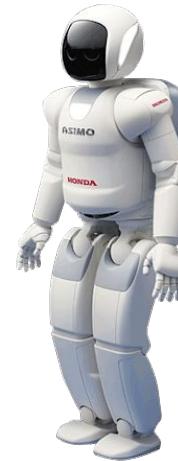


Understanding Human Motion



Changqing Lu
Gabriela Bravo-Illanes
Shivani Guptasarma



Topics list

1. Overview
2. Human motion strategies
3. Robotics applied in biomechanics

Overview

Gabriela Bravo-Illanes

Modeling Human Motion. Overview.

Modeling Human Motion. Overview.



Trajectories

Descriptive models

- Minimum-jerk model (Hand)
 - Quasi-straight smooth trajectories*
 - Bell shaped velocity*
- Fitts Law
- 2/3 power law

Modeling Human Motion. Overview.



Trajectories

Descriptive models

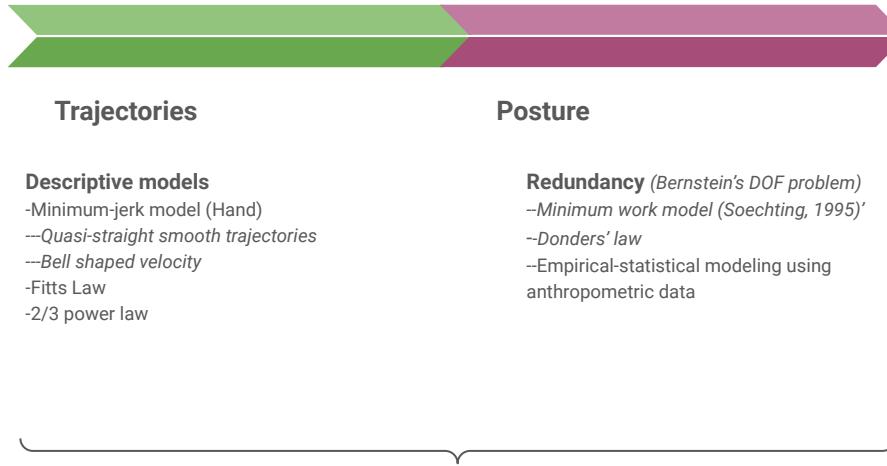
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Posture

Redundancy (Bernstein's DOF problem)

- Minimum work model (Soechting, 1995)'
- Donders' law
- Empirical-statistical modeling using anthropometric data

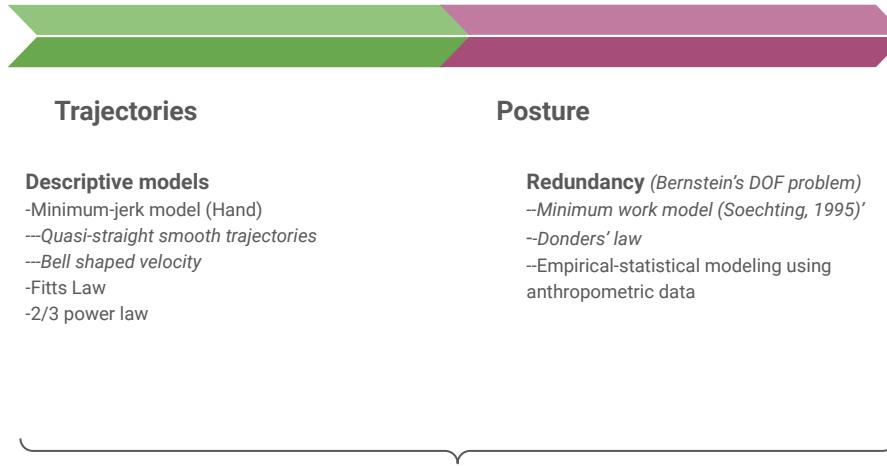
Modeling Human Motion. Overview.



Stochastic Optimal Control

- Task Optimization in the Presence of Signal-Dependent Noise (TOPS) (Miyamoto, 2004)
- Minimal intervention principle(Todorov, 2002)

Modeling Human Motion. Overview.



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- Minimum commanded-torque-change model (Nakano,1999)
- Minimum variance model (Harris, 1998)

Stochastic Optimal Control

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Human motion databases

- Motion primitives
- Learning by imitation (Schaal, 2003)

Sources: Campos, 2009; Gielen,2009; Hiatt, 2017; Simmons, 2005; Millard, 2013

Modeling Human Motion. Overview.



Task Goals

Target location (grasping)

- Visual
- Proprioceptive
- Initial hand location

Predict human actions (Teamwork)

- Probabilistic models
- Machine learning models

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Musculoskeletal models

- Hill-type muscle models
- Cross-type muscle models



Dynamics models

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Stochastic Optimal Control

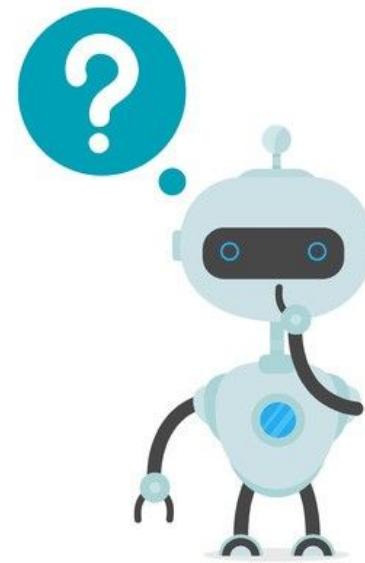
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How understand human motion benefits robotics?



How understand human motion benefits robotics?

How understand human motion benefits robotics?



(Zacharias, 2001)

Human-like motions

- Human robot collaboration
- Safety perception

How understand human motion benefits robotics?



(Zacharias, 2001)

Human-like motions

- Human robot collaboration
- Safety perception



SuitX

Better Designs

- Human wearables
 - Exoskeleton
 - Prosthesis
 - Rehabilitation robotics
- Legged robots
- Hands

How understand human motion benefits robotics?



(Zacharias, 2001)

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SuitX



(Billard, 2013)

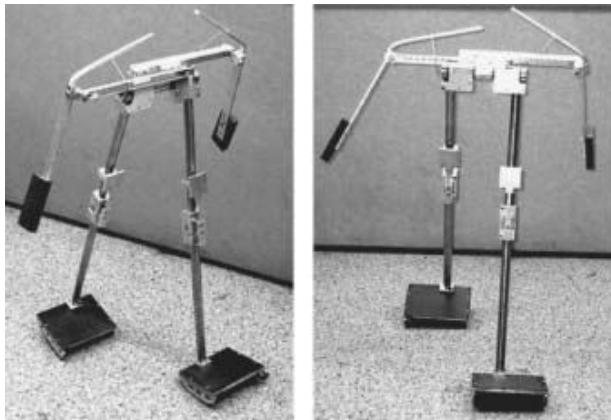
Perform complex tasks

- Controllers inspired in human strategies
- Skills acquisition

How understand human motion benefits robotics?

Robot Design

Passive dynamic walking



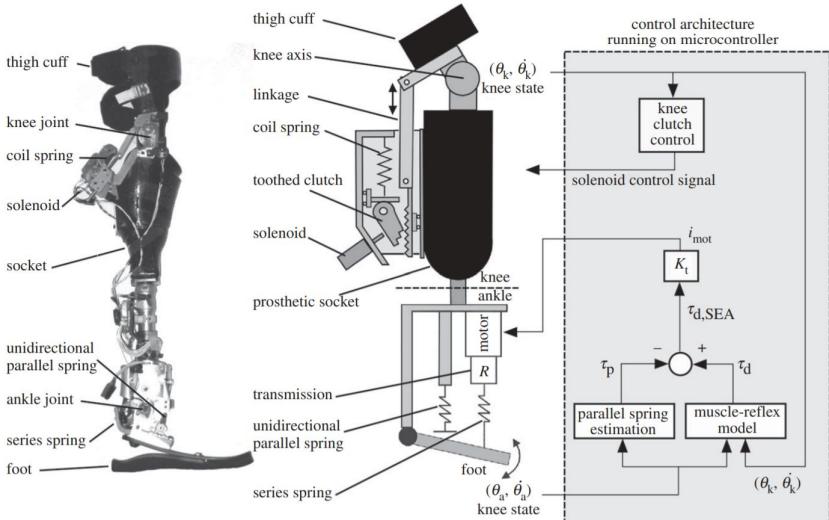
(Collins, 2001)

Imitation of human motion focused on minimizing actuation control

How understand human motion benefits robotics?

