Towards data-driven predictive control of active upper-body exoskeletons for load carrying

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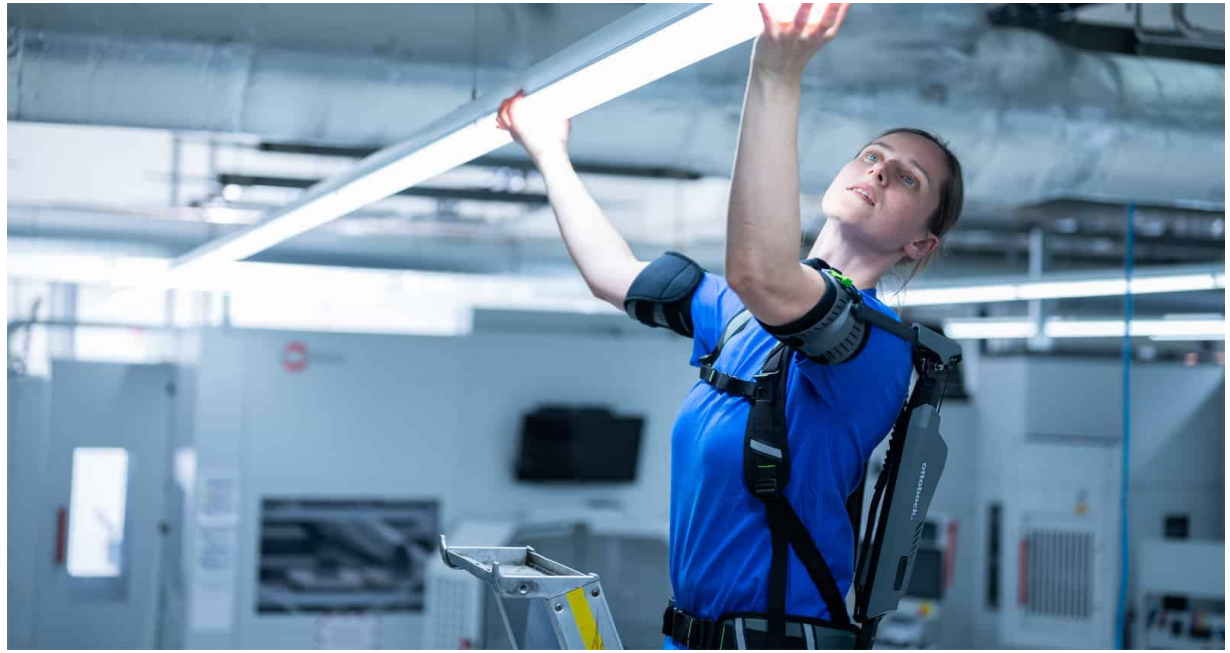
Exoskeletons for WMSD prevention

https://www.nsc.org/safety-first/targeting-prevention-of-work-related-msd

Work-related musculoskeletal disorders (WMSDs): An important issue [1]

Exoskeletons: a possible solution



https://paexo.com/obs/?lang=en

[1] Parent-Thirion A, et al. 2012. Fifth European working conditions survey. Publi. office of the EU

