Professorship of Sport Equipment and Sport Materials
TUM School of Engineering and Design
Technical University of Munich

Towards Predictive Musculoskeletal Simulations of Over-Actuated Human Lumbar Spine Models Using Deep Reinforcement Learning

Gheorghe Lisca, Matthias Kindler, Tanja Lerchl, Cristian Axenie, Thomas Grauschopf and Veit Senner

gheorghe.lisca@tum.de, matthias.kindler@tum.de, tanja.lerchl@tum.de, cristian.axenie@th-nuernberg.de, thomas.grauschopf@thi.de, senner@tum.de

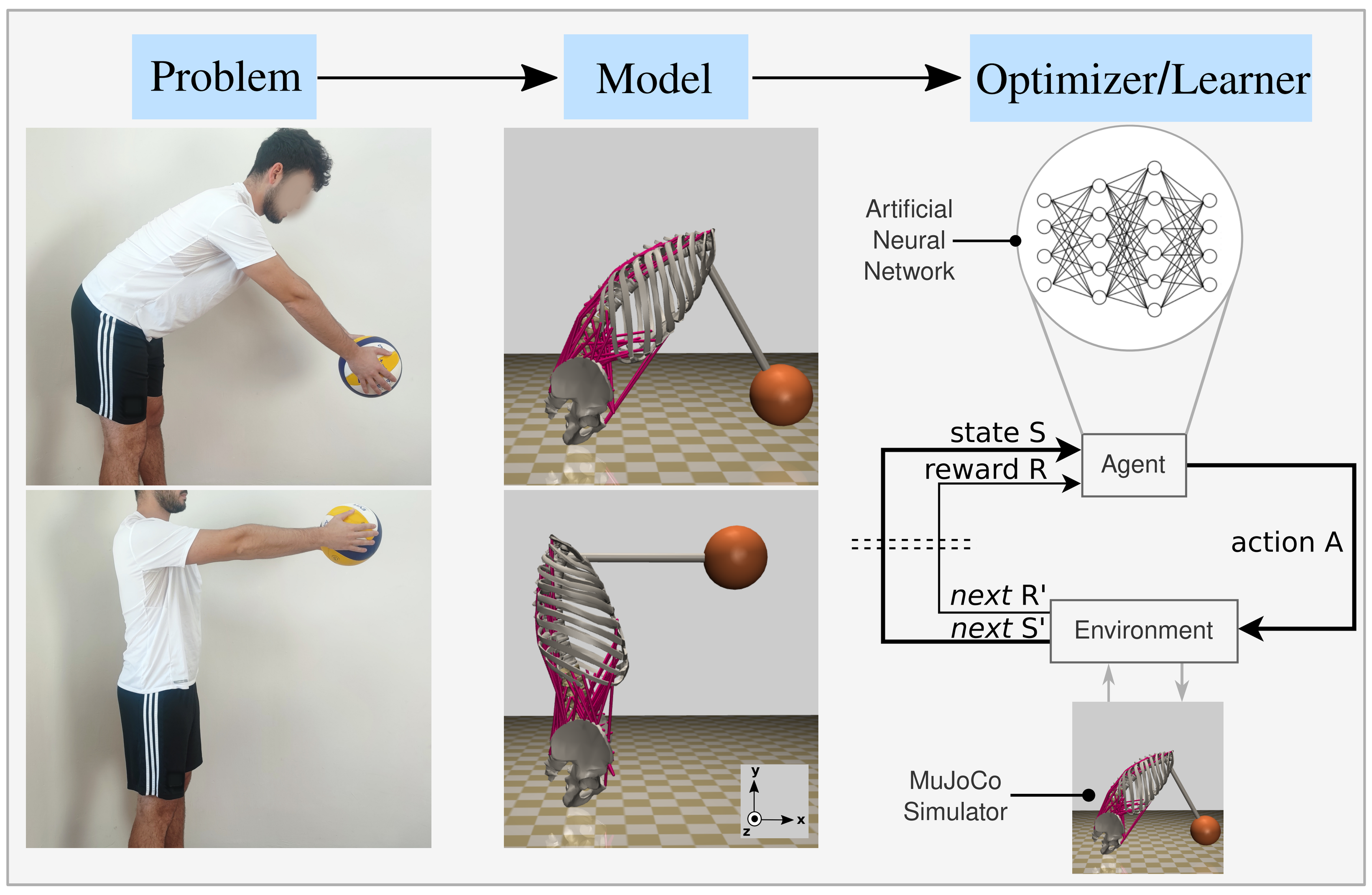


Figure 1: Project workflow from recognizing the problem, to setting up an appropriate model, to using DRL to train an agent to learn the movement.

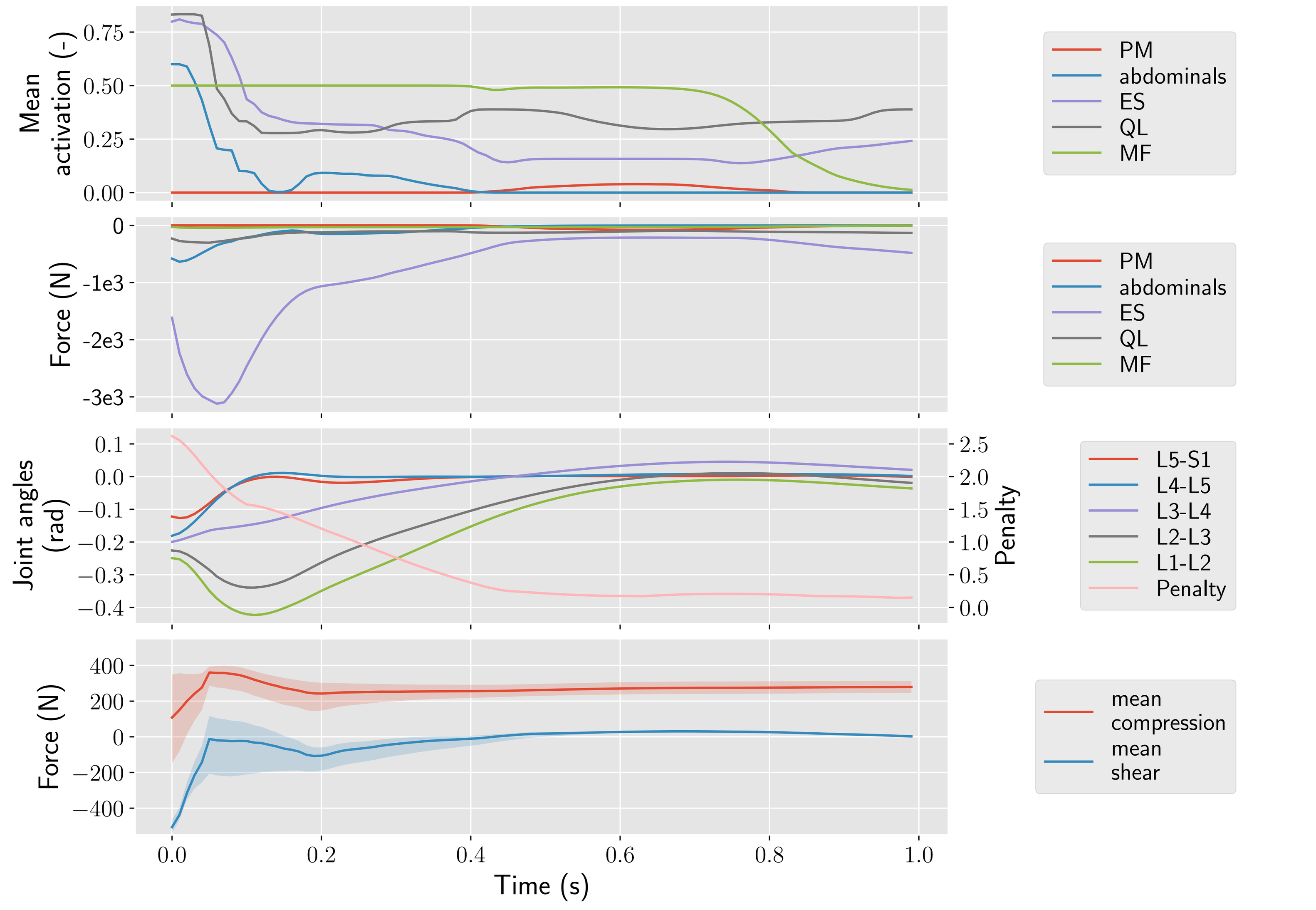
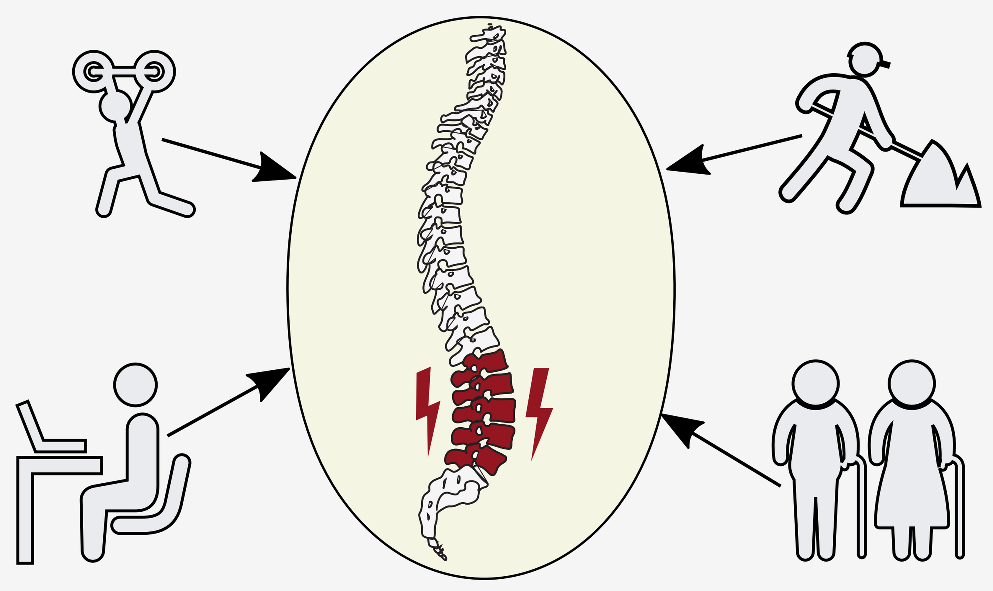