Robot Design

Design and control of Lower Limb wearable systems



Control scheme for powered ankle-foot prosthesis (Markowitz, 2011)

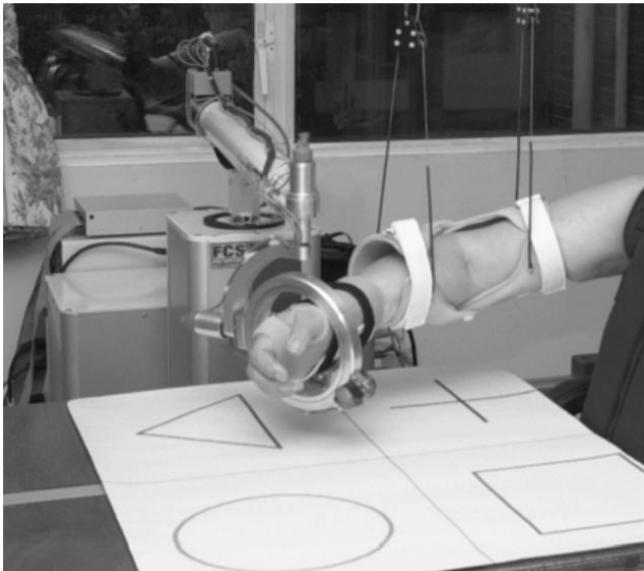
“Understanding muscle-tendon behaviour in human locomotion, roboticists can design robots that seamlessly integrate dynamically with the biological leg”

Siciliano, 2016

How understand human motion benefits robotics?

Motion Planning

Better rehabilitation robots



Stroke Therapy robot GENTLE system (Loureiro, 2003)

“The creation of human-like trajectories is essential for retraining upper limb movements of people that have lost manipulation functions following stroke”

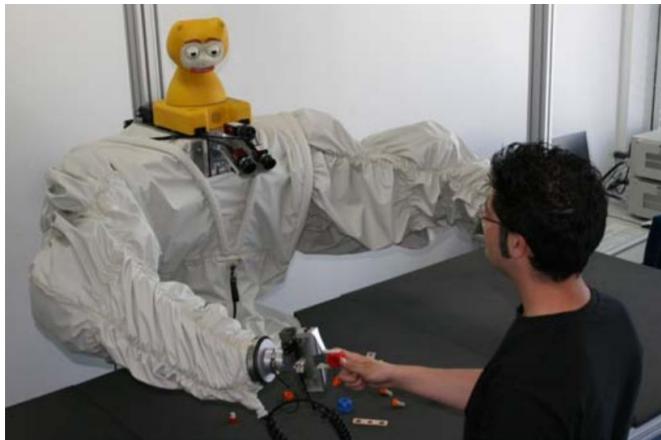
Loureiro, 2003

Source: Loureiro, 2003

How understand human motion benefits robotics?

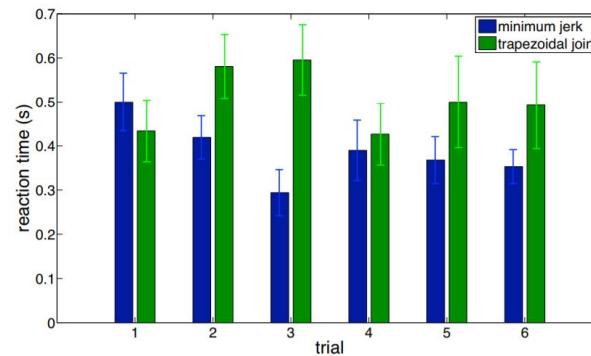
Motion Planning

Human-like movements in Human-robot collaboration

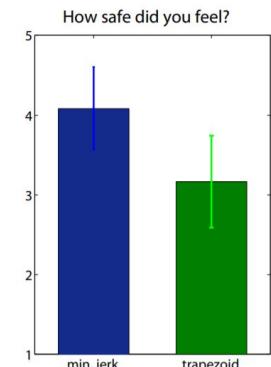


Robots handles human a cube using different speed profiles

“Human Robot interactions should be intuitively simple”



Shorter reaction time for minimum jerk profiles

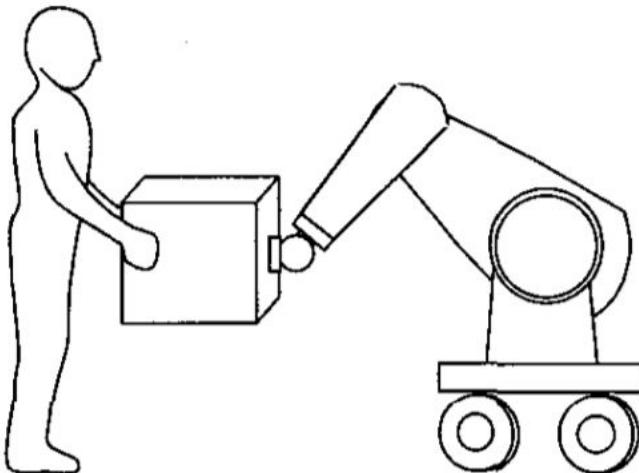


How safe they felt during the experiment

How understand human motion benefits robotics?

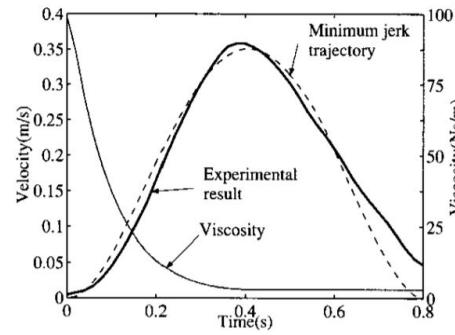
Controllers

Human-robot collaboration

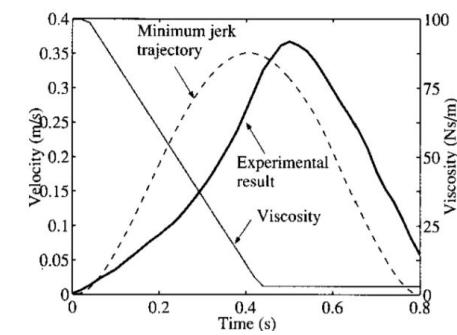


Cooperative task by a robot and a human (Ikeura, 2002)

- Human arm is like a damper model whose damping factor changes optimally so that the cost function becomes minimum
- Robot will have an impedance controller where the damping is optimized to mimic human.



Optimal solution (Ikeura, 2002)

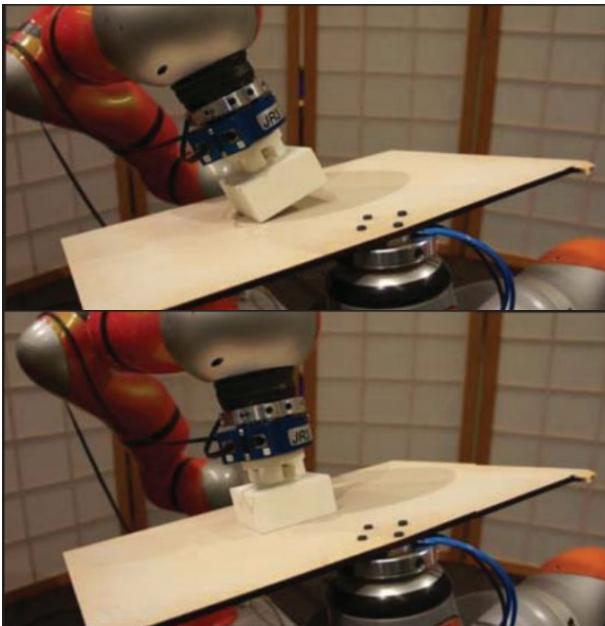


Solution when decreasing damping factor linearly (Ikeura, 2002)

How understand human motion benefits robotics?

Controllers inspired in humans

Surface-surface contact under uncertainty. Compliant contact primitives



Study human strategies to achieve the same task, and replicate them in the proposed control:

- Subjects decrease angular velocity before complete alignment
- They do not control contact force to remain at a fixed value

How understand human motion benefits robotics?

Task Planning

Collaborative tasks with probabilistic Movement primitives

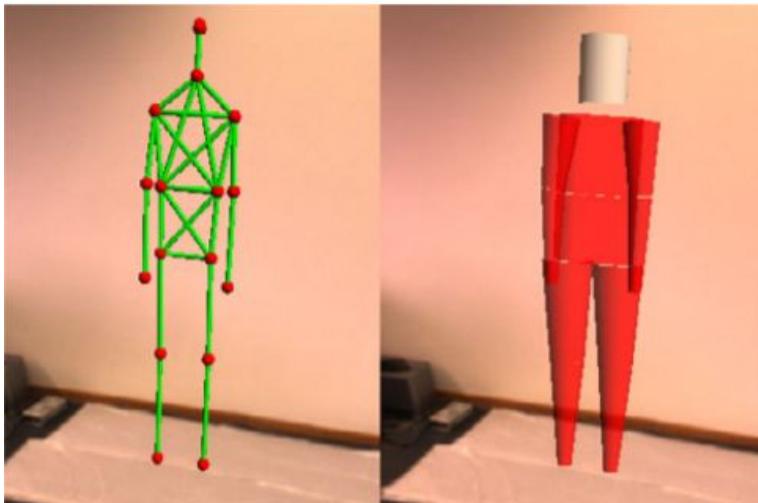


1. Robot learn how to two humans collaborate in assembling a box using motion capture data of theirs wrist.
2. Robot predict human movement based on known motion primitives and probabilistic models
3. Robot predicts and generate appropriate movement primitive

How understand human motion benefits robotics?

Environment perception

Human motion tracking



Models of human-motion helped to create a simplified algorithm for visual tracking of the human movement.

How understand human motion benefits robotics?