Active exoskeletons

Steve Dent/Engadget

Powerful and versatile…

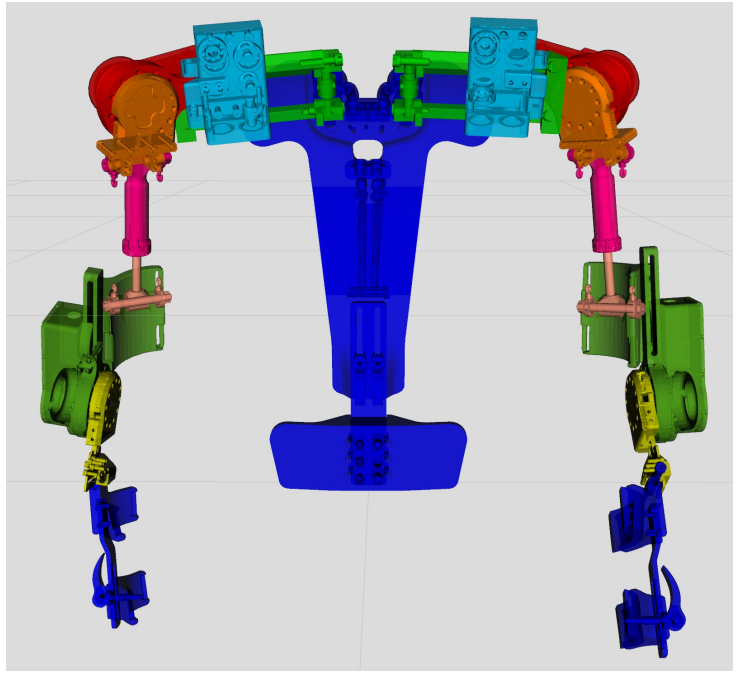
But hard to control…

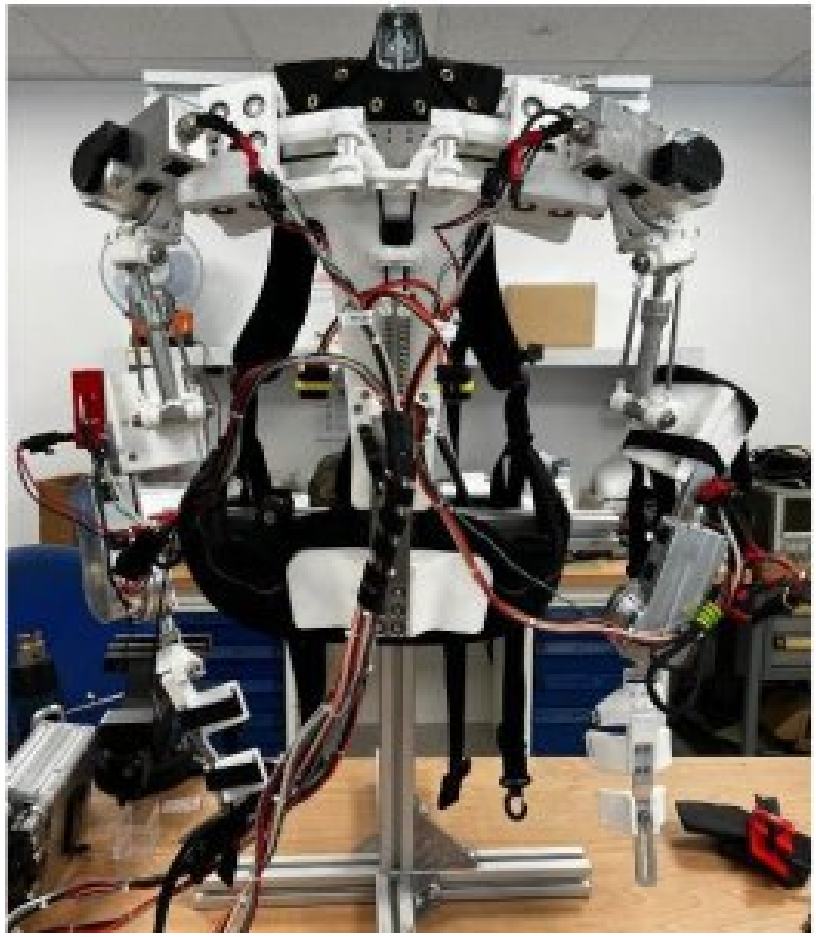
https://www.germanbionic.com/en/5th-generation/

Motion prediction for exoskeleton control

Our Project: Control upper body active exoskeleton using ML-based predictive control for load carrying

