3D Human Pose Estimation with Muscles

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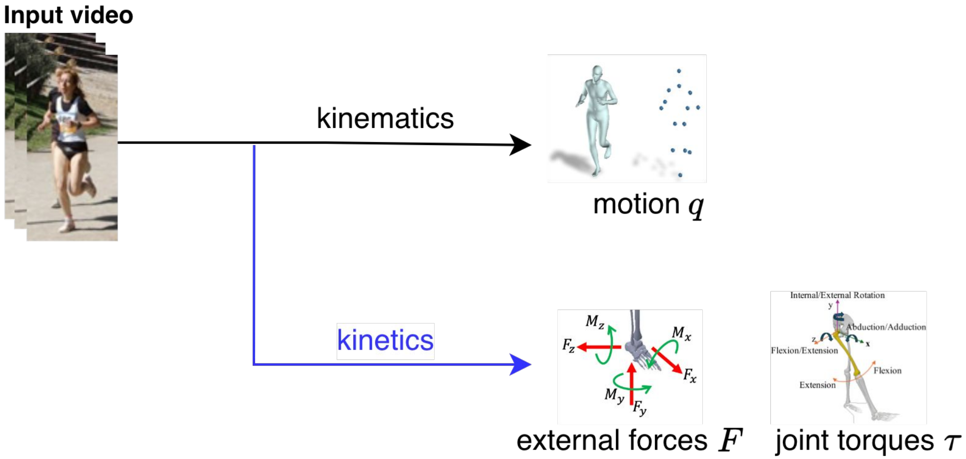
Monocular physics-based human pose estimation

Physics-based human pose estimation (PHPE) aims to reduce motion artifacts and improve contact estimation by enforcing the underlying dynamics equations:

$$M(q, A)\ddot{q} + C\big(q, \dot{q}\big) = \tau + F$$

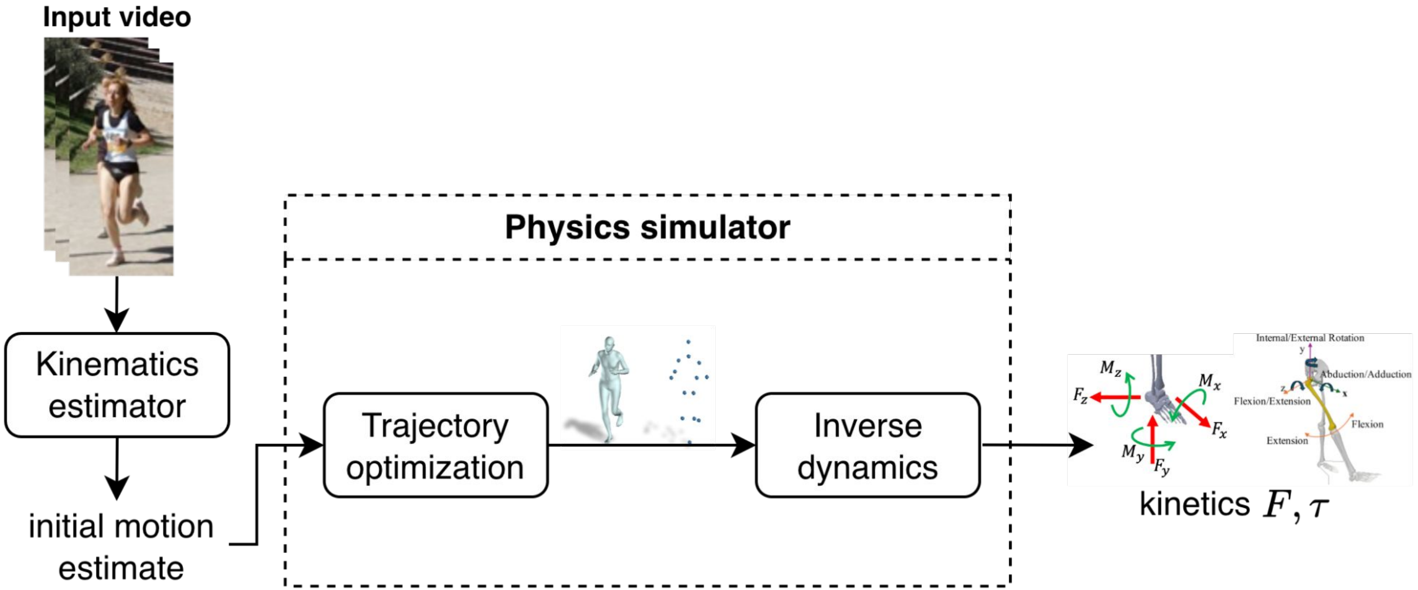
Hence, in addition to human kinematics (motion), we need to estimate the corresponding kinetics (external forces, joint torques, etc).