Learning human skills

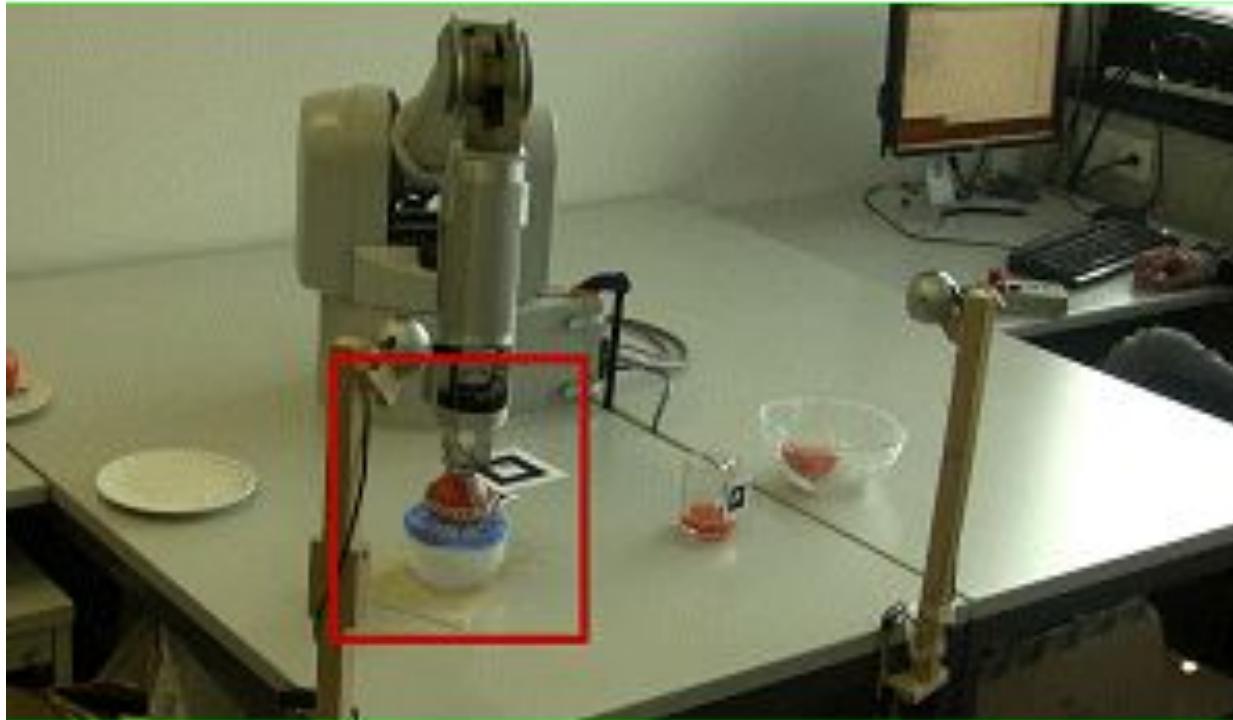
Juicing an orange Task Teaching



How understand human motion benefits robotics?

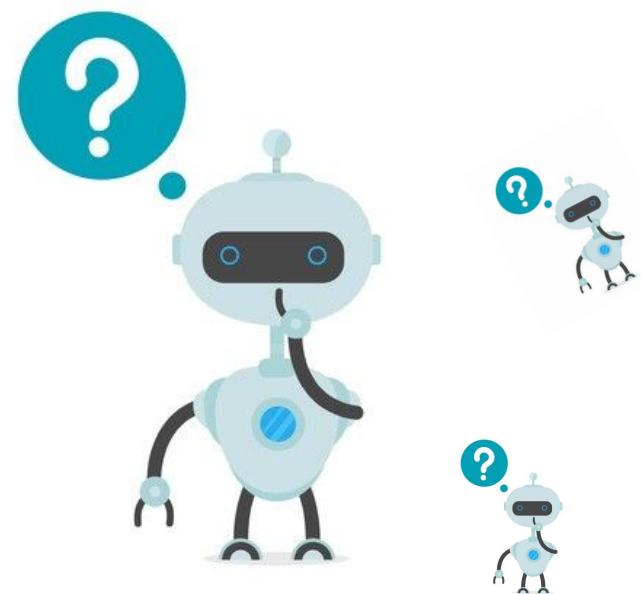
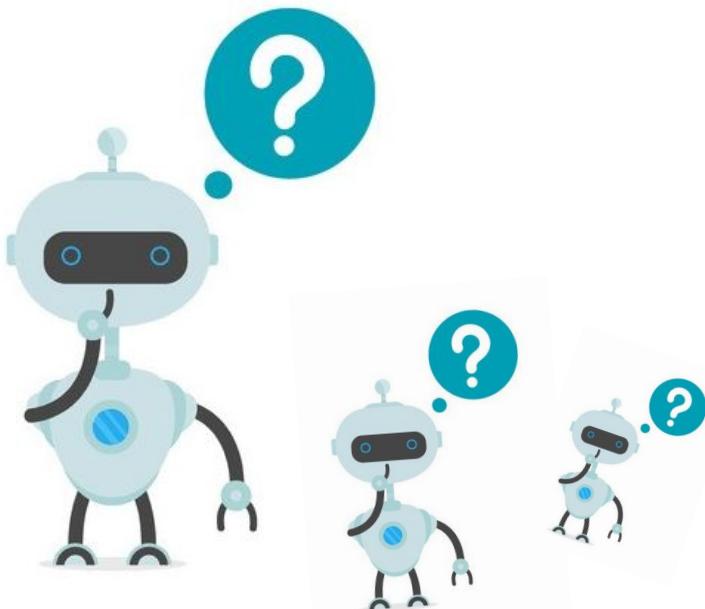
Learning human skills

Juicing an orange Task Reproduction



Source: Billard, 2013

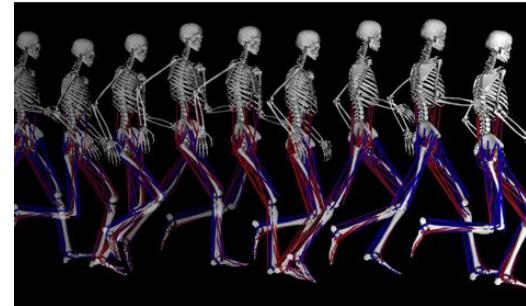
Humans can benefits from robotics concepts?



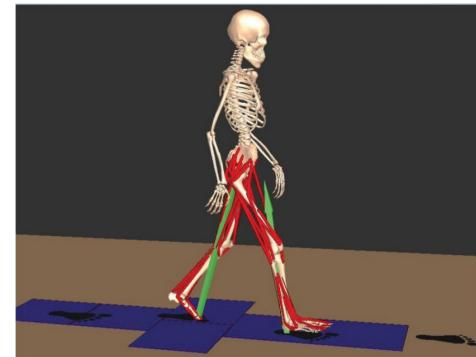
Benefits of applying robotics concepts in human motion modeling

Rehabilitation
-Generation of exercises for physiotherapy (Campos, 2009)
-Assessment of motion disorders (Campos, 2009)
-Rehab. of human digits (Valero-Cuevas, 2000)
Injury/ disorders prevention
-Work-related musculoskeletal disorders (Wang, 2015)
-Ergonomics analysis (De Magistris, 2015)

Improve performance
-Piano (Zhang, 2011)
-Athletics/Sports (Demircan, 2009)
Analyze biomechanical consequences of surgical reconstructions
-Joint replacements
-Tendon transfers
-Post operative function of shoulder (Holzbaur, 2005)



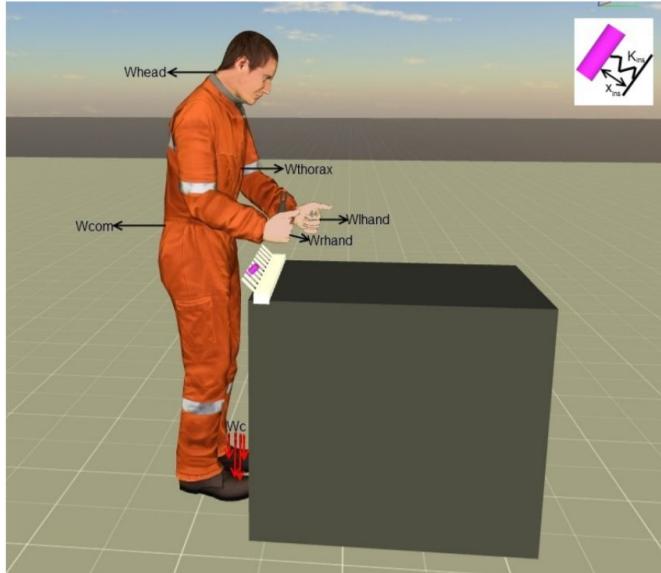
OpenSim (Seth, 2011)



SIMM (Delp, 1995)