- ML-based torque prediction
- Data generation in simulation

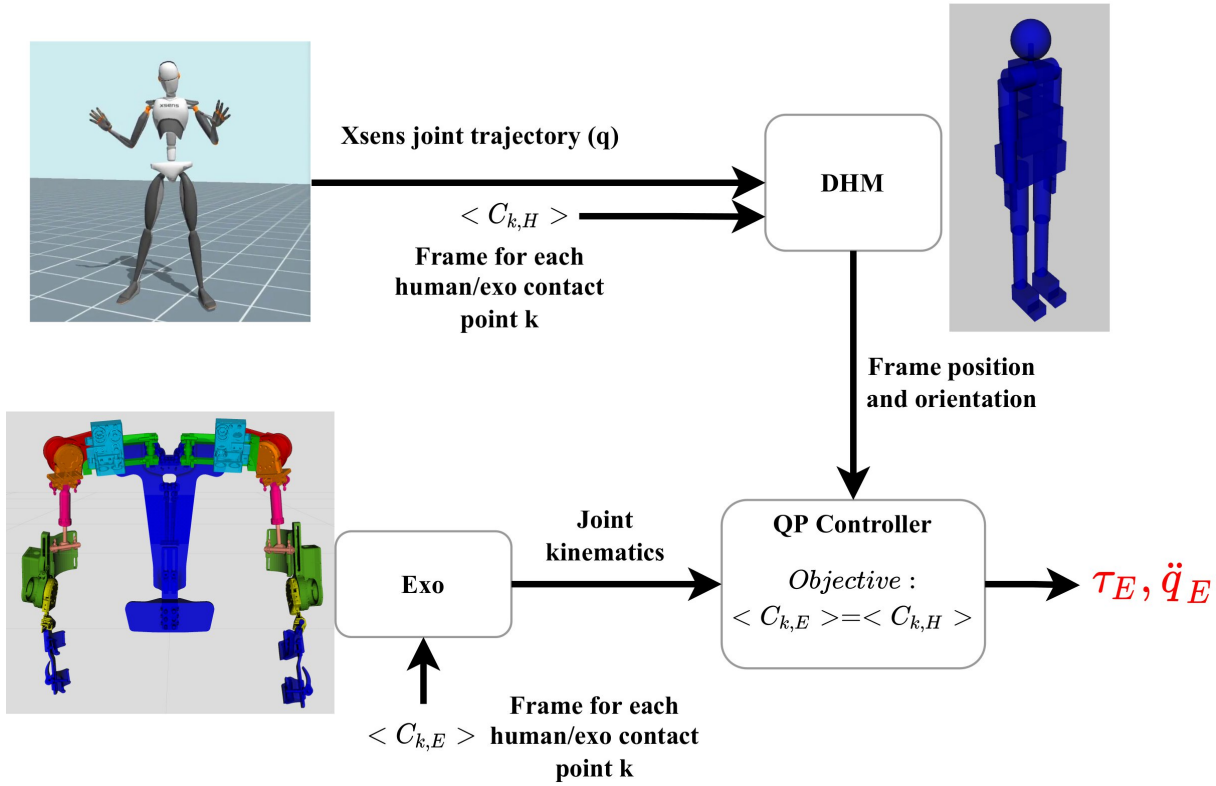


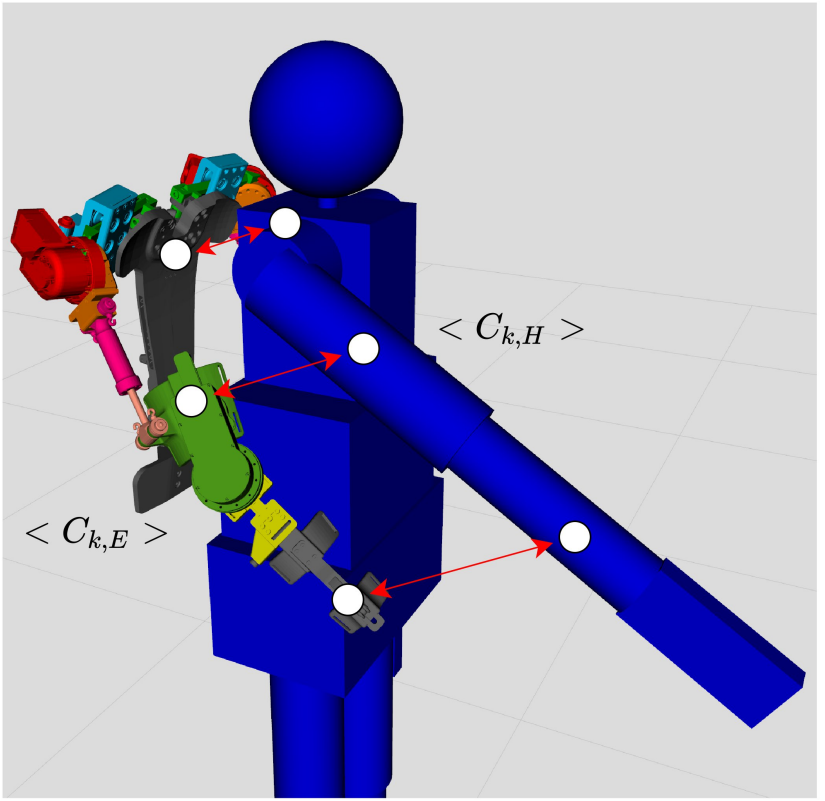


Generating simulated exoskeleton data

Quadratic Programming (QP) controller to control the exoskeleton in simulation

Objective: Minimize the distance between the contact points





