HUMAN POSTURE AND MOVEMENT PREDICTION BASED ON MUSCULOSKELETAL MODELING

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ANYBODY TECHNOLOGY
AnyBody inside project

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M-Tech

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Digital manikins applications:

- ✓ Orthopedi
- ✓ Rehabilitation
- ✓ Clinical bi
- ✓ Ergonom
- ✓ Occupational
- ✓ Industri gn
- ✓ Sports equipment g p ance mization

The digital manikin must
be driven by experimental
kinematic and kinetic data!

Experiment limitations:

- o Time-consuming
- o Technically difficult
- o Potentially unsafe
- o Expensive

Human models

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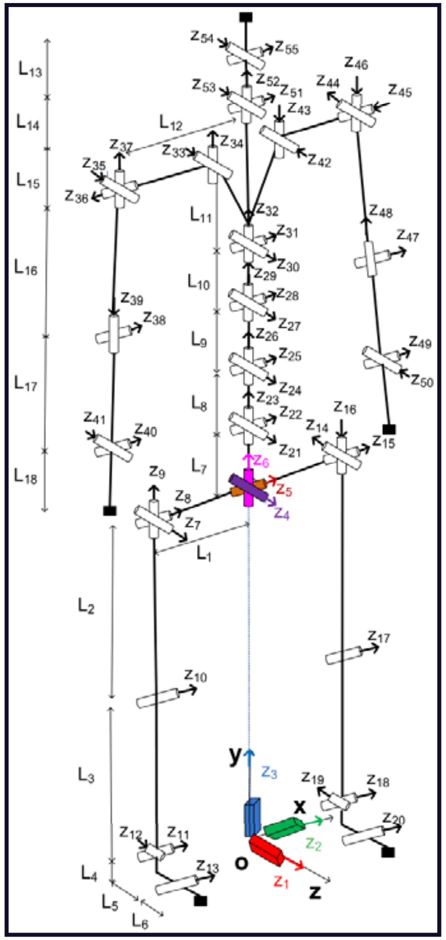
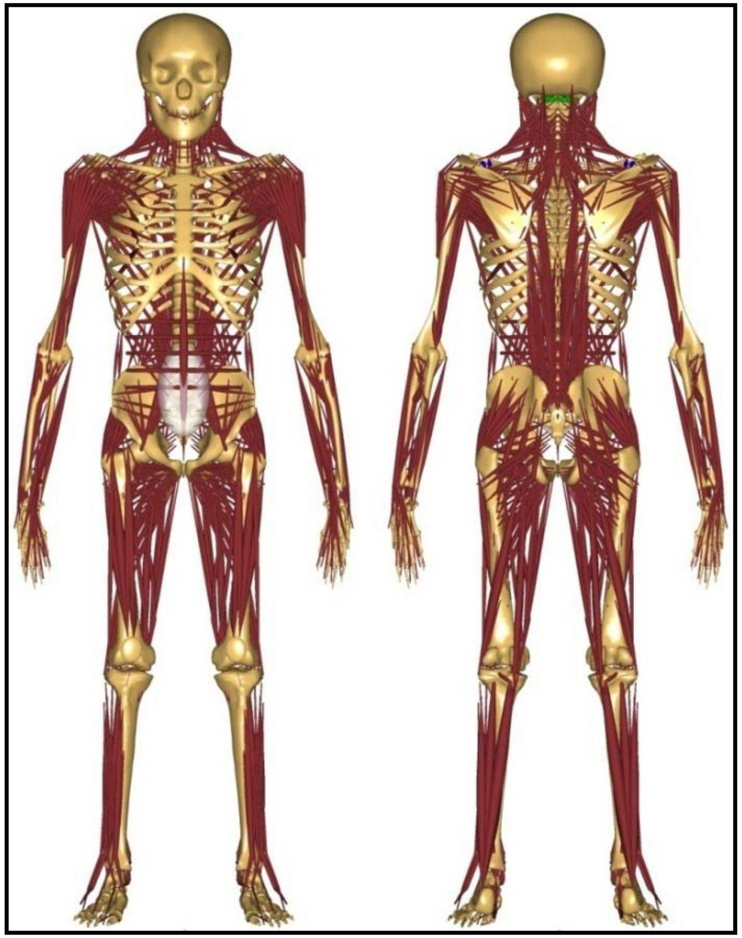
Joint torque model



Digital human skeletal model (Xiang et al., 2010)

Series of rigid segments connected by one or more revolute joints.

AnyBody Musculoskeletal Model



Written in a general scripting language

Simulation models

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Why do we need simulation models?

Direct measurement of muscle force as a fundamental requirement for movement study is restricted to invasive measurement!

Types of simulation model:

☐ Forward dynamics

☐ Inverse dynamics

Redundancy problem

There are more muscles than necessary to generate the motions.

→

Optimization

Minimization of an appropriate cost function is necessary to cope with the redundancy of muscular load-sharing.

Forward and inverse dynamics

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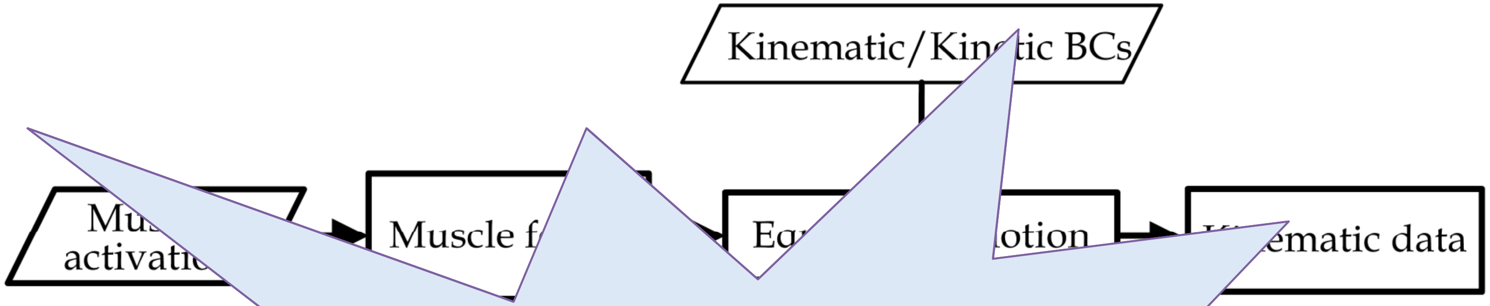
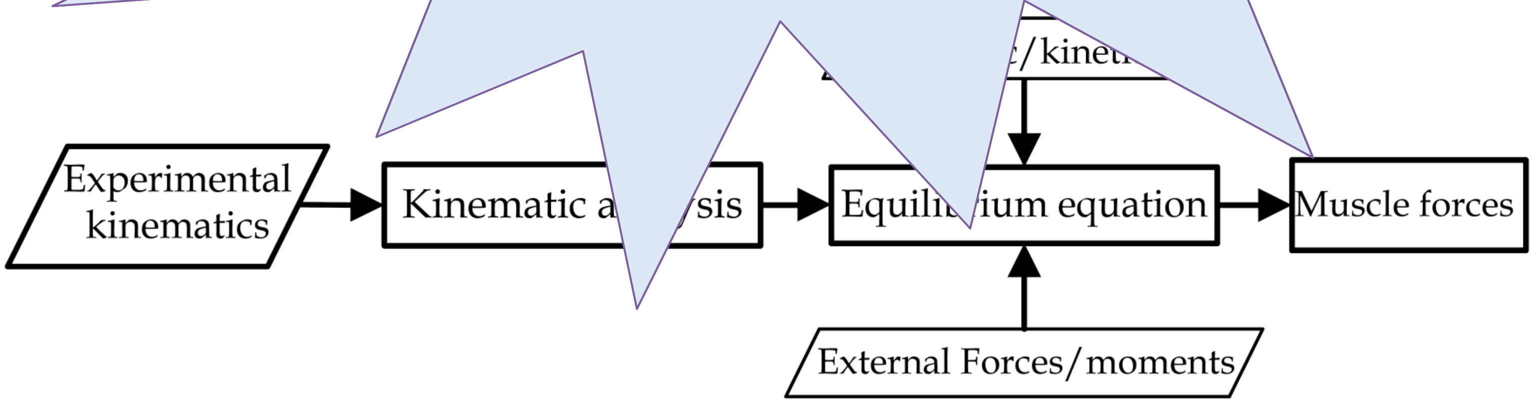
- **Forward dynamics**



In many practical simulation cases, neither the muscle forces nor the motion is known a-priori!