Benefits of apply robotics concepts in human motion modeling

Ergonomics analysis

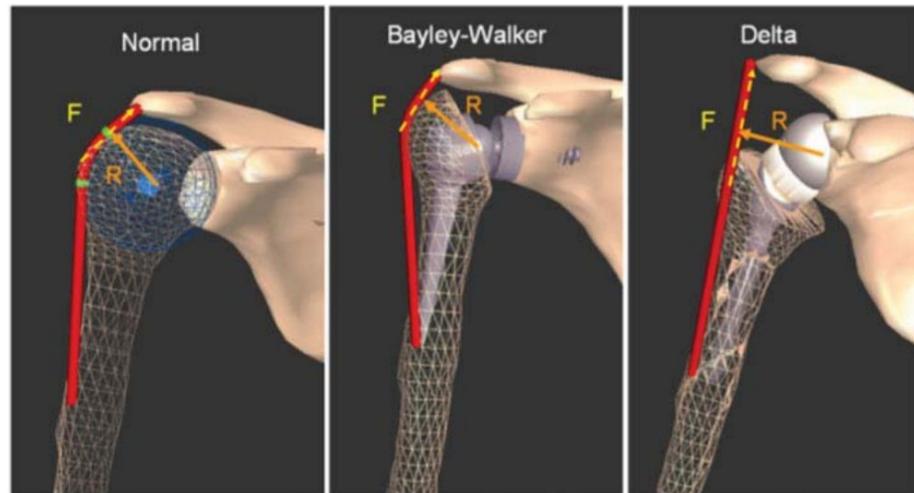


Simulation of insert-fitting task under different conditions (using one hand, using two hands, using a tool). Risk of biomechanical overload measured with OCRA method. (De Magistris, 2015)

Digital human models can be used to help workstation and work activity design to reliably identify and assess workplace induced musculoskeletal disorders and other biomechanical risks factors

Benefits of apply robotics concepts in human motion modeling

Shoulder replacement



Visual representation of the difference in moment arms of the middle deltoid muscle for natural subjects and those with B-W and Delta prostheses (Masjedi, 2010)

Comparison of two shoulder prosthesis full range of motion and joint stabilization using musculoskeletal models (SIMM)

Human Motion Strategies

Changqing Lu

Human motion strategies

Interdisciplinary: Neuroscience, biomechanics, physiology, robotics, computer science...

Methods: simulation on proposed hypothesis, building human motion database...

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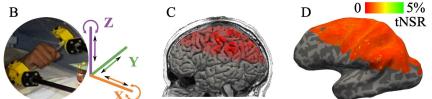
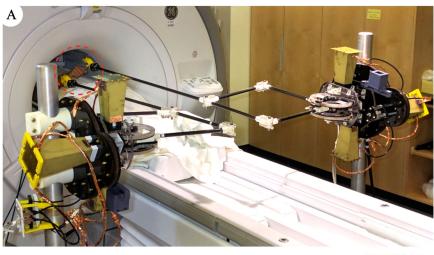


Manual Intelligence Lab (Maycock, 2010)

Human motion strategies

Interdisciplinary: Neuroscience, biomechanics, physiology, robotics, computer science...

Methods: simulation on proposed hypothesis, building human motion database...



Haptic fMRI Interface (Menon, 2017)

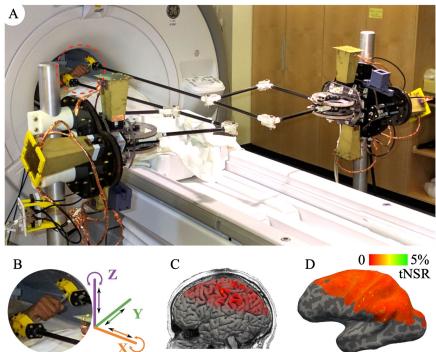


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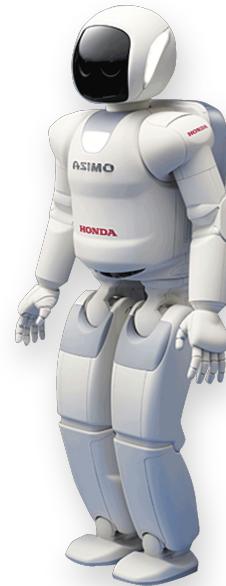


Manual Intelligence Lab (Maycock, 2010)

Robotics

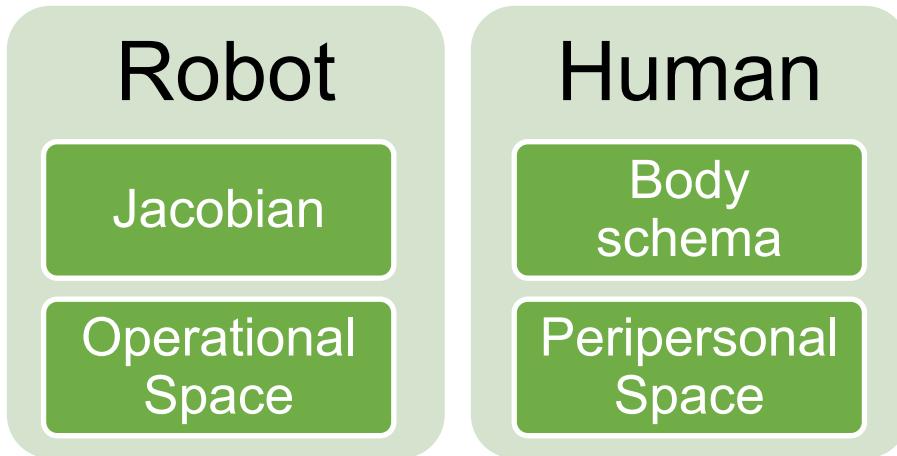
- Manual intelligence
- Cognitive intelligent robots
- Humanoids with **general** application

bio-inspired
human-inspired model

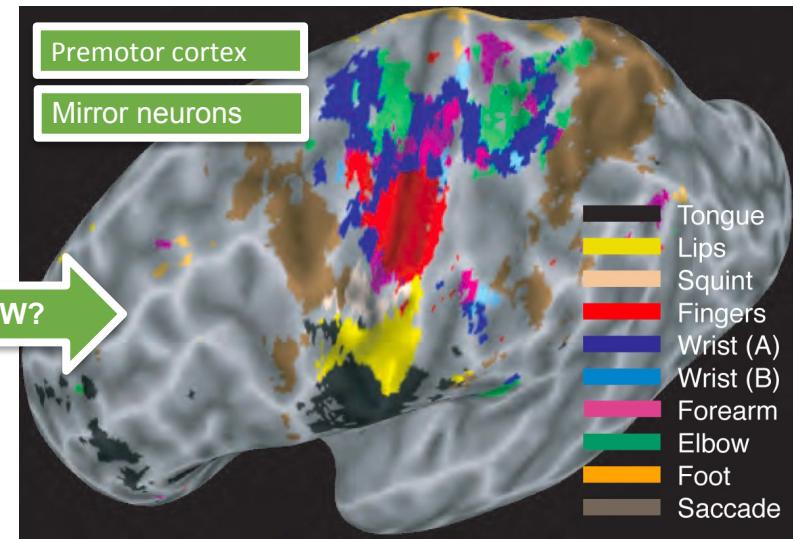
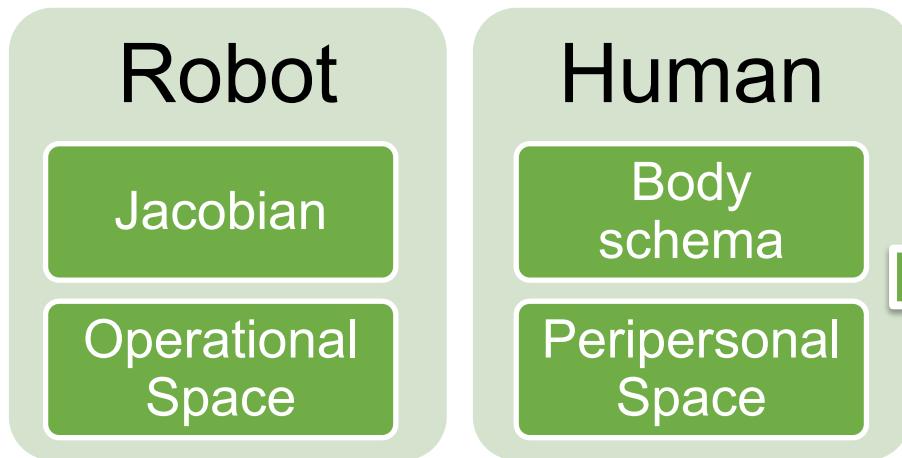


Kinematics – “Body schema” and “Peripersonal space”