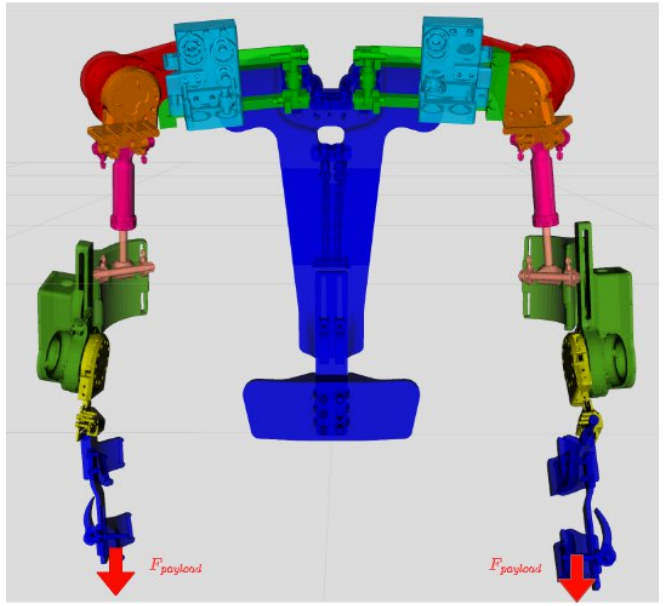
Dataset Generation

Motion capture Dataset

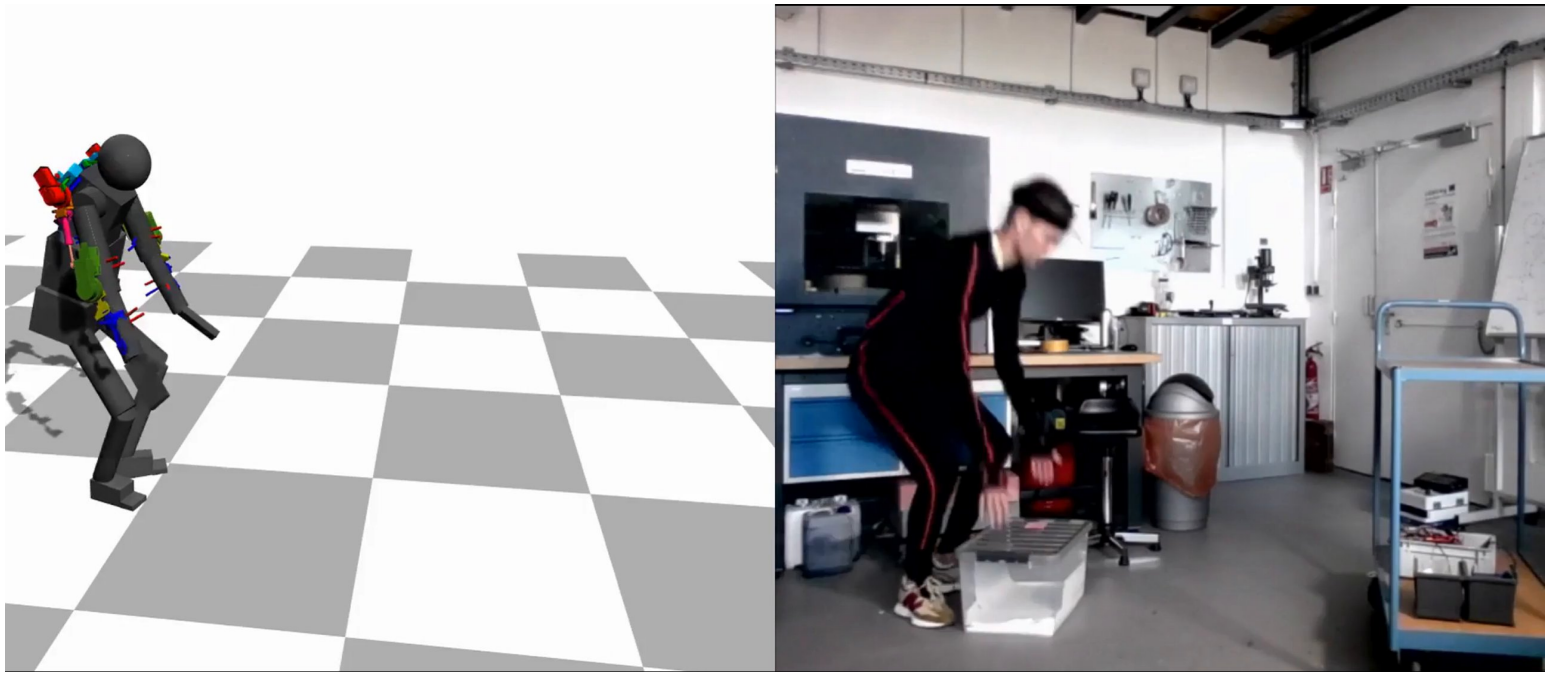
- AndyDataset [1]
- Industry-like activities

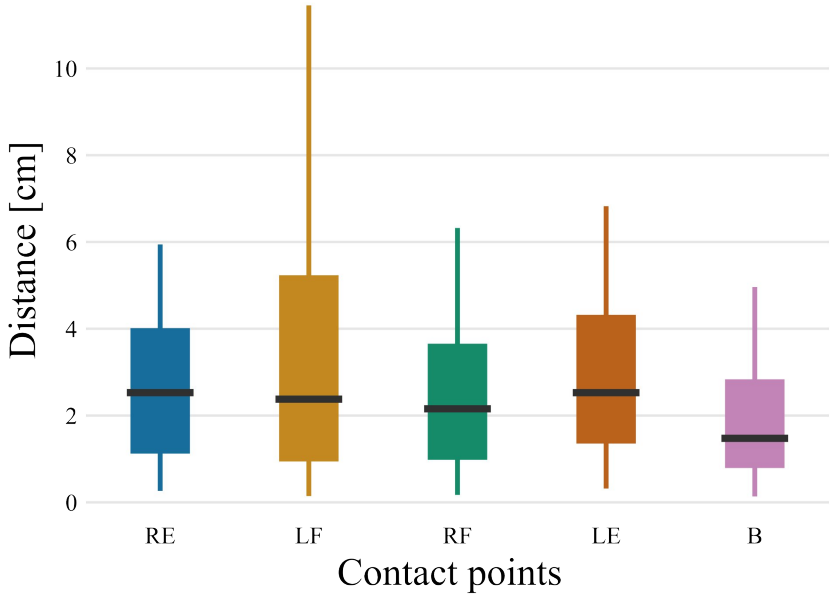
Generated Dataset

- 90 trials of around 2 minutes
- Added external forces (payload)



