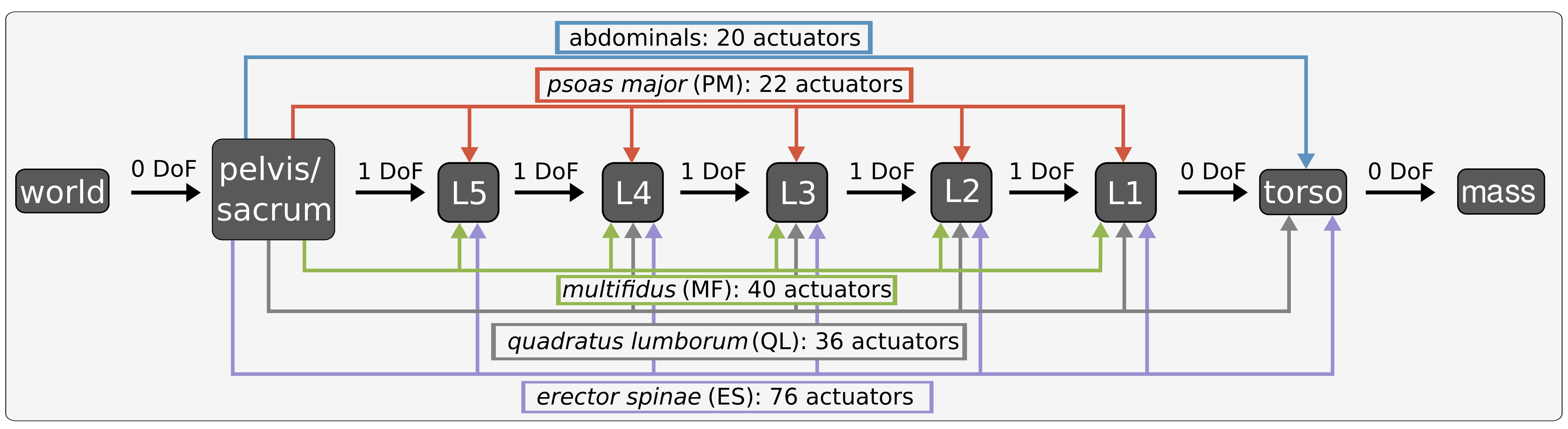

Figure 4: Block diagram of the MBS with indication of the muscle actuator groups.

A new methodology for ...

➧ ... predicting the **muscle activation** and **forces** of a **lumbar spine extension** by leveraging the **Deep Reinforcement Learning** algorithms.

Problems

❢ Clinical problems
- → spine injuries [1].
- → estimation of the spine's mechanical loading.

❢ Limitations of the state-of-the-art optimizers
- → reduced variety of predictive simulations [2].
- → require a complex problem definition.
- → depend on solvers sensitive to initial guesses.

Deep Reinforcement Learning

✯ is Machine Learning based on *trial-and-error*.

✯ ***DRL Algorithm*** (Fig. 1)
- → performs the *Optimizer*'s role.
- → trains the *Agent* to maximize the *reward* which it collects from the *Environment*.
- → improves *Agent*'s *parameters* based on the *episodes* (*trial-and-error* simulations), which the *Agent* performs in the *Environment*.

✯ ***Agent***
- → *observes* the state of the *Environment* and decides the *action* that the *Environment* will perform in the next simulation cycle.

✯ ***Environment***
- → takes *Agent*'s *action* and performs a forward simulation cycle in the MuJoCo [3] simulator.
- → computes the *reward* based on the state of the lumbar spine model inside MuJoCo.

Methodology's steps

✍ **Task**
- ➢ *Learn the **muscle activation** that flexes the torso into a vertical position, as shown in the QR-Linked video* (Fig. 1).

✍ **Lumbar spine's MBS[7] model** (Fig. 4)
- ➢ derived from Christophy's model [4].
  - → partially reimplemented in MuJoCo.
  - → muscle model very similar to OpenSim [5].
- ➢ **Kinematic chain**
  - → *pelvis* and *sacrum* are fixed relative to the *world* coordinate system.
  - → lumbar vertebral bodies *L5*, *L4*, *L3*, *L2* and *L1* rotate in sagittal plane.
  - → *torso* is fixed relative to *L1*.
  - → a *mass* of 5 kg is fixed relative to the *torso*.
- ➢ **Actuation**:
  - → 194 muscle actuators, from 5 muscle groups.
  - → flexors: abdominals and *psoas major*.
  - → extensors: *erector spinae*, *quadratus lumborum*, and *multifidus*.

✍ ***Optimization with DDPG*** [6]:
- ✯ ***Agent***: an ANN[8] as *actor* and an ANN as *critic*
- ✯ ***action***: muscle activation / muscle forces.
- ✯ ***observation***: joint states, joint velocities, muscle forces - all MuJoCo's state variables.
- ✯ ***reward***: *describes* the task.

$$r_t = b - \sum_{i=1}^{5} w_i \cdot |q_{it} - q_{vertical}| \qquad (1)$$

- → b: bonus for reaching the vertical position.
- → q_{it}: joint angle i at time t.
- → w_i: weight parameter of joint i.

Results

✔ **DDPG successfully learned the muscle activation** that the task requires (Fig. 2).

✔ Lumbar joints flex close to the vertical position.

✔ *Erector spinae* dominates the extension.

✔ Absolute peak muscle force per group:

	ES	abs	QL	PM	MF
Peak force (N)	3120	637	303	78	44
Time (s)	0.06	0.01	0.05	0.63	0.05
Episode avg. (N)	775	85	134	25	27

Discussion and Outlook

☞ Muscle, shear and compression forces are within physiological range.

☞ High abdominal activation remains unexplained.

☞ Joint angle trajectories are still not physiological.

☞ Use newer algorithms: PPO[9], SAC[10], TD3[11].

☞ Use model-based / multi-task DRL algorithms.

☞ Insert into the *reward* metrics for physiological realism, i.e. rewarding coupled motion of the vertebrae.

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[7] Multibody Simulation, [8] Artificial Neural Network, [9] Proximal Policy Optimization, [10] Soft Actor Critic, [11] Twin Delayed Deep Deterministic Policy Gradient


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