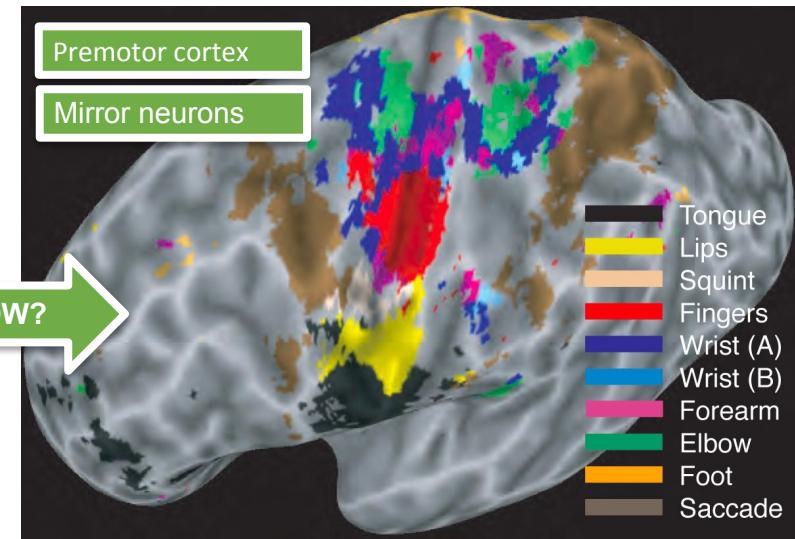
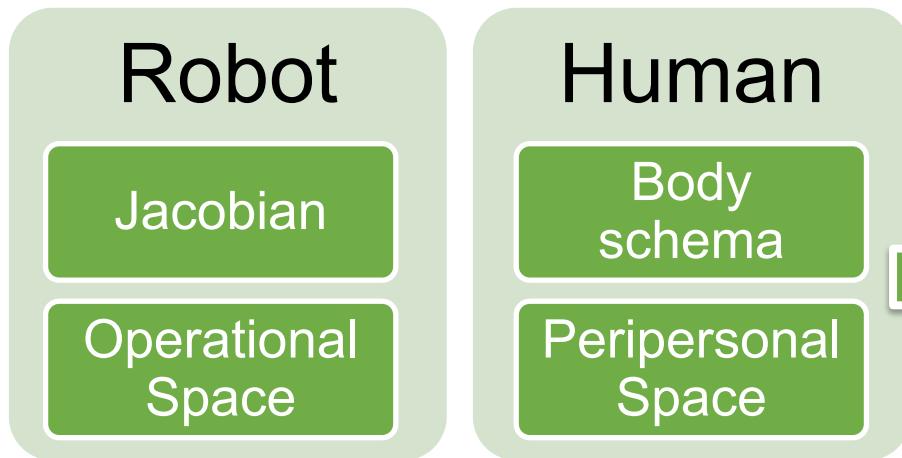
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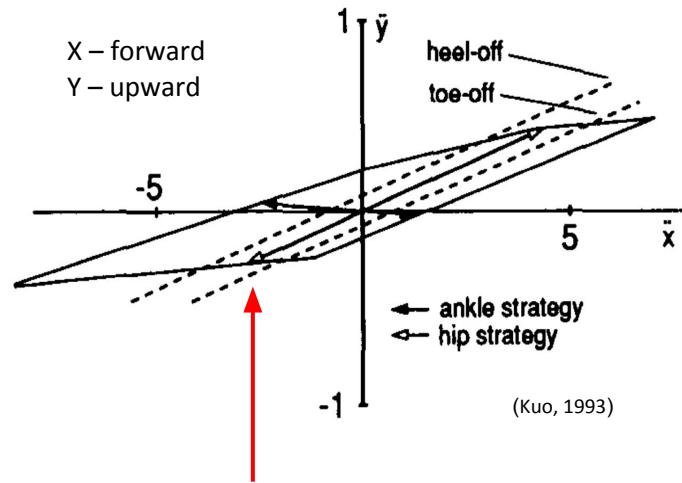
Tool-use: extension of peripersonal space or update of body schema?

Inverse Kinematics: dealing with redundancy

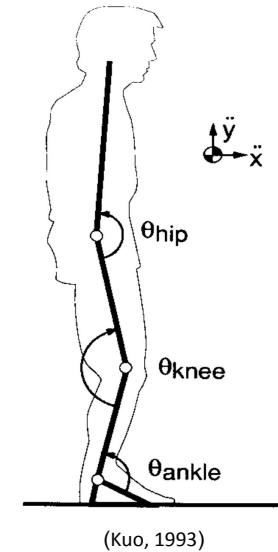
Inverse Kinematics: dealing with redundancy

Posture Stability

- Feasible acceleration set (FAS)
- Hip strategy vs. ankle strategy



hip strategy more
“parallel” to the
constraints



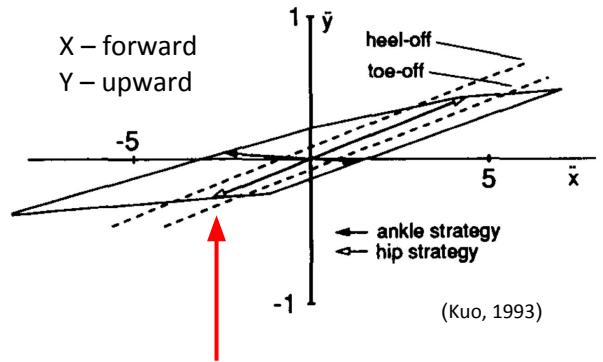
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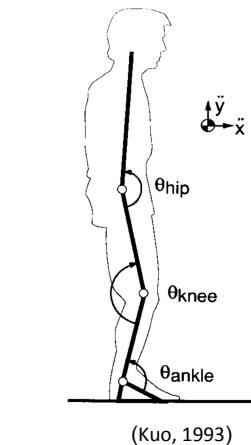
- Feasible acceleration set (FAS)
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Posture Sway

- Exploratory redundant motion
- Responsive forces from the ground



hip strategy more
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constraints



(Kuo, 1993)

Inverse Kinematics: dealing with redundancy

Posture Stability

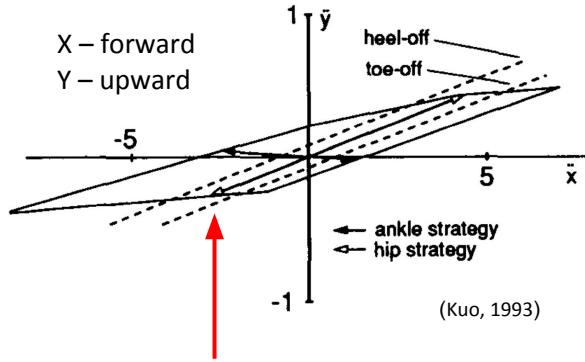
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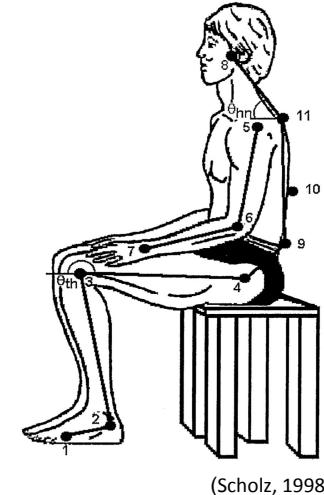
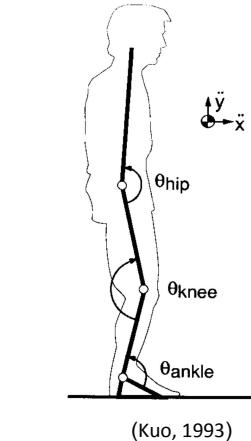
- Exploratory redundant motion
- Responsive forces from the ground

Sit-to-stand Motion

- Identifying the control variables to plan trajectories
- Control stability of body center
 - Head Position less controlled



hip strategy more
“parallel” to the
constraints

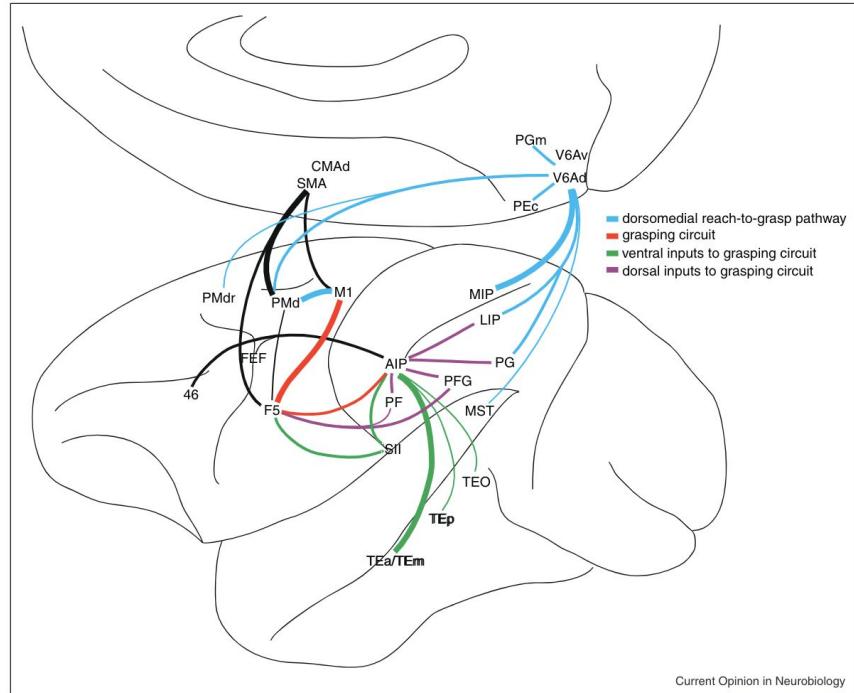


Task Space Control - Grasping

Task Space Control - Grasping

Complex biomechanics

- Transfer visual and spatial information
 - Location/size/shape/orientation...
- Fast process



From neuroscience: Cortical grasping network (Davare, 2011)

Current Opinion in Neurobiology

Task Space Control - Grasping

Parameters input:

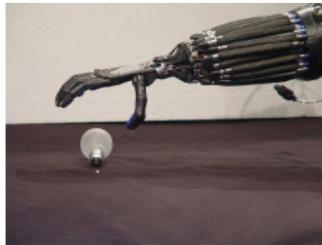
- a relative position
- a relative orientation
- an approach distance

“Pre-grasp” phase

Position and joints angles



4 predetermined grasp
strategies



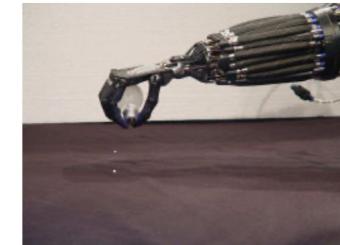
(a) Pre-grasp pos.