Simulation results





Error distribution over all the samples for each contact point

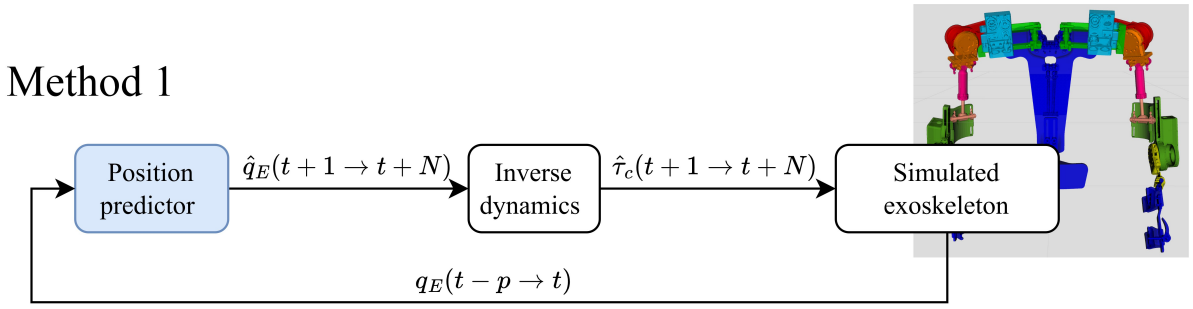
Torque prediction

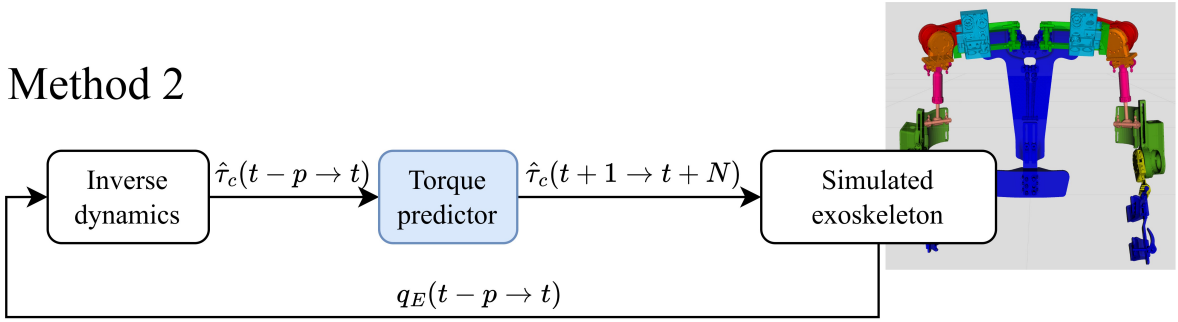
Method 1: PJ+ID

- LSTM-Based joint position prediction
- Dataset generated from AndyDataset
- Inverse dynamics

Method 2: ID+PT

- Inverse dynamics
- Dataset generated from AndyDataset
- LSTM Based joint torque prediction