- **Inver**



State-of-the-art

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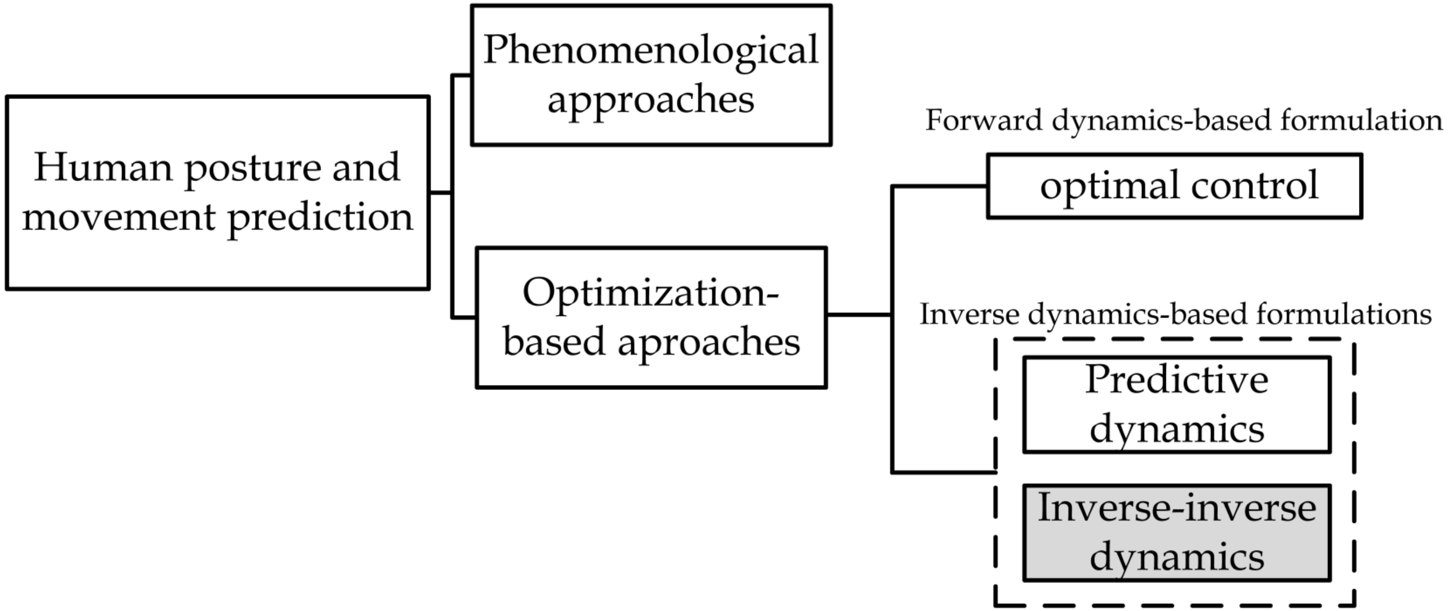
Research questions

I. Can we resolve the indeterminacy by formulating the human movement as an optimization problem?

II. What is the objective function?

III. Does any single formulation predict a wide range of human posture/movements?



Human posture and movement prediction

Phenomenological approaches

Optimization-based aproaches

Forward dynamics-based formulation

optimal control

Inverse dynamics-based formulations

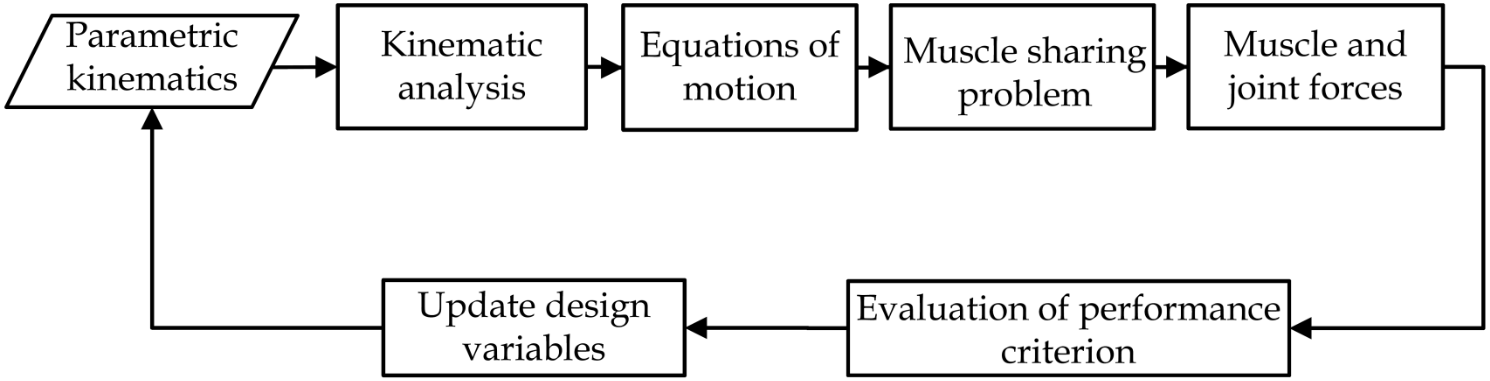
Predictive dynamics

Inverse-inverse dynamics

The novelty of inverse-inverse dynamics is to generalize the idea of using an inverse dynamics-based formulation for human posture and movement prediction by using a detailed musculoskeletal model.

State-of-the-art

Inverse-inverse dynamics


Parametric kinematics
Kinematic analysis
Equations of motion
Muscle sharing problem
Muscle and joint forces
Evaluation of performance criterion
Update design variables

Find: $q_i, \quad i \in \{1, \dots, n^{(C)}\}$

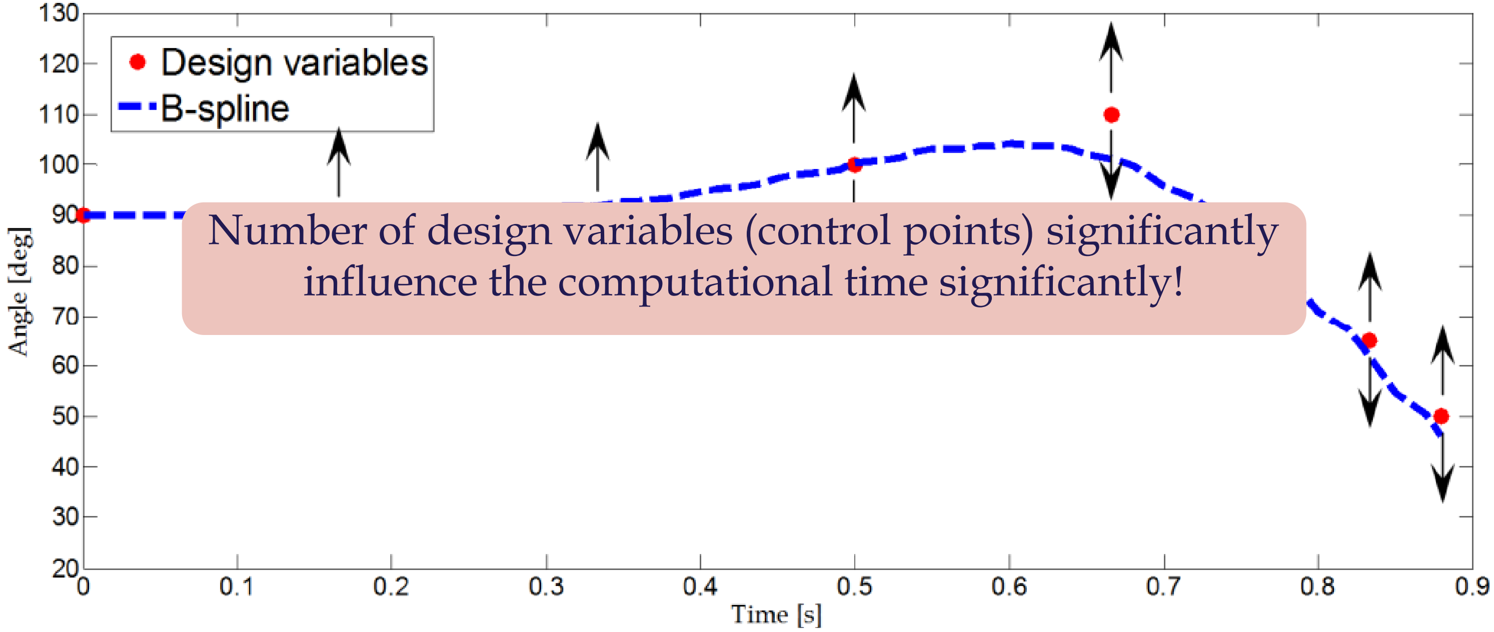
To: minimize performance criterion

S.t:

$$\left\{ \begin{array}{ll} \text{Anatomical joint angle limits:} & \theta_i^L \le \theta_i \le \theta_i^U, \quad i \in \{1, \dots, n^{(D)}\} \\ \text{Muscle strength:} & 0 \le f_i^{(M)} \le N_i, \quad i \in \{1, \dots, n^{(M)}\} \\ \text{Dynamic Stability} & \\ \text{Obstacle and Self avoidance} & \\ \text{Environmetal Constraints} & \end{array} \right\}$$

Movement parameterization

The joint angles are parameterized by means of time functions controlling the motion. Time function could be B-spline, Polynomial, Fourier series and etc.