(b) Grasp position.



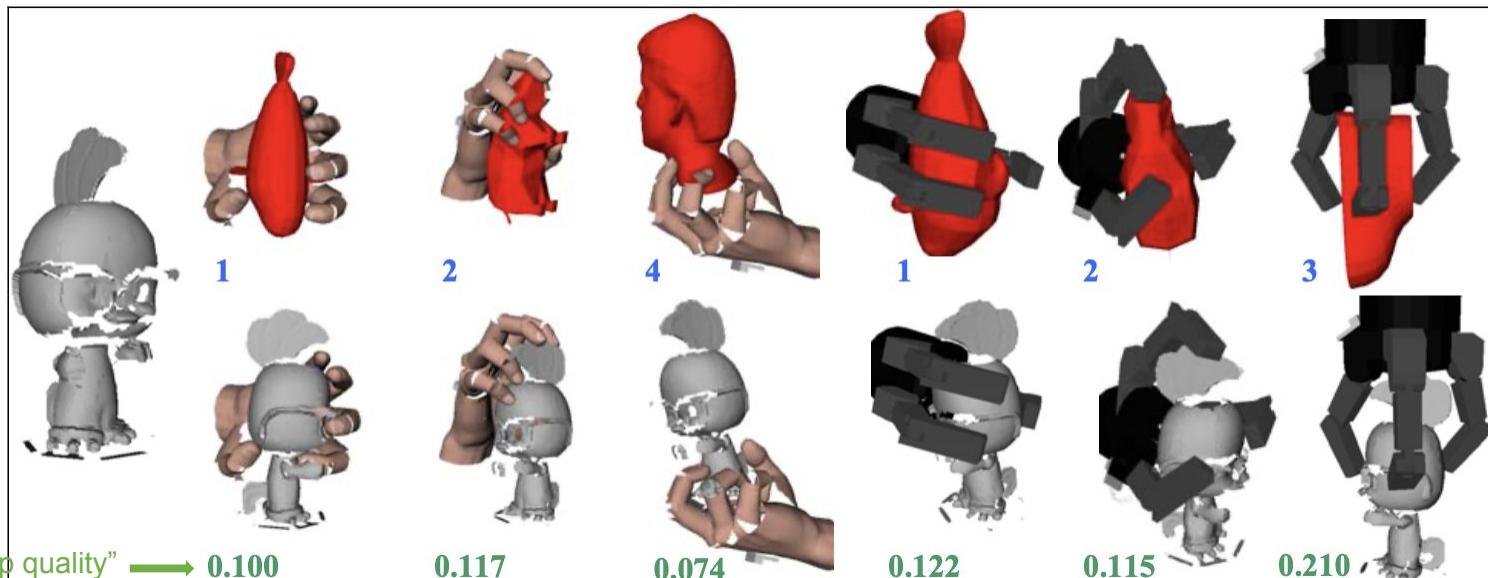
(c) Object grasped.



(d) Object lifted.

Task Space Control - Grasping

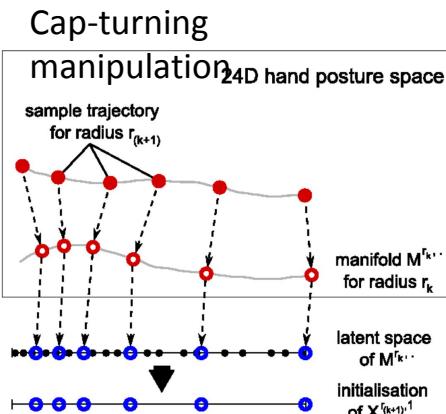
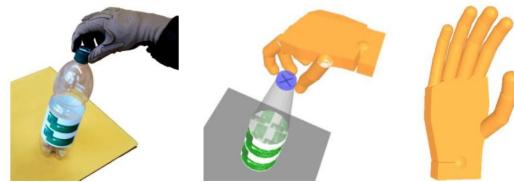
Data-driven grasp: constructing a grasp database; low-dimension “eigengrasp”



Task Space Control – Object manipulation

Task Space Control – Object manipulation

Manipulation manifolds: incorporating **time** as a manipulation parameter



Training with small amount of data

(Steffen,2008)

Task Space Control – Object manipulation

Manipulation manifolds: incorporating **time** as a manipulation parameter



Cap-turning

manipulation

2^{4D} hand posture space

sample trajectory

for

radius

$r_{(k+1)}$

for

radius

r_k

manifold

$M^{r_{k+1}}$

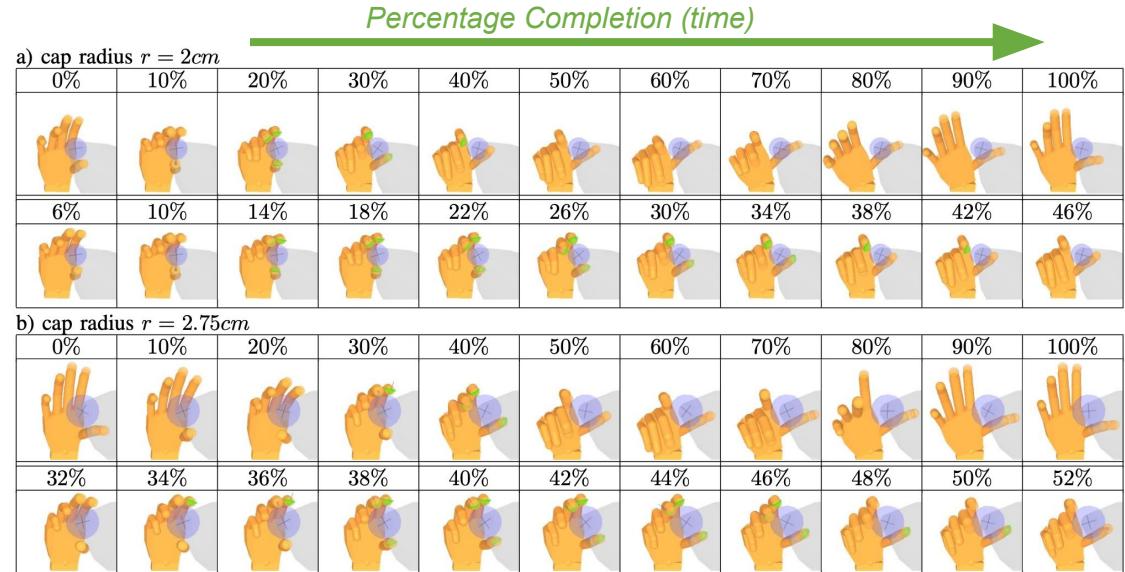
for

radius

r_k

latent space
of $M^{r_{k+1}}$
initialisation
of $X^{(k+1),1}$

Training with small amount of data



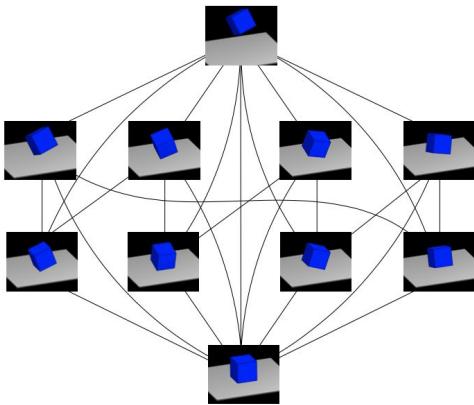
Result: turning caps with different radius with one manipulation manifold

(Steffen,2008)

Task Space Control – Object manipulation

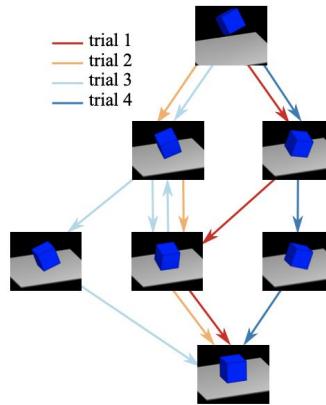
Contact manipulation tasks: traversing the contact-state graphs