Optimization-based PHPE [20,19,77,64,41,82,59]

<u>Method 1 (with a physics simulator):</u>

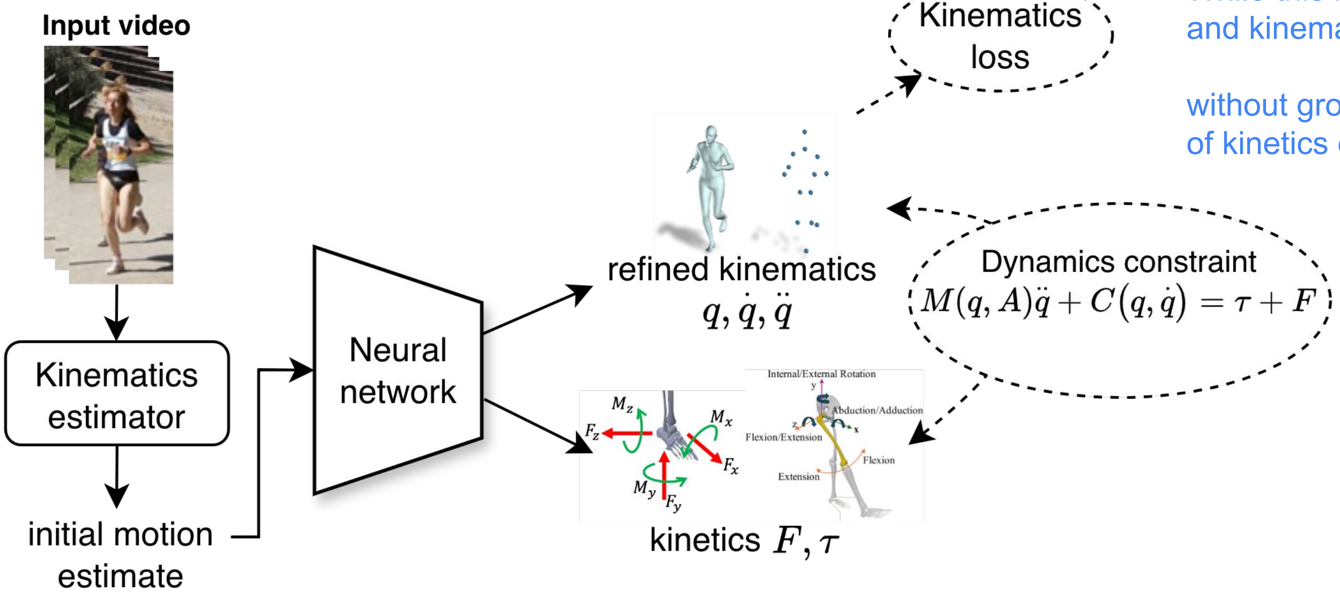
Reconstruct the predicted motion using trajectory optimization with an external physics simulator.



Regression-based PHPE [85,37,63]

<u>Method 2 (without a physics simulator):</u>

Directly regress kinetics, while enforcing a dynamics loss by minimizing residual force.

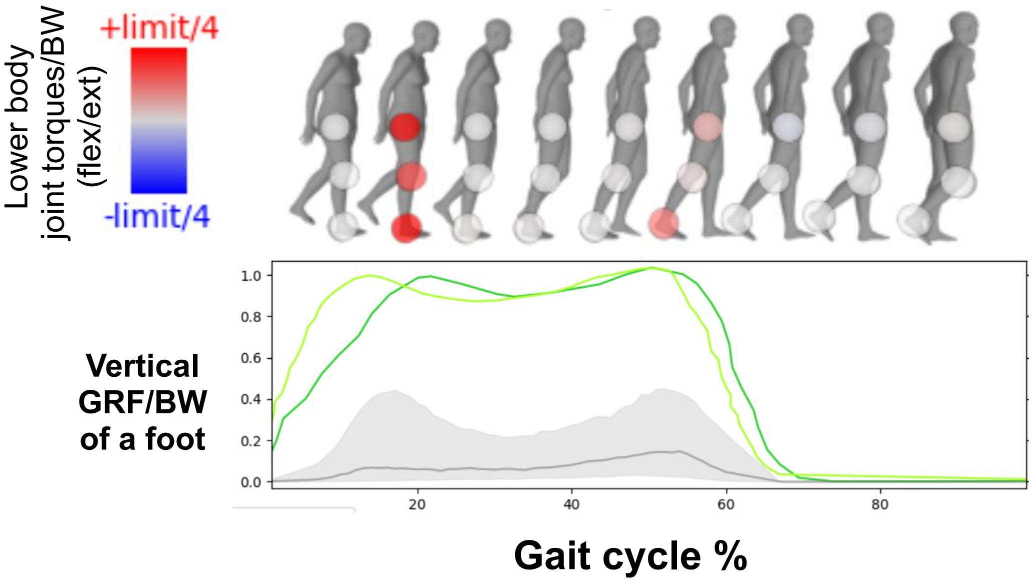


While this improves contact estimation and kinematic plausibility metrics,

without ground-truth force labels, reliability of kinetics estimation unknown.