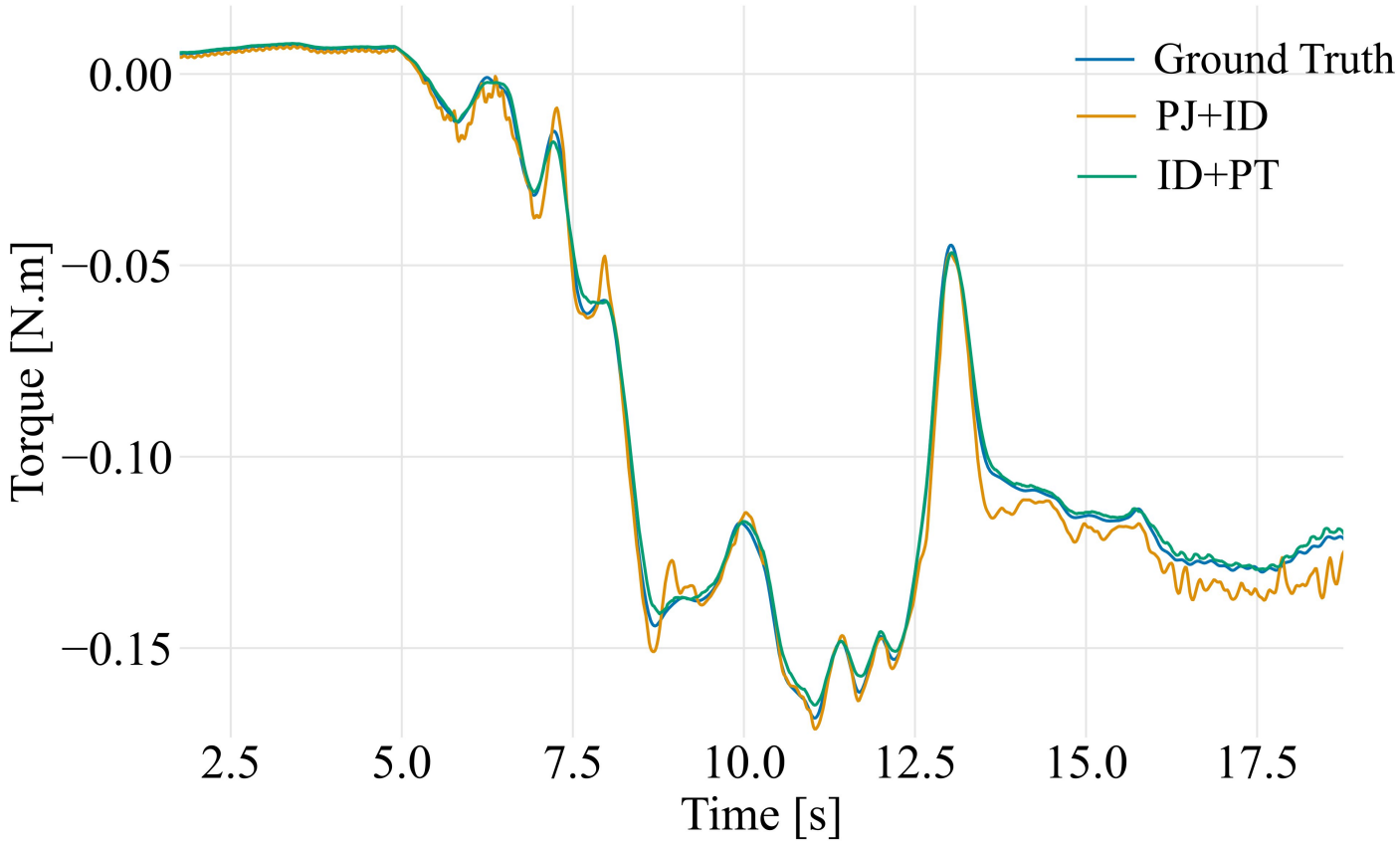




Torque prediction results

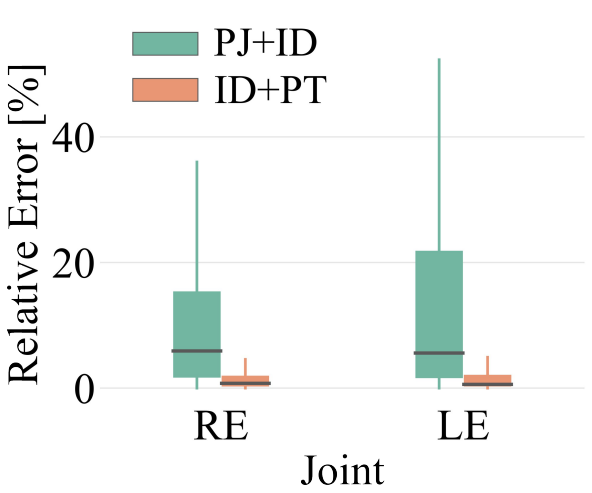
Continuous prediction

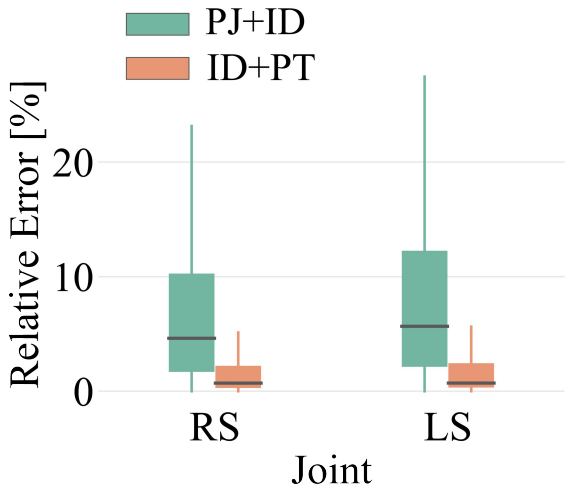
- Sliding window
- 500ms of past
- 100ms in the future



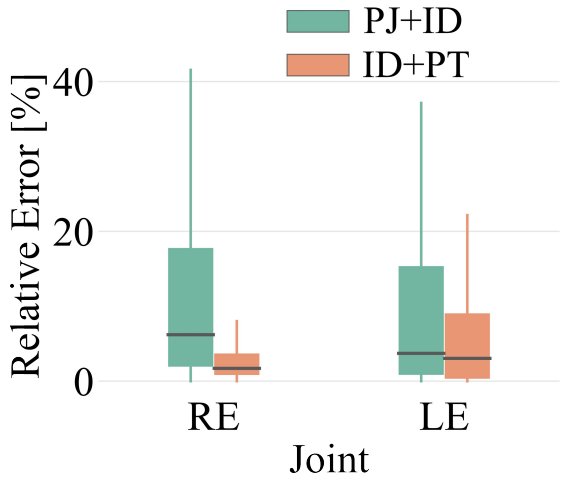
Continuous prediction (concatenation of the predictions over 100ms)