Figure 2: Episode rollout on trained DDPG agent. Penalty is reward without bonus. Forces and activations correspond to the muscles described in Fig. 3

Motivation



- Aging population and sedentary lifestyle associated with chronic back pain
- in the US, 42% of all work-related musculoskeletal injuries affect the Lumbar spine (LS)
- Increased risk of LS injuries in weight-/powerlifting athletes [1]

Project idea:

- learn lumbar muscle forces
- in a musculoskeletal LS model
- performing a rapid extension
- with a heavy object

Muscle redundancy problem:

- musculoskeletal systems have more variables than equations
- no unique solution
- optimization techniques required

Deep Reinforcement Learning:

- Machine Learning based on *trial-and-error*
- learns through environment interaction and feedback
- trains an ANN[1] as an approximation function that maps environment states to actions

Purpose of the study:

- Explore the potential of DRL[2] algorithms for being used in predictive simulations of over-actuated lumbar spine models

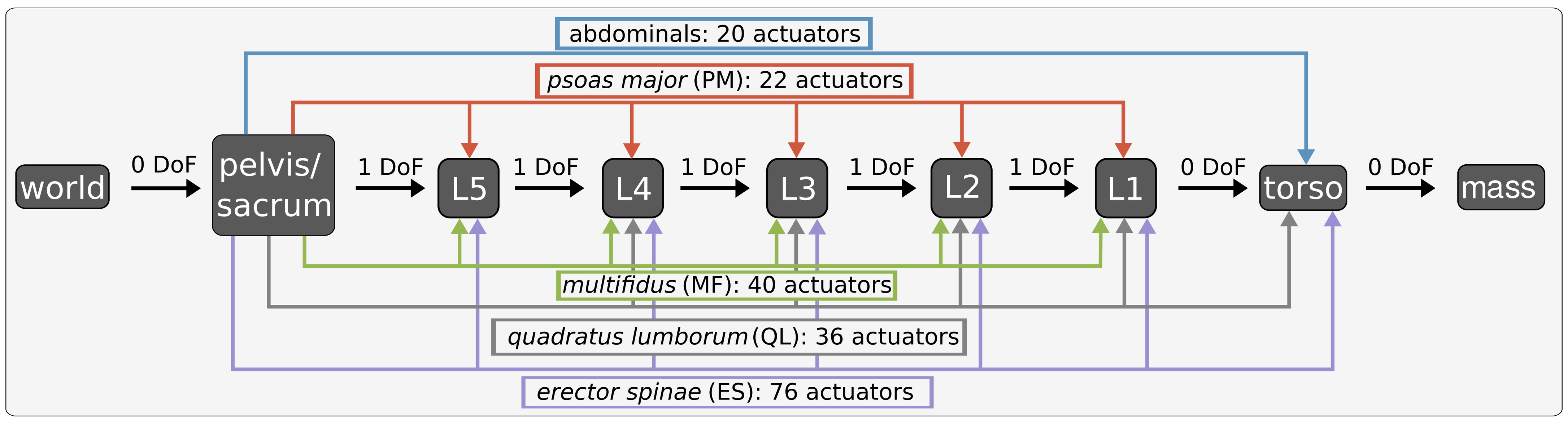


Figure 3: Block diagram of the MBS with indication of the muscle actuator groups.

Methods

Lumbar spine model:

- MBS[3] model implemented in MuJoCo [2]
- based on LS model by Christophy [3]

Kinematic chain (see Fig. 3)

- *pelvis* and *sacrum* are fixed to the world frame
- lumbar vertebral bodies (*L5, L4, L3, L2, L1*) can rotate in sagittal planeNovel
- *mass* (5 kg) fixed to *torso*, which is fixed to *L1*

Actuation (see Fig. 3)

- 194 muscle actuators, from 5 muscle groups
- flexors: abdominals and *psoas major*
- extensors: *erector spinae*, *quadratus lumborum*, and *multifidus*

Optimization with DDPG[4]:

- trains an ANN optimized to accumulate the maximum reward
- the reward *describes* the objective
- a *rapid extension* is described through:

$$r = b - \sum_{i=1}^{5} w_i \cdot |q_i - q_{i,\text{target}}| \quad (1)$$

- q_i, $q_{i,\text{target}}$ – joint (target) angles
- w_i – weight parameter for each vertebrae
- b – bonus for reaching the target position

Results

- DDPG's training converged (Fig. 2)
- lumbar joints come close to target
- *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 in phyiological range
- high abdominal activation unexplained
- joint angle trajectories not physiological

☞ use newer algorithms: PPO[5], SAC[6], TD3[7]
☞ use model-based / multi-task DRL algorithms
☞ include metrics for physiological realism into the reward function
  – promote energy efficiency by penalizing high choice of actions
  – promote physiological joint states by rewarding coupled motion

[1] Ritsch, M. (Sept. 2020). *Sports Orthopaedics and Traumatology*, 36.
[2] Todorov, E., Erez, T., and Tassa, Y. (2012). *International Conference on Intelligent Robots and Systems.*
[3] Christophy, M. et al. (Jan. 2012). *Biomechanics and Modeling in Mechanobiology*, 11.

[1] Artificial Neural Network, [2] Deep Reinforcement Learning, [3] Multibody Simulation, [4] Deep Deterministic Policy Gradient, [5] Proximal Policy Optimization, [6] Soft Actor Critic, [7] Twin Delayed Deep Deterministic Policy Gradient