Examples of implausible kinetics (gait)

Regressed kinetics from a **SOTA pose estimator** [85] vs **biomechanics** references [72,18,76,8,29,75,55,80,62],

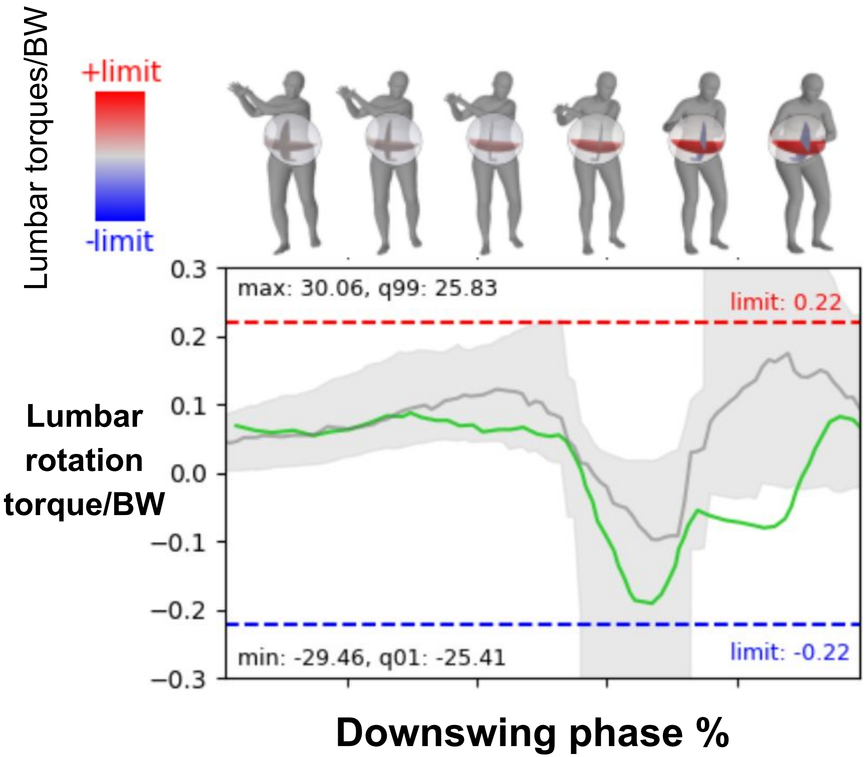


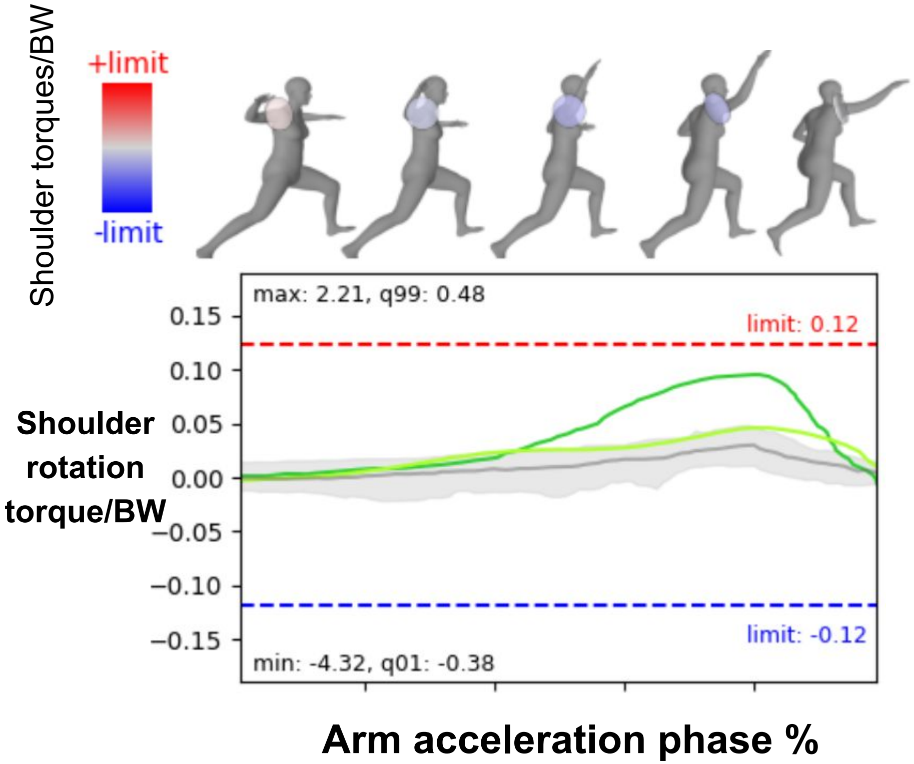
Gray: regressed kinetics from PHPE [85] (median with 25-75% quantile band).