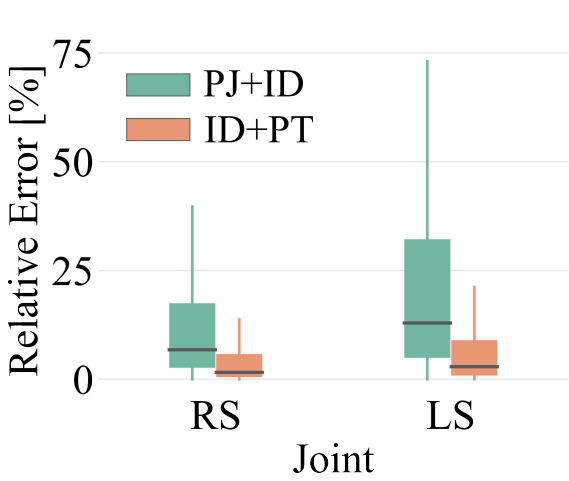
Torque prediction results: Relative error





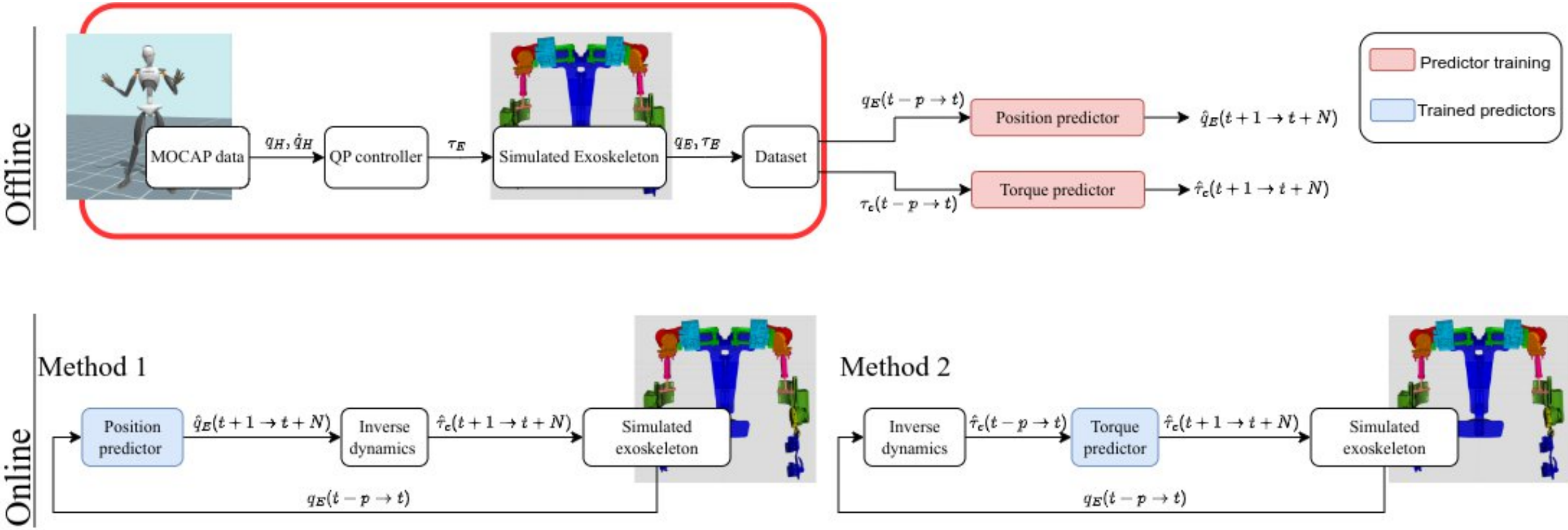
Relative error distribution over all the test samples for 5.5kg