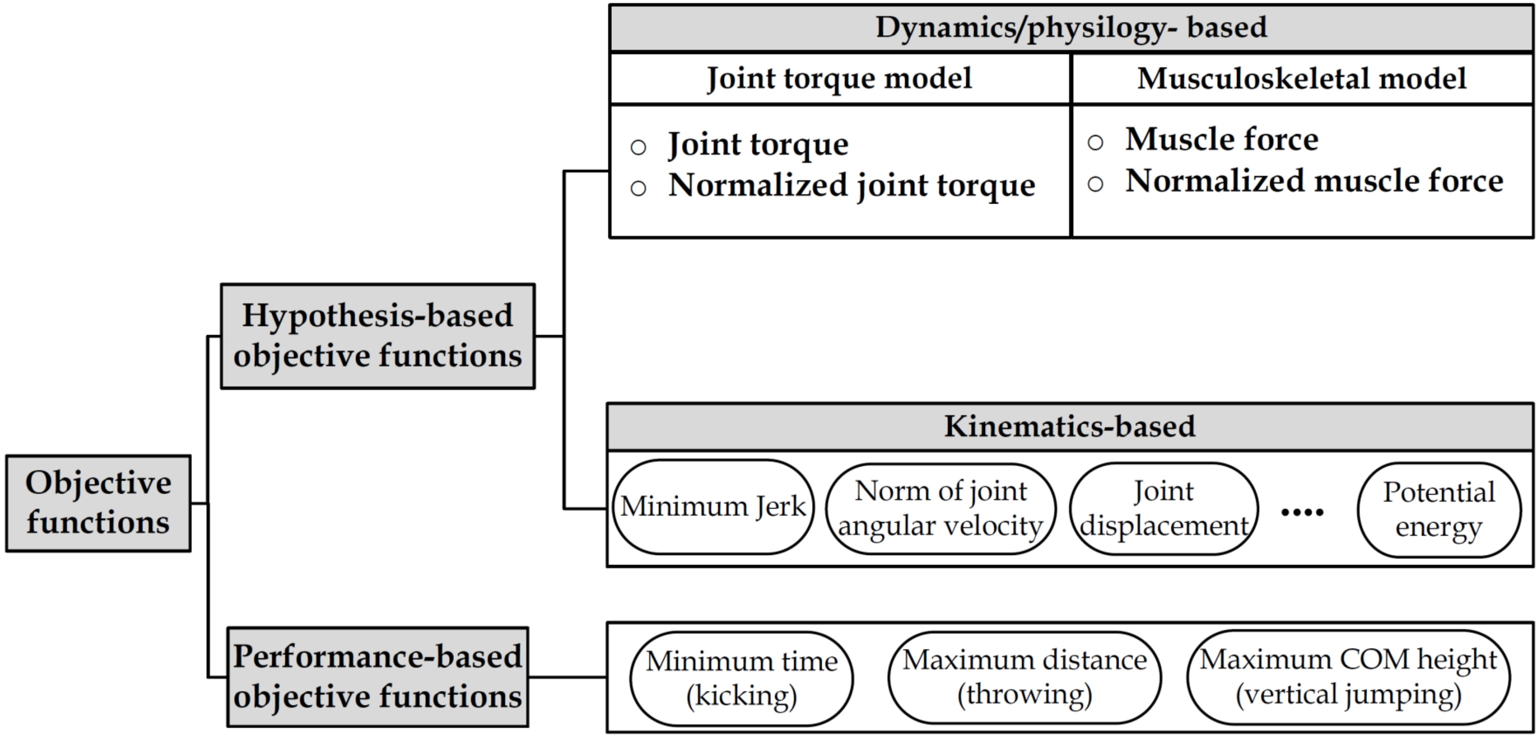


Number of design variables (control points) significantly influence the computational time significantly!

- ❑ Identification of the level of parameterization complexity remains a challenging task.
- ❑ The machine parameters can be considered as design variables.

Objective function definition

The optimality hypothesis in human movement prediction is that movements are planned to optimize a performance criterion.



Objective functions

Hypothesis-based objective functions

Dynamics/physilogy- based

Joint torque model	**Musculoskeletal model**
○ **Joint torque** ○ **Normalized joint torque**	○ **Muscle force** ○ **Normalized muscle force**

Kinematics-based

Minimum Jerk

Norm of joint angular velocity

Joint displacement

....

Potential energy

Performance-based objective functions

Minimum time (kicking)

Maximum distance (throwing)

Maximum COM height (vertical jumping)

Optimization

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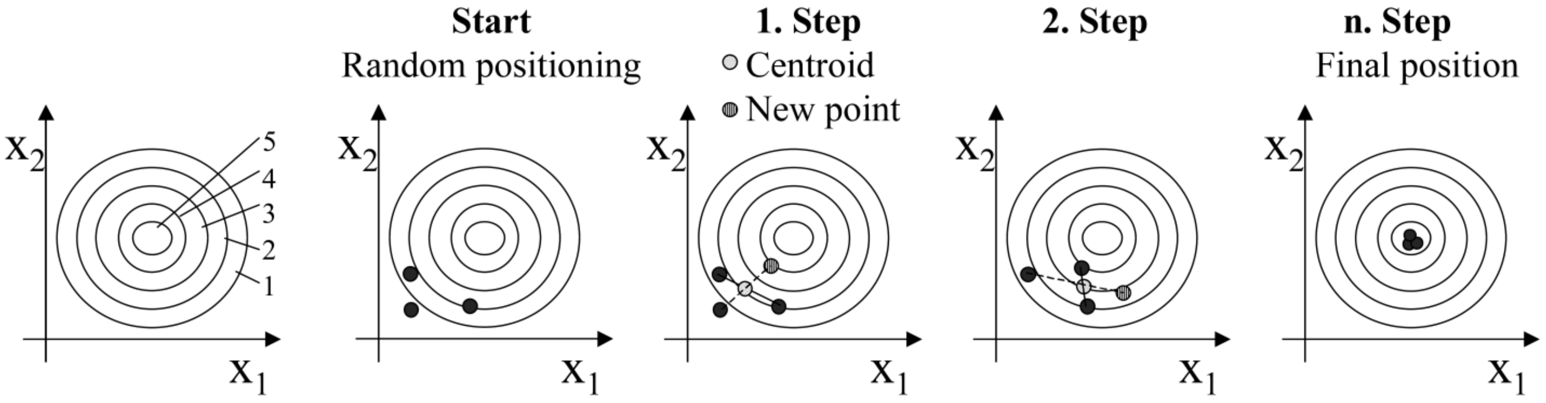
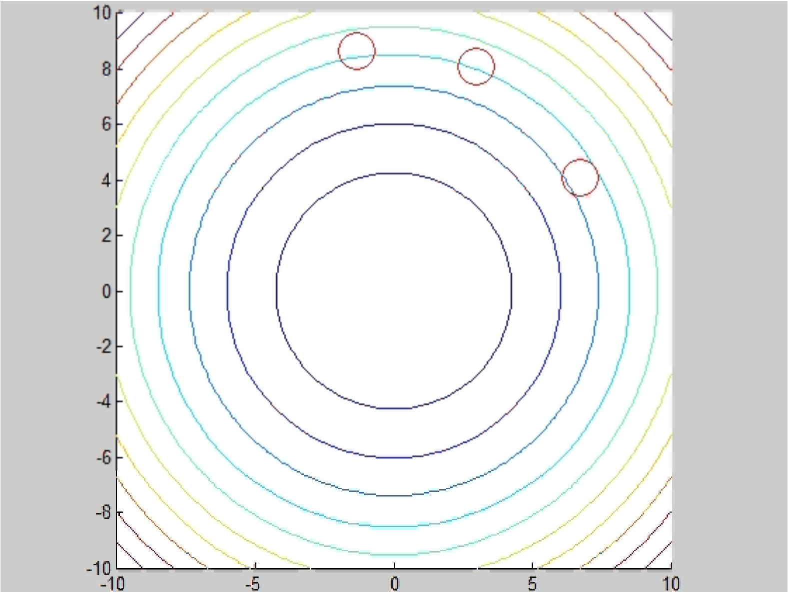
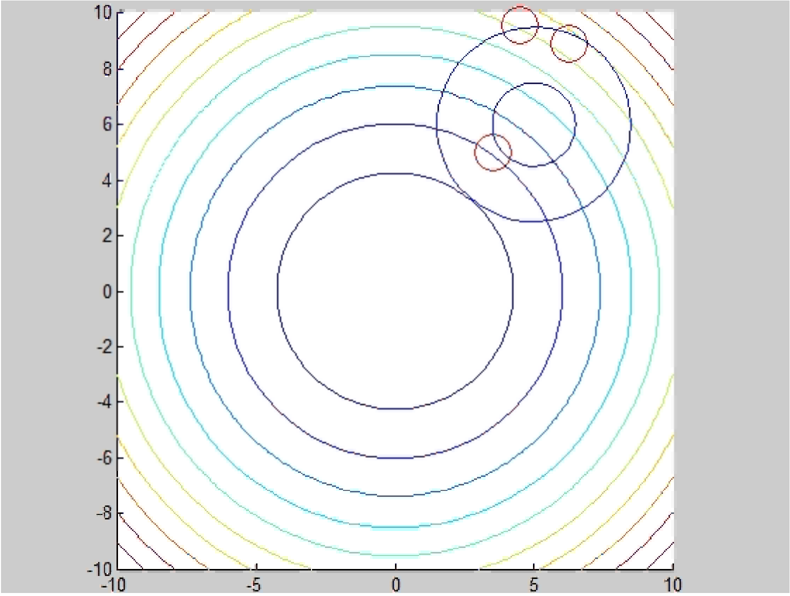
Complex method: a non-gradient optimization technique!



Unconstrained



Constrained



Validation

Error quantification

A quantitative validation metric originally proposed by Geers (1984) was used to quantify the differences between the predicted and measured results.

$$M = \sqrt{\frac{v_{cc}}{v_{mm}}} - 1$$

$$P = \frac{1}{\pi}\arccos\left(\frac{v_{mc}}{\sqrt{v_{mm}v_{cc}}}\right)$$

$$C = \sqrt{M^2 + P^2}$$

$$v_{mm} = \frac{1}{t_2 - t_1}\int_{t_1}^{t_2} m(t)^2 dt$$

$$v_{cc} = \frac{1}{t_2 - t_1}\int_{t_1}^{t_2} c(t)^2 dt$$

$$v_{mc} = \frac{1}{t_2 - t_1}\int_{t_1}^{t_2} m(t)c(t) dt$$

If the experimental data and computational results are identical, M, P and C will be zero!