All values scaled by body weight (BW)

Green curves are values collected from other biomechanics studies for comparison of trends and magnitudes.

Examples of implausible kinetics (golf, baseball)

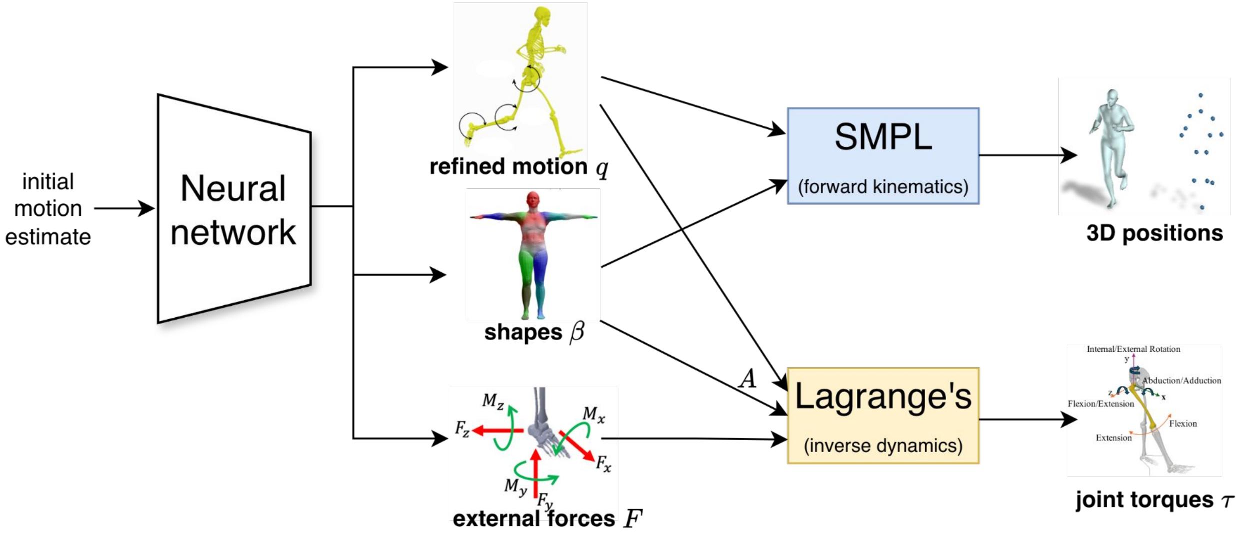




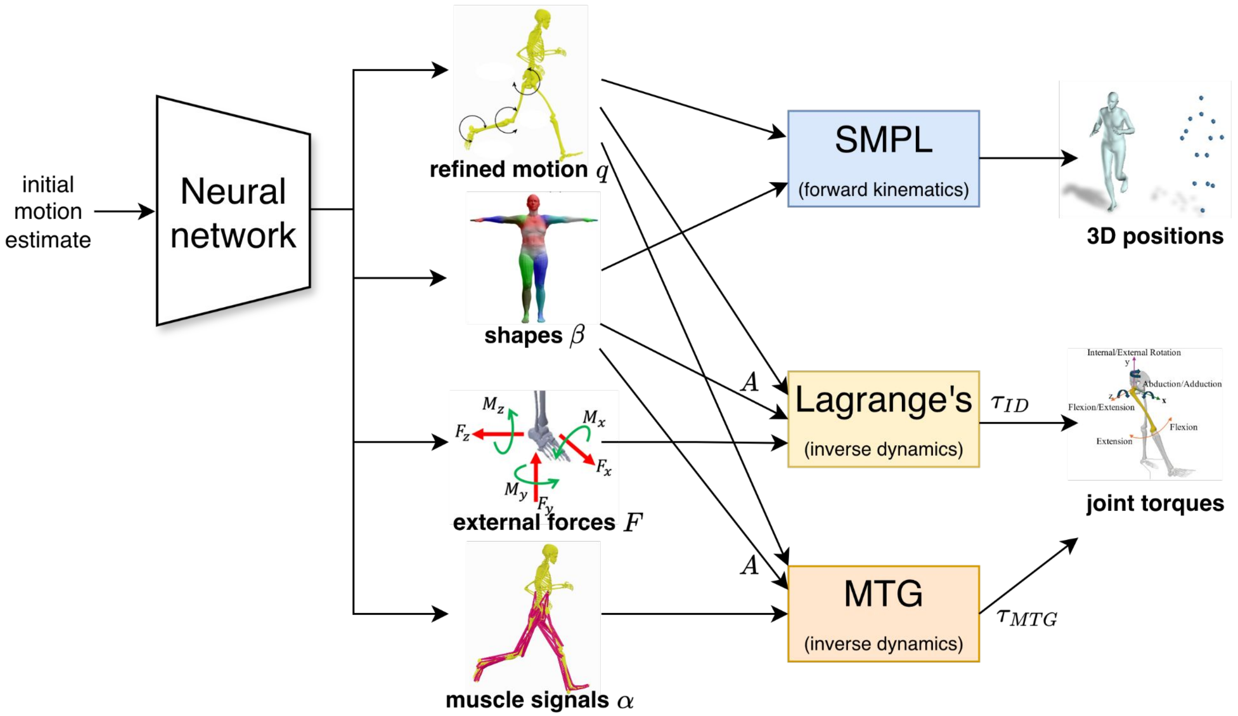
Regression-based PHPE

Problem
Kinetics prediction (RHS) is underconstrained.

$$M(q, A)\ddot{q} + C(q, \dot{q}) = \tau + F$$



MusclePose



Problem

Kinetics prediction (RHS) is underconstrained.

$$M(q, A)\ddot{q} + C(q, \dot{q}) = \tau + F$$

Proposed

Add a parametric MTG module as another way to predict torques.

$$L_\tau = |\tau_{ID} - \tau_{MTG}|$$

(i.e. use MTGs as a regularizer)

Muscle torque generators (MTGs) [51,25]

Motivation:

- **simplicity**: MTGs are simplified muscle models that approximate torque at the joint level from joint kinematics (q), muscle activation signals ($\boldsymbol{\alpha}$), and anthropometric features (A).

joint kinematics q, activations α, anthropometrics A $\longrightarrow$ $\boxed{\text{MTG}}$ $\longrightarrow$ τ_{MTG}

- **compatibility**: MTGs consist of parametric equations that are differentiable and can be directly incorporated into existing learning frameworks.