Relative error distribution over all the test samples for 0.0kg

Conclusion


Offline
MOCAP data
$q_H, \dot{q}_H$
QP controller
τ_E
Simulated Exoskeleton
q_E, τ_E
Dataset
$q_E(t-p \to t)$
Position predictor
$\hat{q}_E(t+1 \to t+N)$
$\tau_c(t-p \to t)$
Torque predictor
$\hat{\tau}_c(t+1 \to t+N)$
Predictor training
Trained predictors
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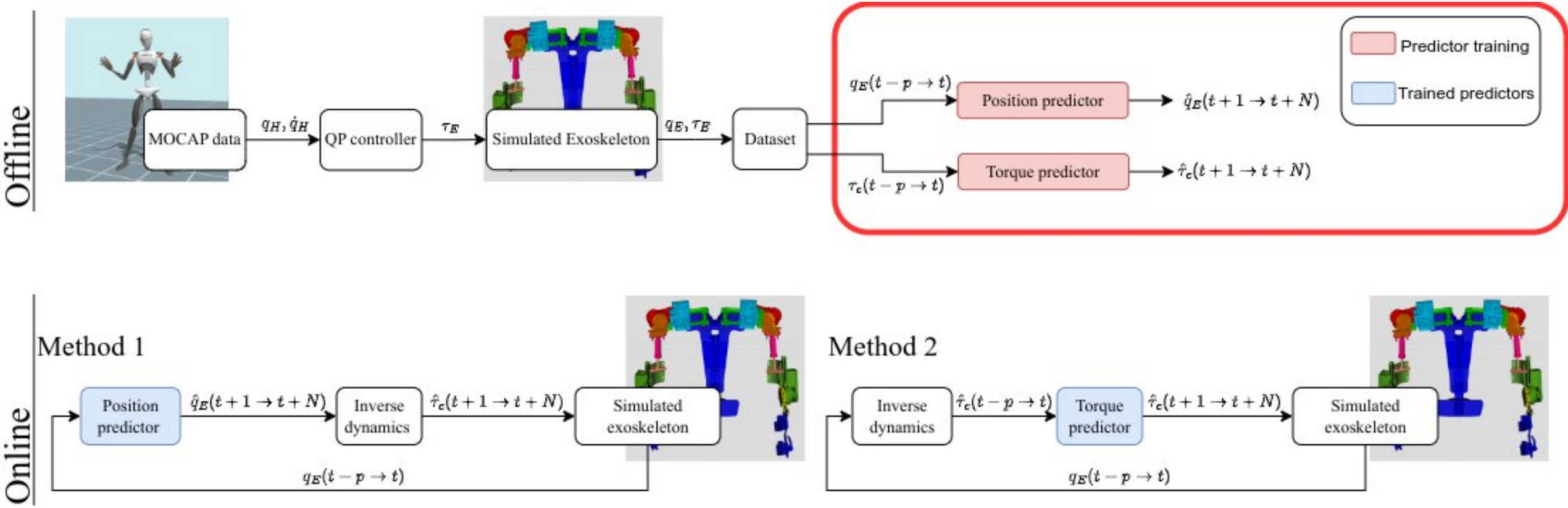
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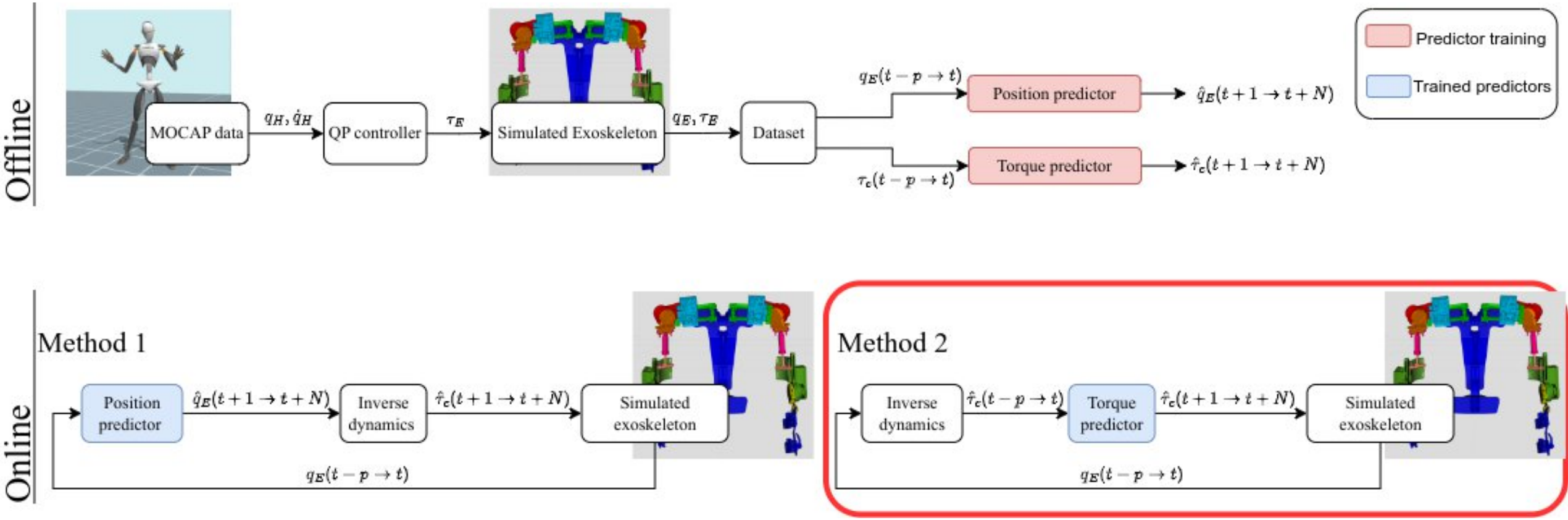
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Thanks for listening !

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