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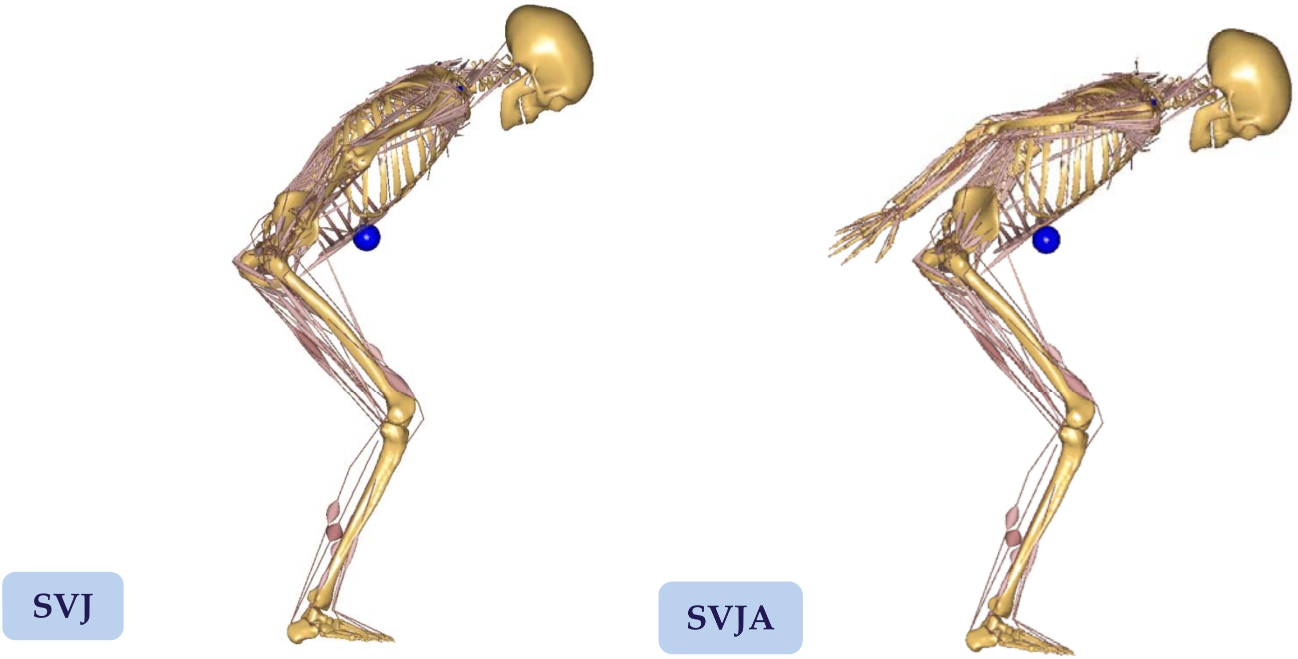
Can we formulate the human movement prediction as an optimization problem?



Human modeling and parameterization

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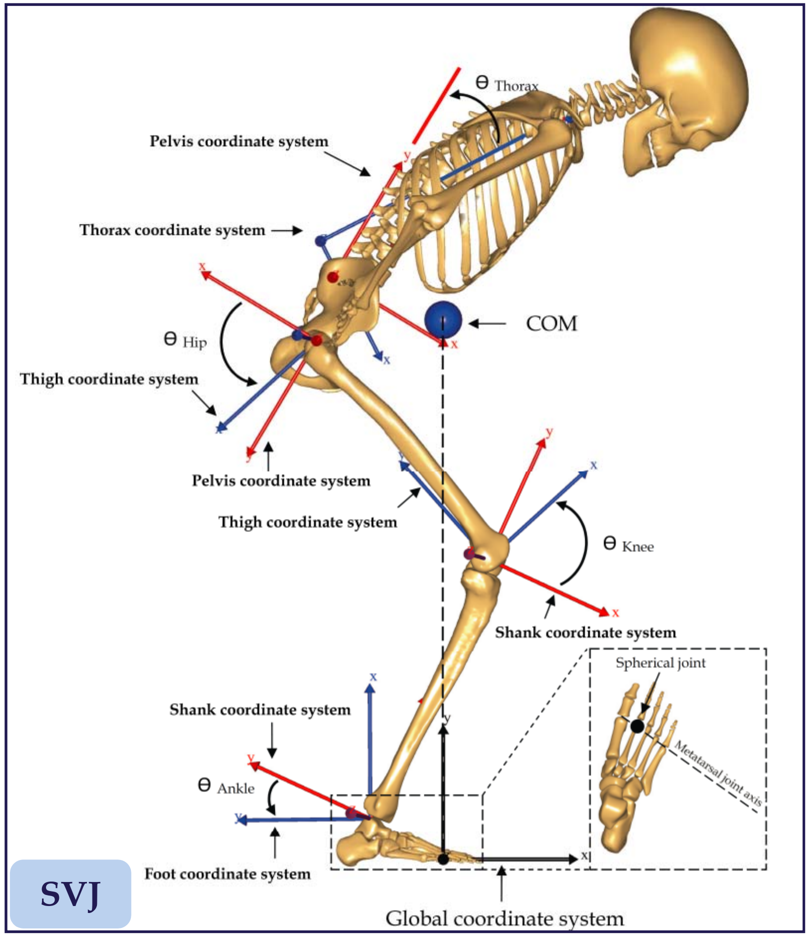
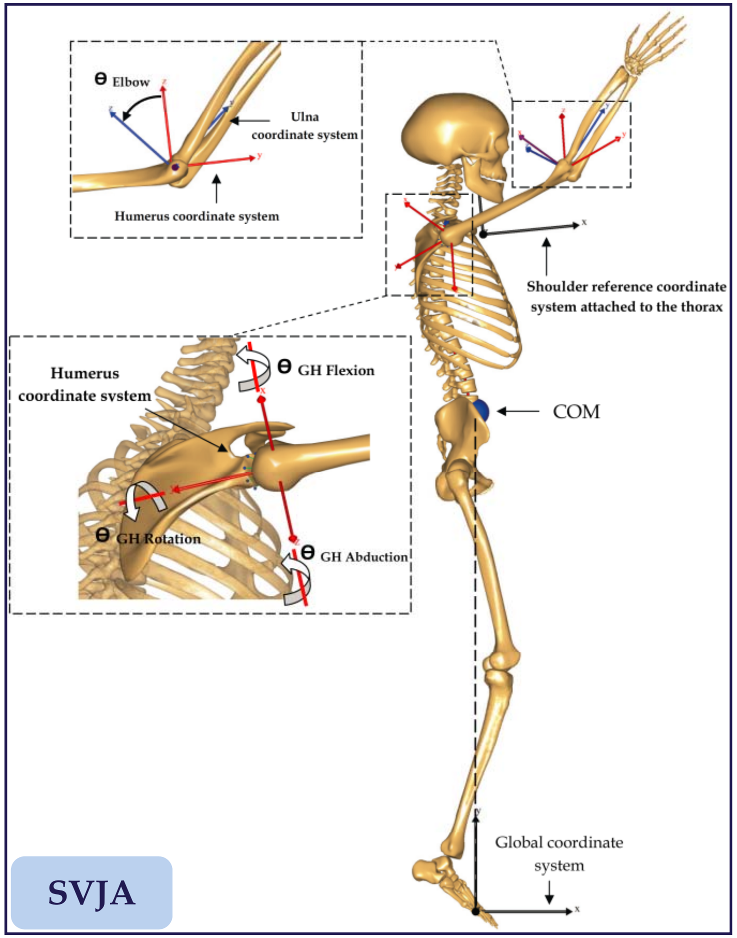




We used **12** control points for each joint angle to discretize the motion over the entire jumping time by means of a fourth order **B-spline** curve.

Optimization problem definition

- ☐ Objective function for the movement prediction:

$$F = Y_{\mathrm{COM@take-off}} + (V_{\mathrm{COM@take-off}})^2 / 2g$$

- ☐ Optimization:

Find: $q_i, \quad i \in \{1, \ldots, n^{(C)}\}$

To: $\text{minimize } -\left(Y_{\mathrm{COM@take-off}} + (V_{\mathrm{COM@take-off}})^2 / 2g\right)$

S.t:

$$\theta_i^L \le \theta_i \le \theta_i^U, \quad i \in \{1, \ldots, n^{(D)}\}$$

$$0 \le f_i^{(M)} \le N_i, \quad i \in \{1, \ldots, n^{(M)}\}$$

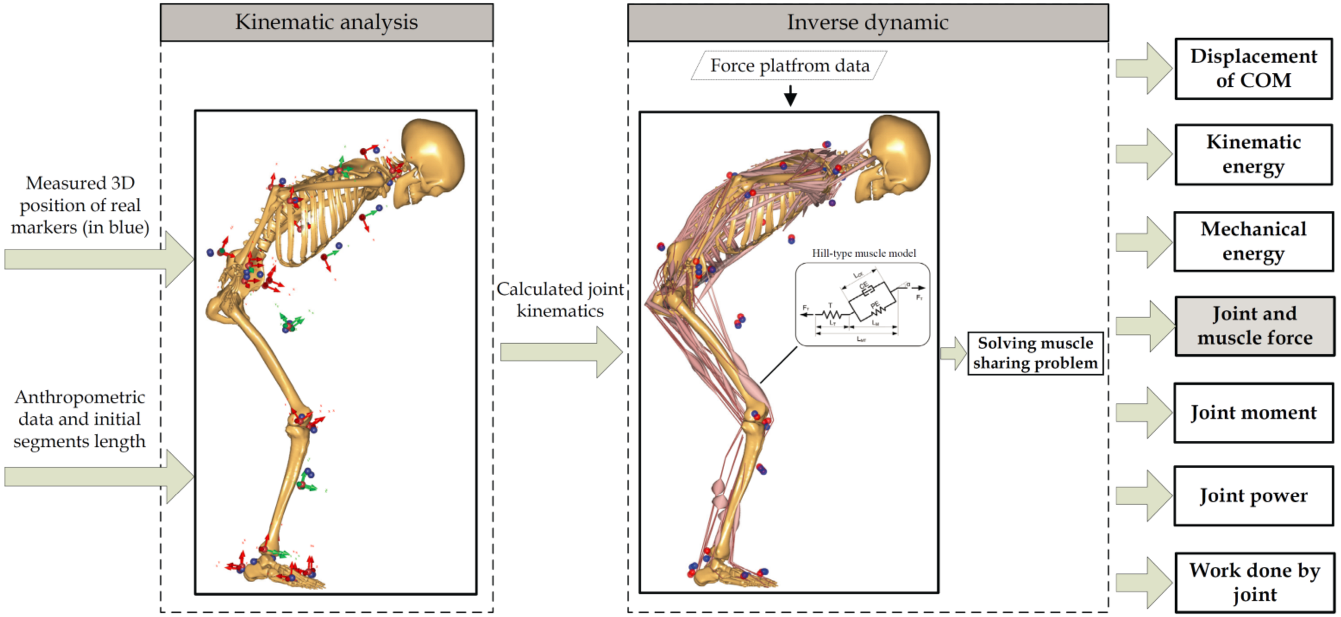
Experimental study

Experimental study

Subjects: A group of six healthy males volunteered for the test.

Instrumentation:
- **39** reflective skin markers
- Two adjacent force platforms (sampling at 1000 Hz).
- Eight infrared cameras (sampling at 250 Hz)

Test protocol:
- Squat vertical jumping (6 trials)
- Squat vertical jumping with arm swing (6 trials)
- The data set comprised 6 (subjects) × 5 (trials) × 2 (test conditions)



Measured 3D position of real markers (in blue)

Anthropometric data and initial segments length

Kinematic analysis

Calculated joint kinematics

Inverse dynamic

Force platfrom data

Hill-type muscle model

Solving muscle sharing problem

Displacement of COM

Kinematic energy

Mechanical energy

Joint and muscle force

Joint moment

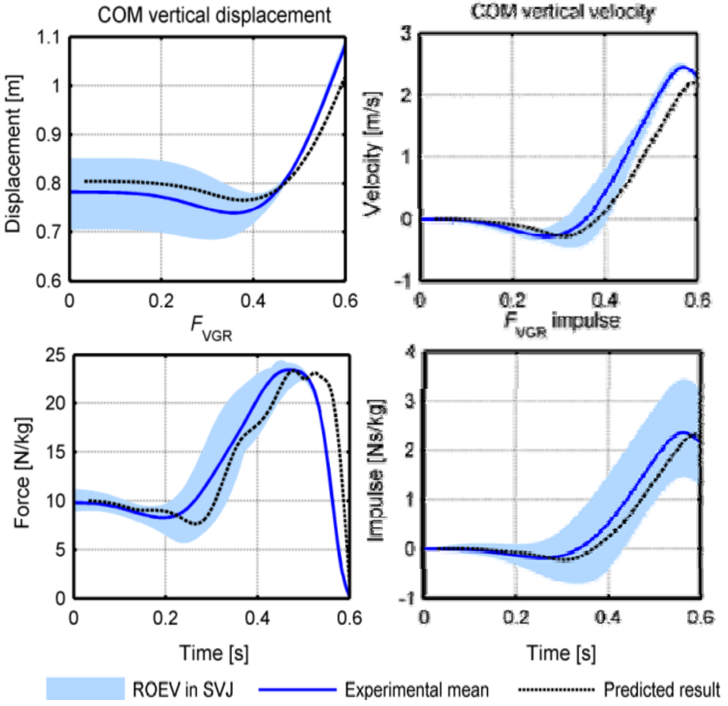
Joint power

Work done by joint

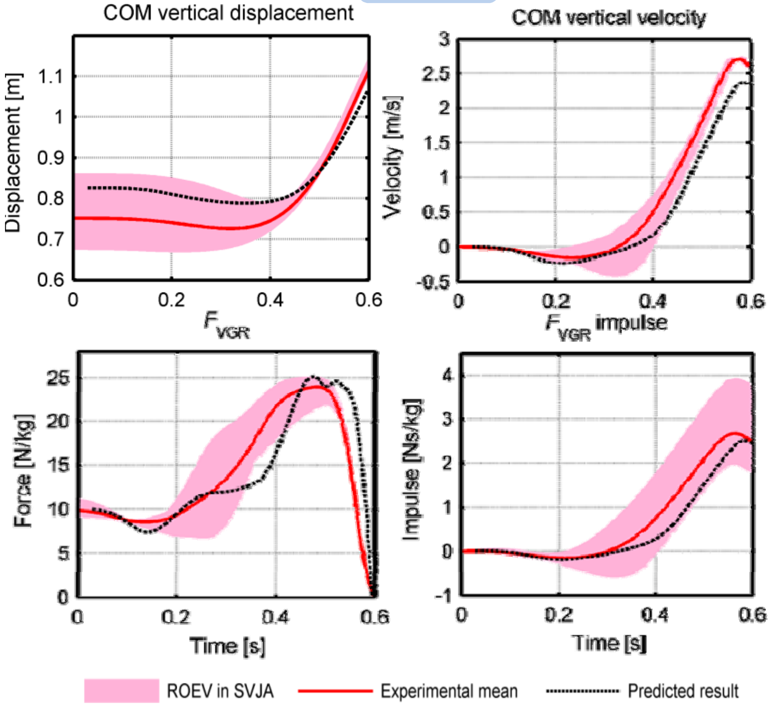
Results …

The predicted jumping time in SVJ and SVJA is **0.570** (s) and **0.573** (s) respectively

SVJ



SVJA



		NRMSE	r^2	M	P	C
SVJ	COM vertical displacement (m)	0.082	0.985	0.011	0.011	0.015
	COM vertical velocity (ms^{-1})	0.096	0.976	-0.206	0.047	0.211
	F_{VGR} (Nkg^{-1})	0.122	0.791	0.004	0.061	0.061
	F_{VGR} impulse ($Nskg^{-1}$)	0.079	0.973	-0.125	0.048	0.134
SVJA	COM vertical displacement (m)	0.150	0.952	0.049	0.017	0.052
	COM vertical velocity (ms^{-1})	0.099	0.982	-0.208	0.048	0.214
	F_{VGR} (Nkg^{-1})	0.155	0.701	-0.006	0.078	0.078
	F_{VGR} impulse ($Nskg^{-1}$)	0.118	0.955	-0.201	0.065	0.211

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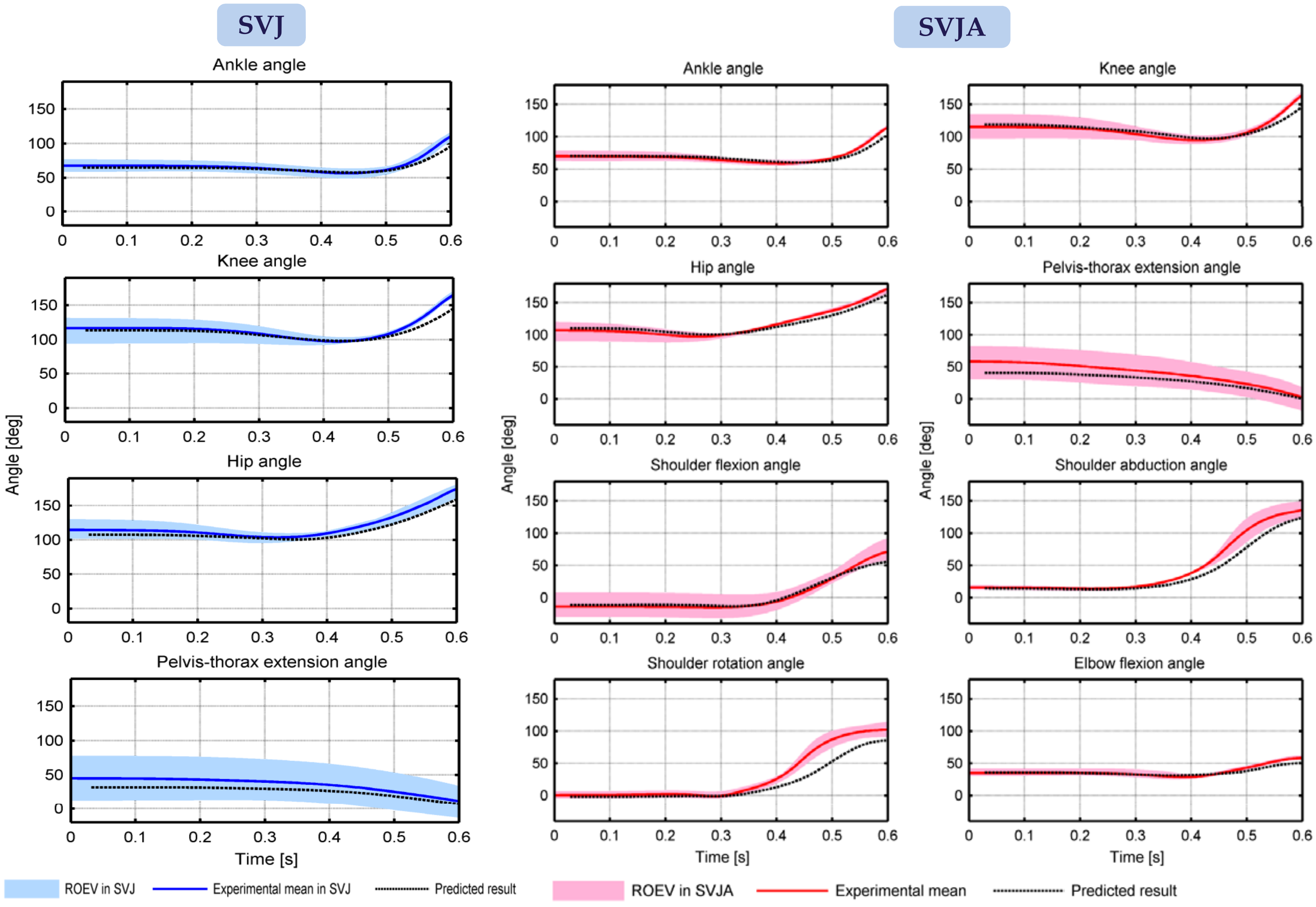
Predicted and experimental values of the joint angles in SVJA and SVJA.