muscle activation $\alpha \in [0, 1]$

peak isokinetic torque $\tau_0(A)$

$$\tau_{MTG} = \tau_{active} + \tau_{passive}$$

$$\tau_{active} = \alpha \tau_\omega \tau_\theta \tau_0$$

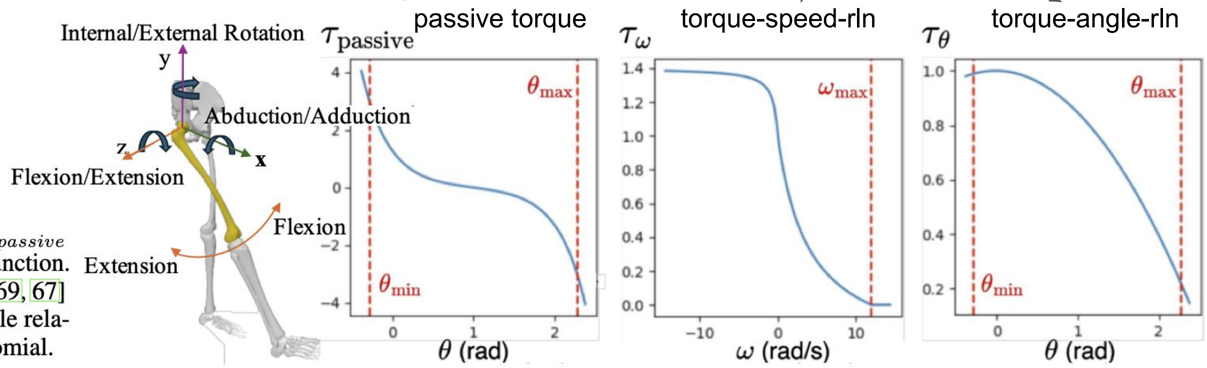
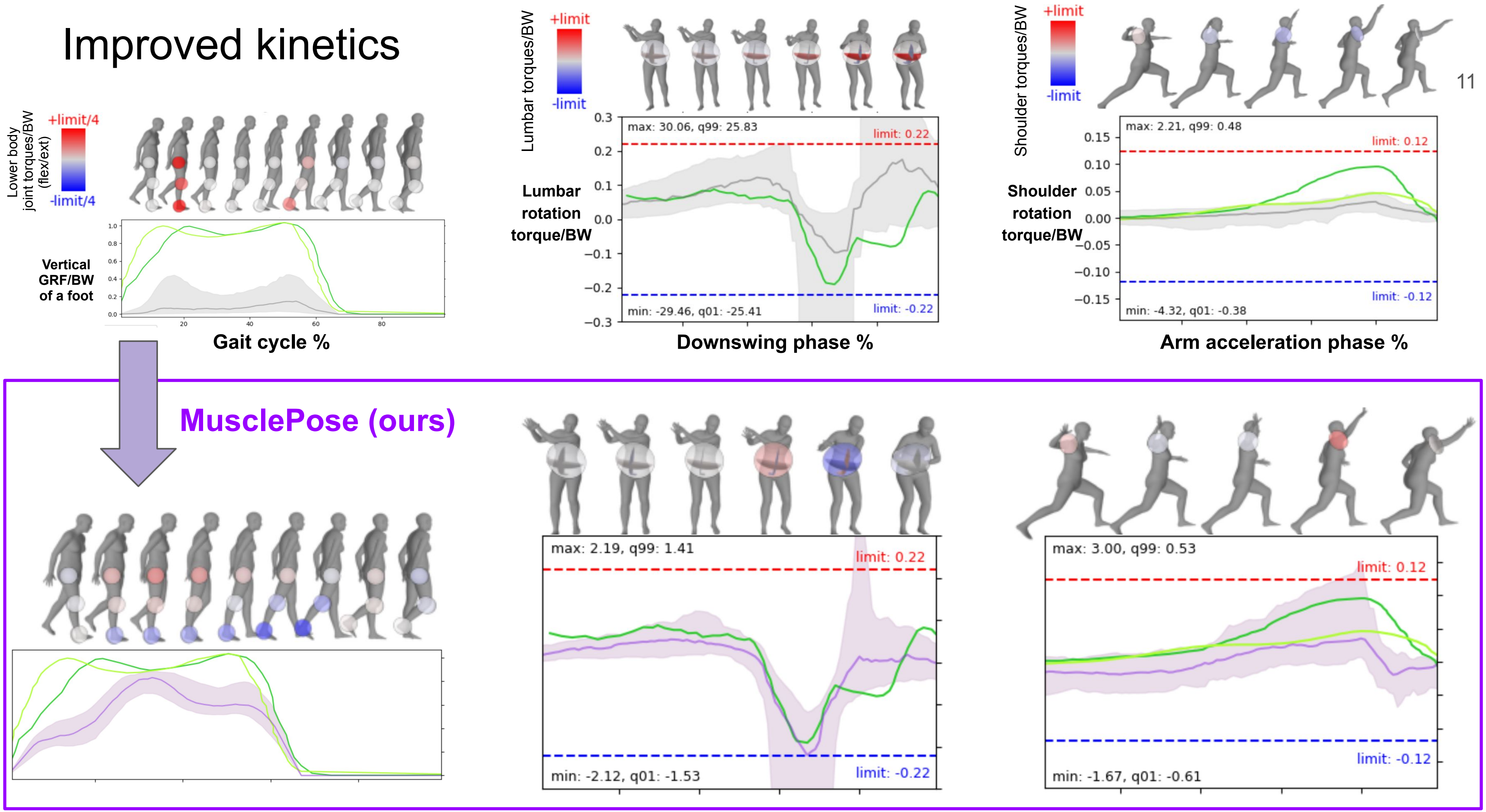


Figure 2: Examples of MTG curves for hip flexion. $\tau_{passive}$ models the passive torque [79] as a double exponential function. τ_ω models the active-torque–angular-speed relationship [69, 67] as a piecewise function. τ_θ models the active-torque-angle relationship [21, 33] as the non-negative portion of a polynomial.