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		NRMSE	r^2	M	P	C
SVJ	Ankle angle (deg)	0.067	0.997	-0.038	0.012	0.040
	Knee angle (deg)	0.080	0.990	-0.033	0.011	0.035
	Hip angle (deg)	0.102	0.995	-0.058	0.006	0.058
						0.273
SVJA						0.025
						0.018
						0.020
	Pelvis-thorax angle (deg)	0.200	0.991	-0.263	0.011	0.263
	Shoulder flexion angle (deg)	0.053	0.991	-0.150	0.031	0.153
	Shoulder abduction angle (deg)	0.107	0.980	-0.190	0.031	0.192
	Shoulder rotation angle (deg)	0.162	0.956	-0.306	0.064	0.312
	Elbow flexion angle (deg)	0.112	0.965	-0.040	0.025	0.047

Inverse-inverse dynamics can reproduce the coordinated motion .

Predicted and experimental mean of the $Y_{\mathrm{COM@take\text{-}off}}$, $V_{\mathrm{COM@take\text{-}off}}$ and jump height in SVJA and SVJ.

	Averaged experimental results			Predicted results		
	SVJ	SVJA	Enhancement (%)	SVJ	SVJA	Enhancement (%)
$Y_{\mathrm{COM@take\text{-}}}$						
$V_{\mathrm{COM@take\text{-}of}}$						
jump heig						

This approach is also capable of predicting the jump height enhancement in squat vertical jumping with arm swing.

Example II

What is the optimization criterion for a movement under investigation?

Musculoskeletal model of a bicycle rider with 176.6 cm height and 69.8 kg weight

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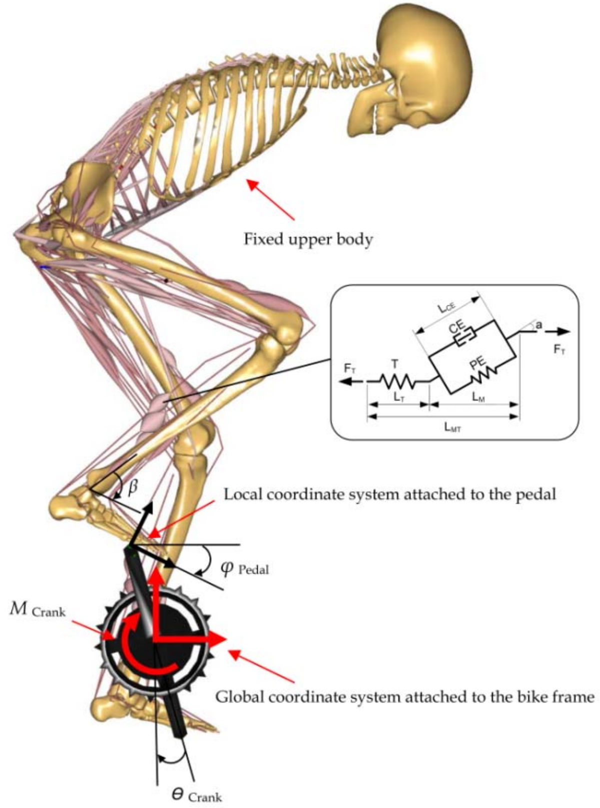
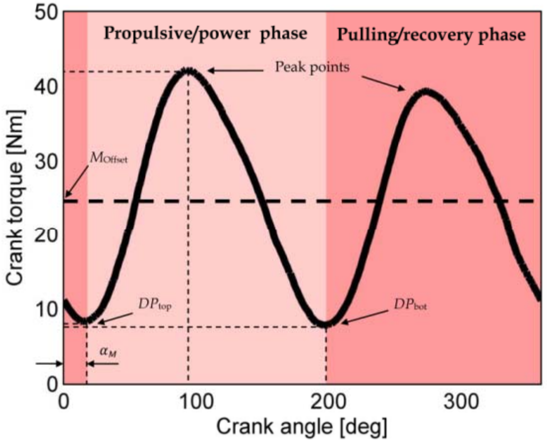


$$\varphi_{\text{Pedal}} = \sum_{i=1}^{3} [A_i \cos(\omega_i t) + B_i \sin(\omega_i t)]$$

$$\omega_i = (i-1)2\pi f$$

$$\mathbf{A} = [A_1, A_2, A_3]; \quad \mathbf{B} = [B_1, B_2, B_3]$$



$$M_{\text{Crank}} = M_{\text{Offset}} + (M_{\text{Offset}} - M_{DP_{\text{top}}}) \sin(4\pi f t + \alpha_M)$$

❑ Objective function:

$$F = \frac{1}{T}\int_0^T \left[\sqrt[p]{\sum_{i=1}^{n^M} \left(\frac{f_i^{(M)}}{N_i}\right)^p} \right]^q dt$$

$$p, q \in \{1, 2, 3, 4, 5\}$$

$$F = \max_t \; \max_i \left(\frac{f_i^{(M)}}{N_i} \right)$$

❑ Optimization:

Find: $\{A_1,\ A_2,\ A_3, B_1, B_2, B_3,\ M_{DP_{\text{top}}}, \alpha_M\}$

To: minimize F

S.t: $\beta_{\text{lower}} \le \beta \le \beta_{\text{upper}}$
$0 \le f_i^{(M)} \le N_i, \quad i \in \{1, \dots, n^{(M)}\}$

Experimental study

Experimental study

Subjects: A group of nine male cyclists volunteered for the test (with their own bike)

Instrumentation:

The output power and pedaling cadence were sampled at 10 Hz using SRM.

Test protocol:

- Three tests on level terrain and three tests on uphill terrain (4.8% grade).
- One test with preferred gear ratio, the two other tests with one gear ratio above and one gear ratio below the preferred gear ratio.
- All test were performed during **1 min** at a power output representing 90% peak power output.

Mean pedaling cadence and power output of the cyclists during experimental conditions

Cycling condition	Pedaling cadence ± SD (rpm)	Power output ± SD (W)
level terrain at low cadence (LL)	87.8±8.8	240±16.8
level terrain at preferred cadence (LP)	94.7±8.2	239.5±18.8
level terrain at high cadence (LH)	101.9±8.3	238.9±17.9
Uphill terrain at low cadence (UL)	74.9±9.5	245.2±12.2
Uphill terrain at preferred cadence (UP)	82.2±12.0	246.5±14.7
Uphill terrain at high cadence (UH)	87.7±13.0	242.8±14.6

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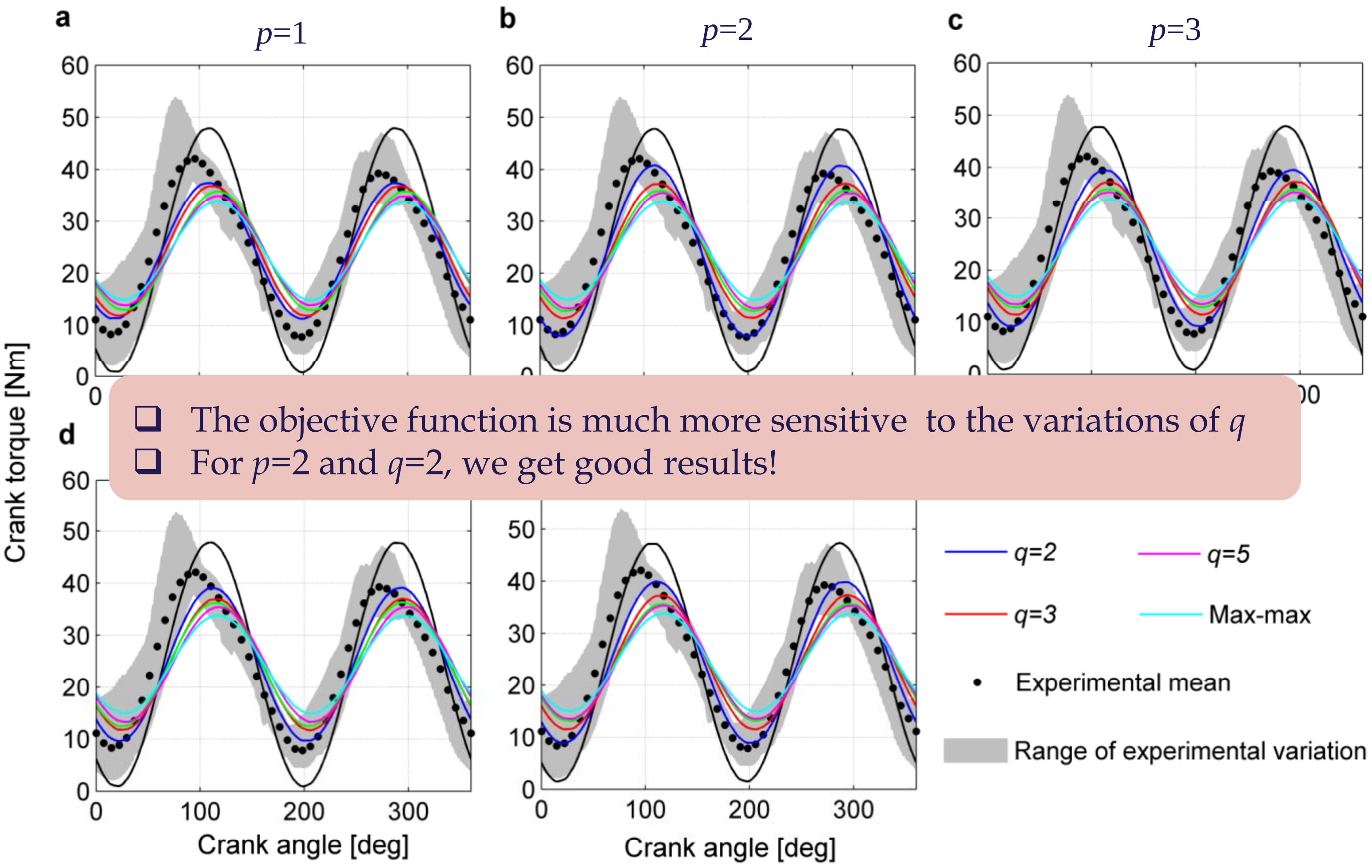
Predicted and experimental data for pedaling on level terrain at preferred cadence



- ☐ The objective function is much more sensitive to the variations of q
- ☐ For p=2 and q=2, we get good results!

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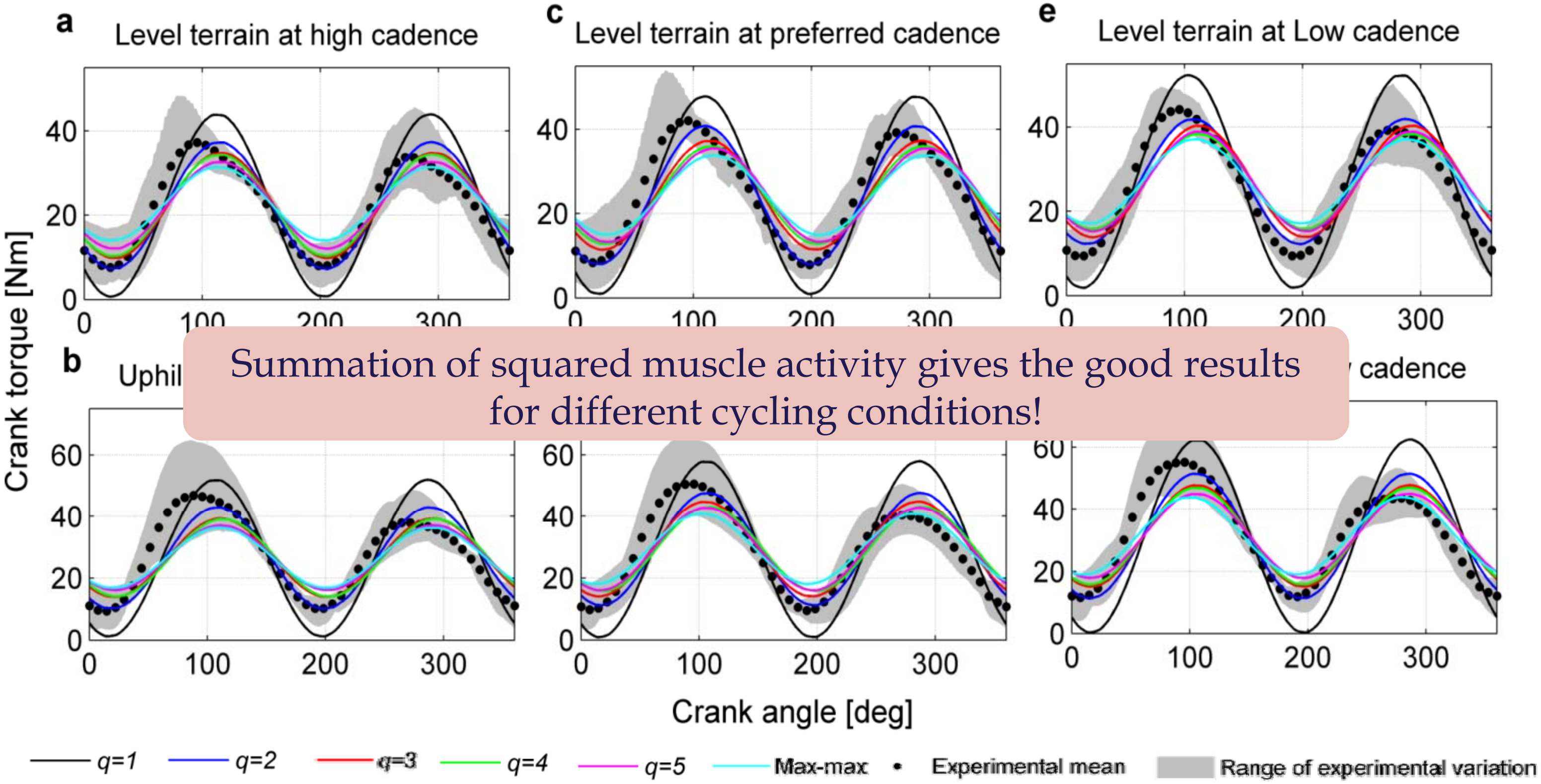

Summation of squared muscle activity gives the good results for different cycling conditions!

Averaged errors for all cycling conditions (p=2)

	q=1	q=2	q=3	q=4	q=5	Max-max
Mean NRMSE ± SD	0.222	0.125	0.146	0.158	0.162	0.167
Mean r^2 ± SD	0.849	0.878	0.810	0.787	0.788	0.843
Mean M ± SD	0.098	0.018	0.034	0.042	0.049	0.057
Mean P ± SD	0.079	0.050	0.058	0.063	0.065	0.066
Mean C ± SD	0.127	0.052	0.069	0.077	0.083	0.088

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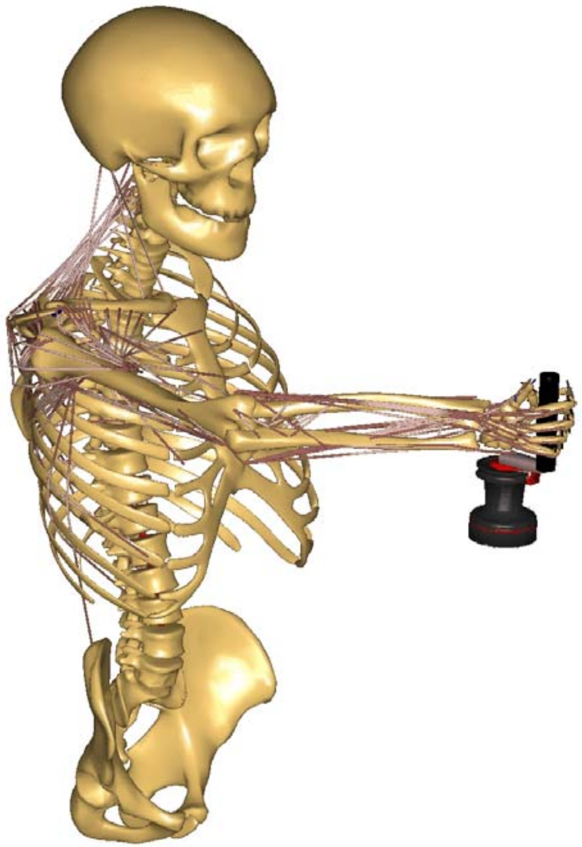
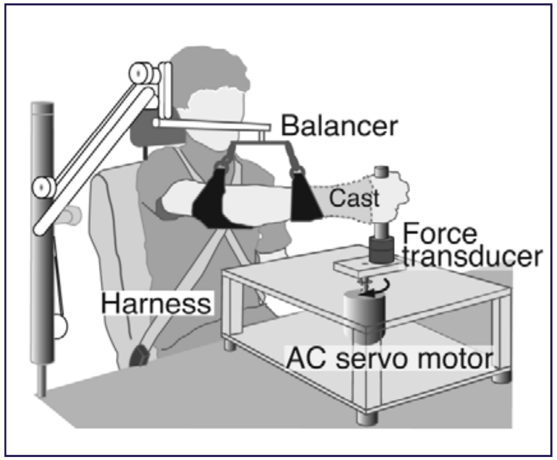
Does a performance criterion defined based on muscle activity predict wide range of human movement?





Experimental setup of crank-rotation task
[Ken Ohta et al., 2004]

$$\boxed{I\ddot{\theta}_{\text{Crank}} + B\dot{\theta}_{\text{Crank}} = r\boldsymbol{e}^{T}\boldsymbol{F}}$$

$I = 0.02\ \text{Kg.m}^2$
$B = 0.37\ \text{Nms/rad}$
$\boldsymbol{F}$: Hand contact force

- Four subjects
- Different starting points
- The angular velocity is zero at the beginning and ending of the task.
- 100 clockwise circular reaching movement at subjects' own pace.