Results

Improved kinetics



Kinetics evaluation

		Kinetic plausibility		$\mathrm{GRF}_v^{/W}$			$\mathrm{GRF}_v^{/W}$ (%f)		
		$\mathbf{F}_{res}^{/W}\downarrow$	MTV	{med	q99	max}	< {0.01,	0.1,	0.5}
†H36M	CLIFF	-	-	-			-		
	PhysPT	0.4	5.3	{0.4	2.4	10.0}	{7.2	20.8	60.0}
	MusclePose	**0.1**	2.5	{1.0	1.2	3.0}	{3.0	3.0	5.2}
†3DPWoc	CLIFF	-	-		-			-	
	PhysPT	0.9	27.0	{0.5	1.2	3.9}	{5.3	11.8	52.4}
	MusclePose	**0.3**	12.1	{1.0	1.6	4.3}	{5.3	5.3	6.3}

Fres: mean residual force scaled by body weight.

MTV (mean torque variation): mean absolute change in joint torques over consecutive frames (in Newton*metres/frame) to assess torque continuity.

GRFv %f: percent of frames where the total vertical GRF is below (1, 10, 50% body weight).

Kinematics evaluation

		Pos.	Kinematic plausibility			Float (%f)		
		MJE↓	ACC↓	FS	GP	$\mathcal{H}_{min} > \{1, 10, 20\}$mm		
†H36M	CLIFF	**46.5**	26.3	-	-		-	
	PhysPT	50.6	13.7	34.7	6.8	{59.0	31.6	8.5}
	MusclePose	48.4	**12.9**	37.2	26.0	{8.0	3.0	1.3}
†3DPWoc	CLIFF	**24.0**^{P}	13.8^P	-	-		-	
	PhysPT	25.9^P	**3.0**^{P}	7.8	11.2	{82.9	73.9	57.2}
	MusclePose	27.6^P	4.3^P	12.8	30.8	{6.0	4.7	3.7}

MJE: mean joint positional error in mm.

ACC (acceleration loss): mean L2 norm in mm/frame2 between the predicted and ground truth keypoint accelerations to access jitter.

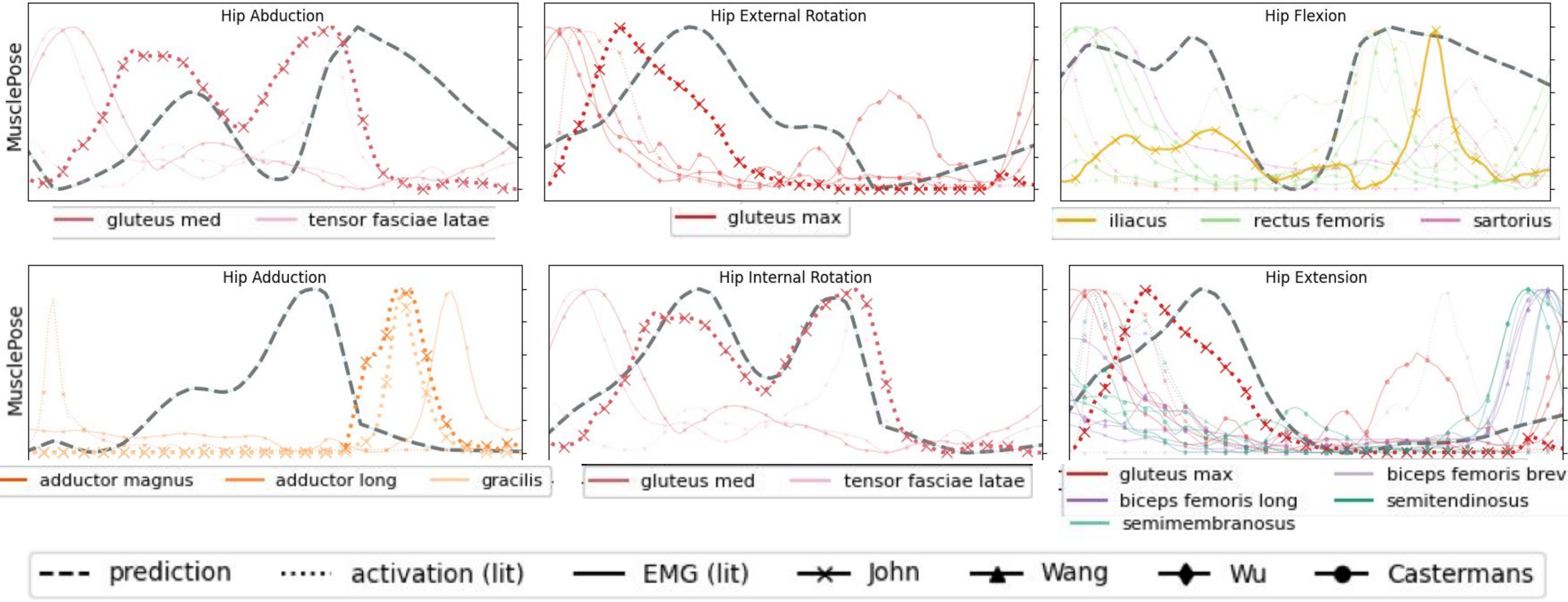
FS (foot skating): average displacement in mm of vertices in contact with the ground in consecutive frames.

GP (ground penetration) is the average vertical distance to the ground in mm of vertices below the ground.

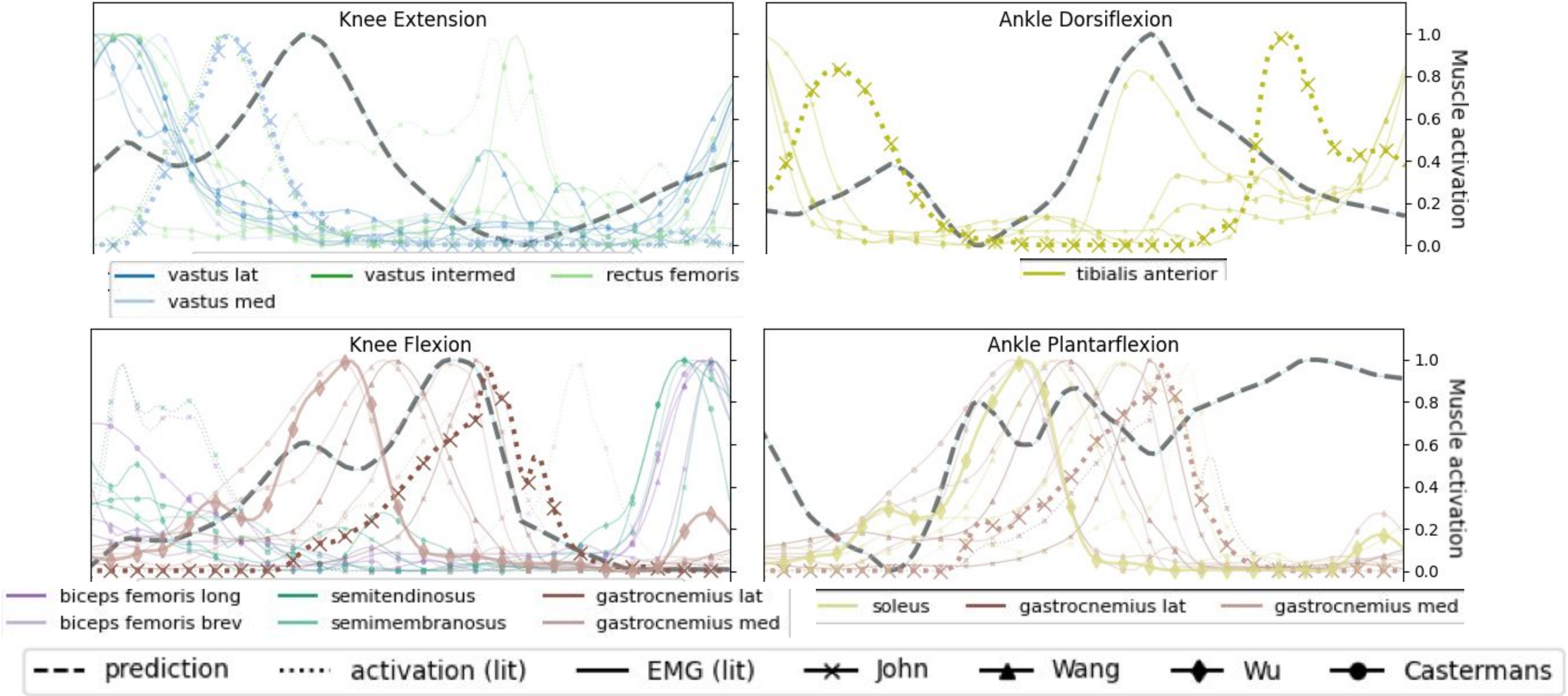
Floating %f: percent of frames the minimum vertex height is above (1, 10, 20mm).

Inferred muscle signals (gait – hip)

Mean muscle activation signal predictions (dashed) compared to activations (dotted) and EMG data (solid) collected from other gait studies [72,76,8,29]. Min-max scaling applied to all.



Inferred muscle signals (gait – knee, ankle)



Summary of contributions

We introduced MusclePose as a regression-based PHPE to infer human dynamics from monocular videos,

- this is the first pose estimator to incorporate muscle dynamics modeling, predict muscle activation signals, and predict detailed human anthropometrics,
- we showed improvements in biofidelity, while maintaining competitive positional accuracy.

Thanks!

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