Human modeling, movement parameterization

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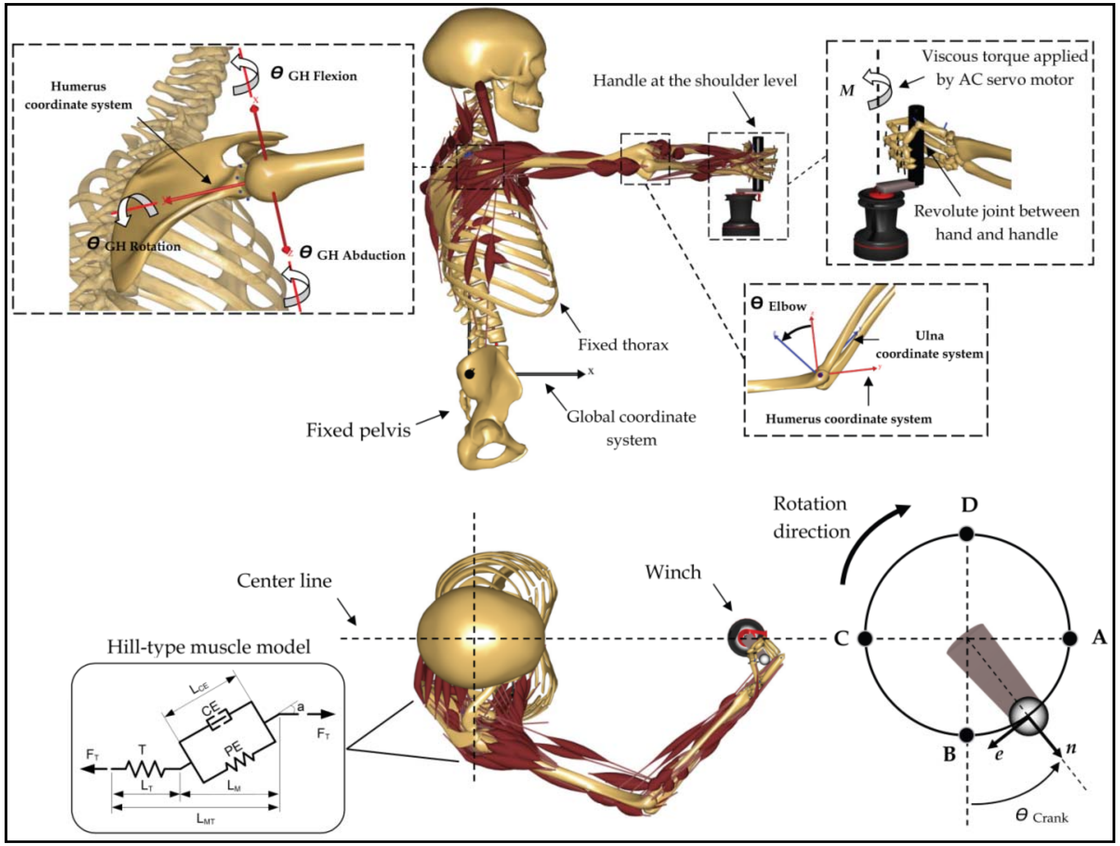

❑ Objective function:

$$F = \int_0^T \dot{E}^M_{Total}\,dt$$

$$\dot{E}^M = \frac{P_{\text{mech}}}{\mu}, \begin{cases} \mu = 0.25 & \text{for muscle shortening} \\ \mu = -1.2 & \text{for muscle lengthening} \end{cases}$$

❑ Optimization:

Find: $q_i, \quad i \in \{1, \dots, n^{(C)}\}$

To: minimize $\int_0^T \dot{E}^M_{Total}\,dt$

S.t: $\theta_i^L \le \theta_i \le \theta_i^U, \quad i \in \{1, \dots, n^{(D)}\}$

$0 \le f_i^{(M)} \le N_i, \quad i \in \{1, \dots, n^{(M)}\}$

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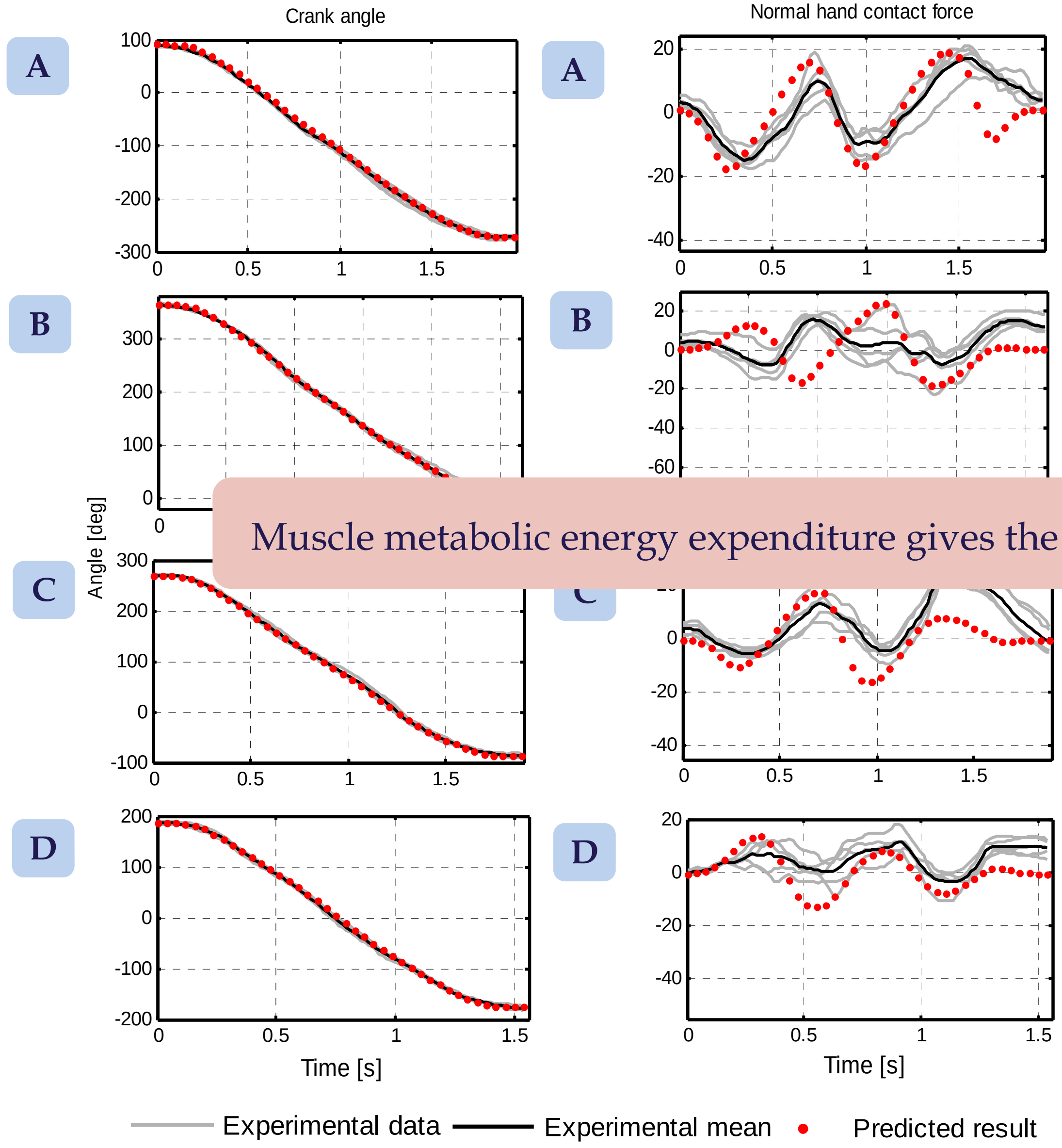
- o Example III

Concluding remarks

Future works



Muscle metabolic energy expenditure gives the good result!

	Crank angle	Normal hand contact force
	Starting point A	
NRMSE	0.013	0.190
r^2	0.999	0.660
M	0.007	0.159
P	0.009	0.258
C	0.012	0.303
	Starting point B	
NRMSE	0.007	0.522
r^2	0.999	0.005
M	0.006	0.404
P	[illegible]	0.503
[illegible]	[illegible]	0.645
	ting point C	
[illegible]	[illegible]	0.327
r^2	0.999	0.401
M	0.003	0.229
P	0.004	0.327
C	0.006	0.399
	Starting point D	
NRMSE	0.009	0.466
r^2	0.999	0.443
M	0.002	0.072
P	0.008	0.358
C	0.009	0.365

Concluding remarks

Can we formulate the human movement prediction as an optimization problem?

The results of the jumping study indicated that human movement prediction can treated as an optimization problem.

What is the appropriate objective function for human movement prediction?

The results of the pedaling study indicated that for a movement under investigation a range of performance criteria should be evaluated in order to find an appropriate objective function.

Does any single formulation predict a wide range of human posture/motion?

The results of the crank-rotation task indicated that an objective function defined appropriately based on muscle force/activity can predict natural human posture and movement.

Future works

☐ Defining a proper optimality criterion to solve the muscular load sharing problem remains a major challenge. One of the unanswered research questions is how the CNS chooses one of the possible muscle activation sets.

☐ Although a performance criterion defined based upon the muscle activity seems to be a good choice, more investigation is needed to uncover how the CNS governs human posture and motions.

☐ In order to investigate the capability of the inverse-inverse dynamics technique to predict more complicated movements, cases like normal and perturbed gait would be most relevant.