A. Full contact state graph

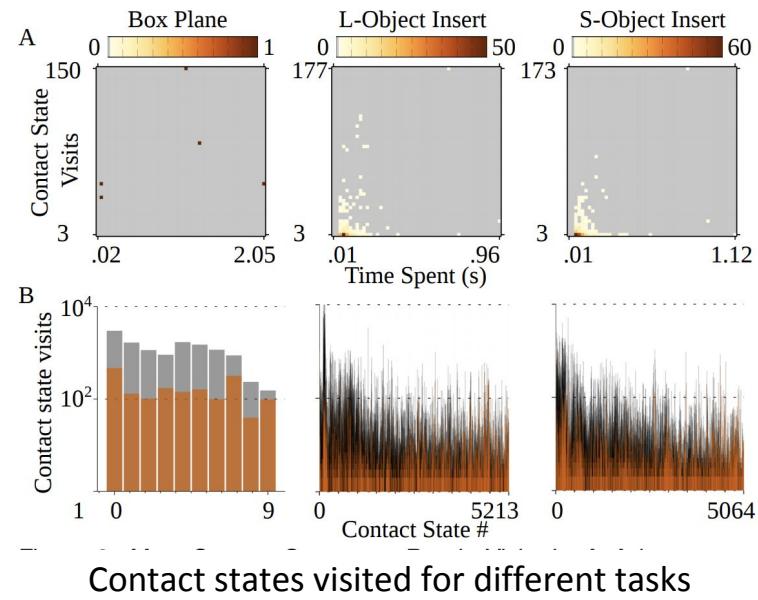


Subset of contact states

B. Empirical contact state sub-graph



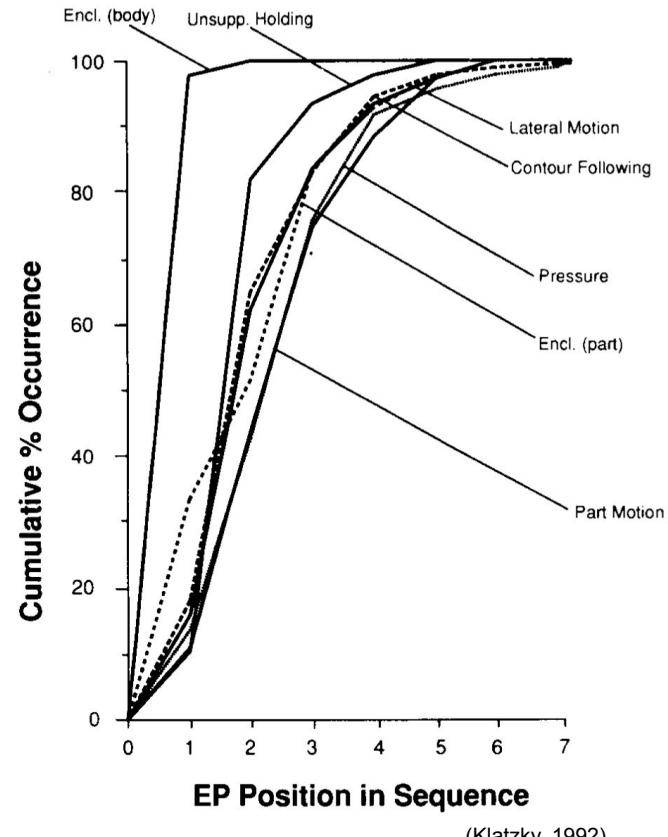
(Klingbeil, 2014)



Task Space Control – Hands as perceptual tools

Two-stage haptic exploration for object identification (1992)

- Stage 1: Grasp and lift
- Stage 2:
 - contour following
 - lateral motion
 - Enclosure
 - unsupported holding
 - ...



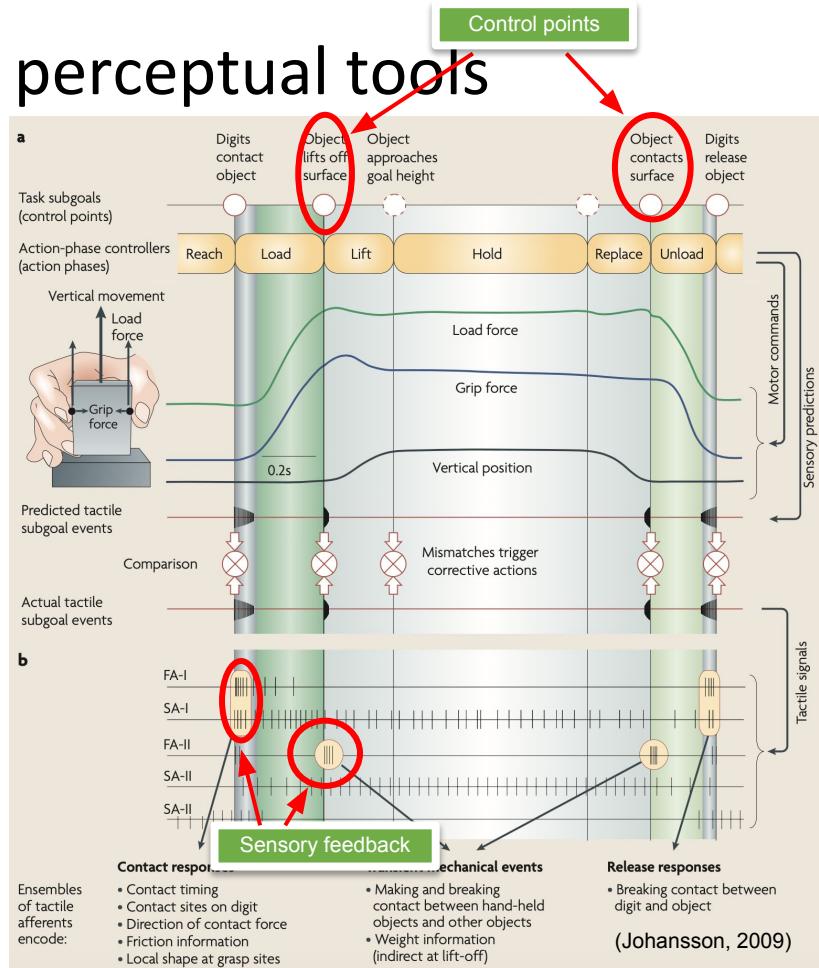
Task Space Control – Hands as perceptual tools

Difficult to understand in a higher neuroscience level...

Task Space Control – Hands as perceptual tools

Observed:

- Sensory feedback defining “control points”
- Corrective actions (predicted/actual)



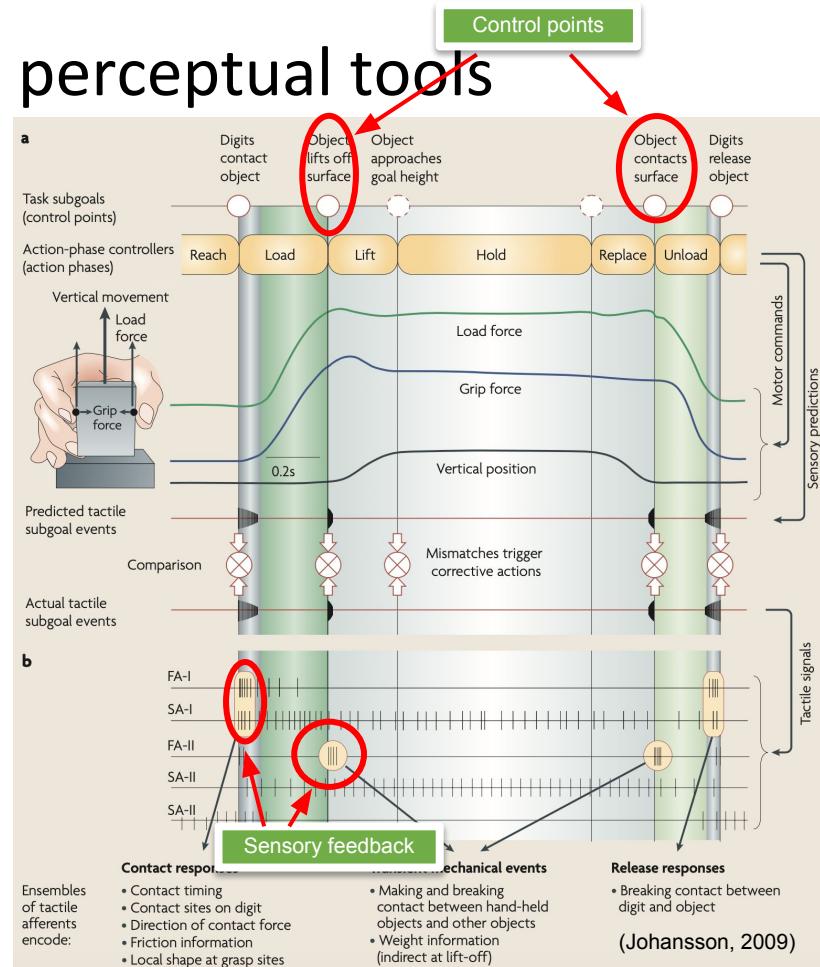
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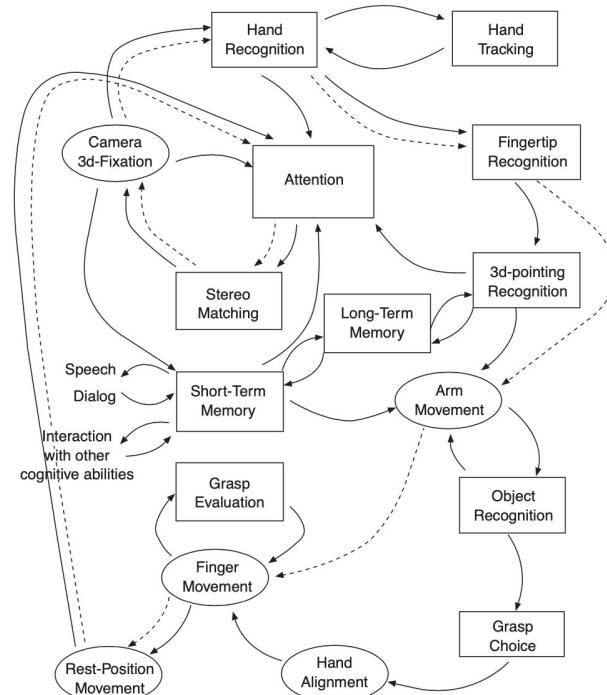
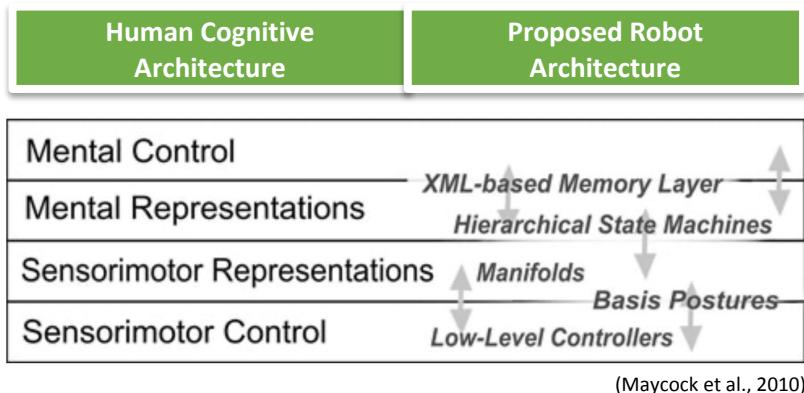
Unanswered:

- Which brain regions control manipulation?
- What is the CNS embodiment for a given manipulation task?
- What mechanisms coordinating sensory interactions and predictions?



Robotics and Neuroscience - Cognitive nature of action

Robotics and Neuroscience - Cognitive nature of action



Functional modules of the **GRAVIS** architecture (Schack, 2009)

Robotics Applied in Biomechanics

Shivani Guptasarma

Some questions about human movement

What are the principles governing it?

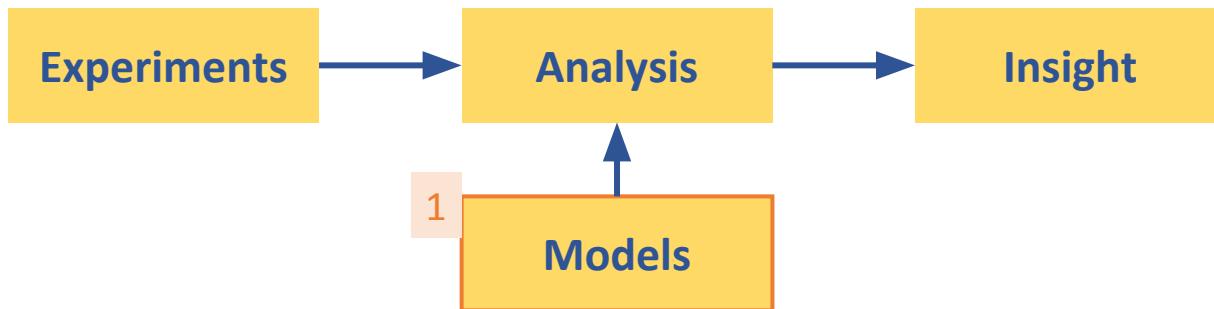
What are the mechanisms causing it?

How can we “improve” it?

How can we imitate it?

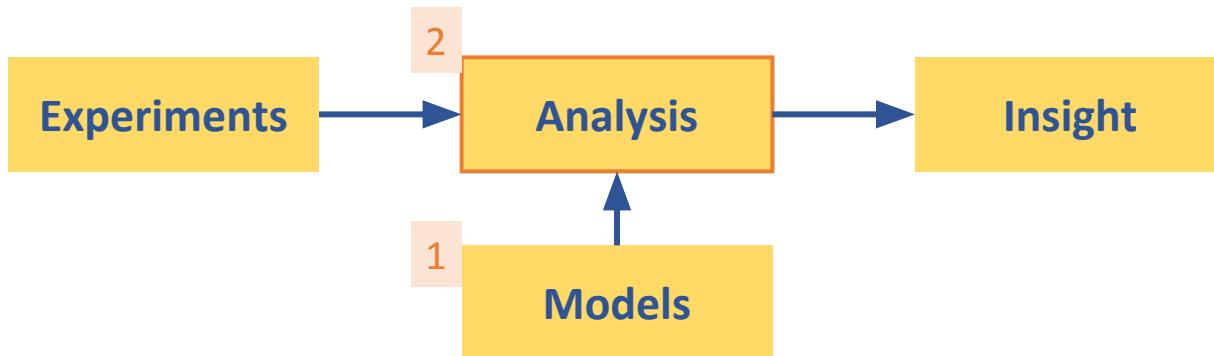
Some questions about human movement

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Some questions about human movement

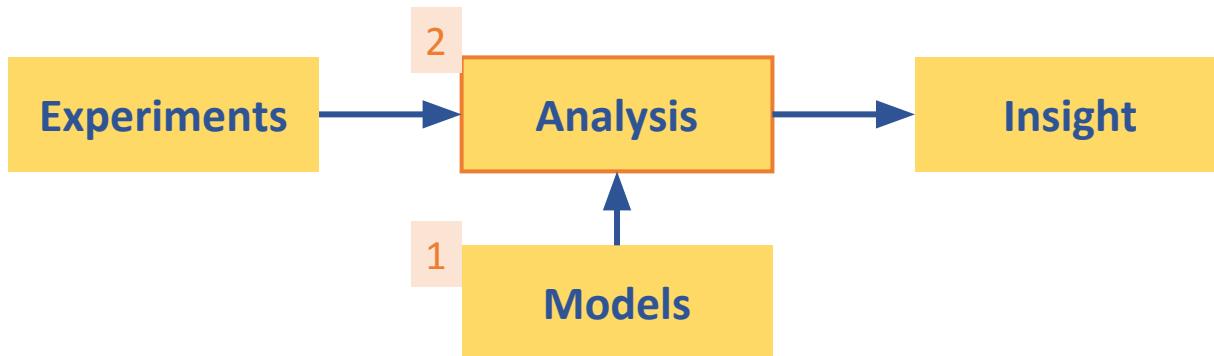
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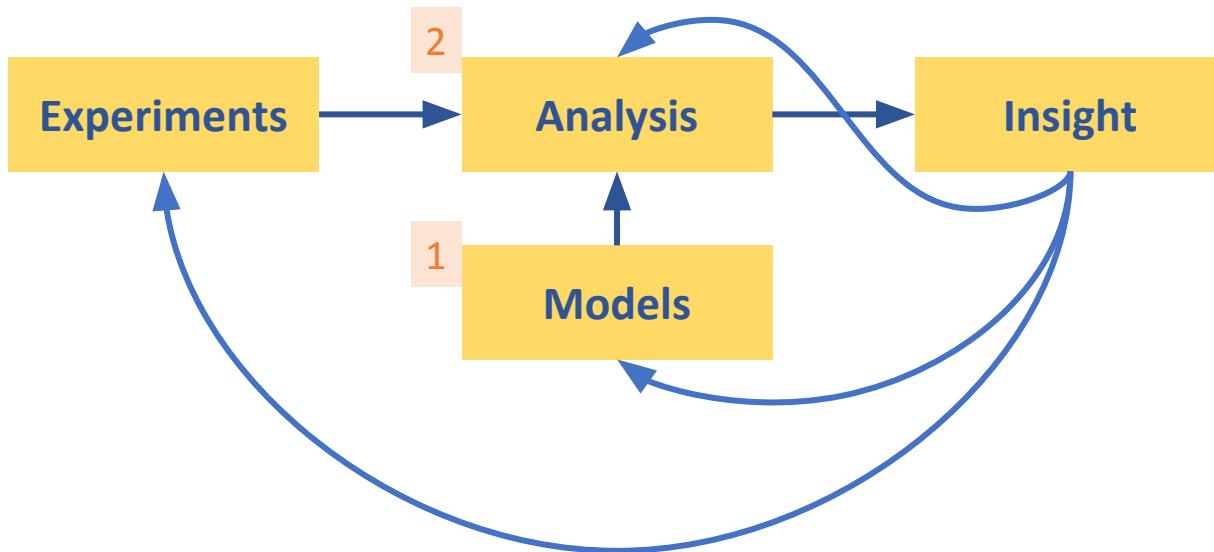
How can we “improve” it?
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Some questions about human movement

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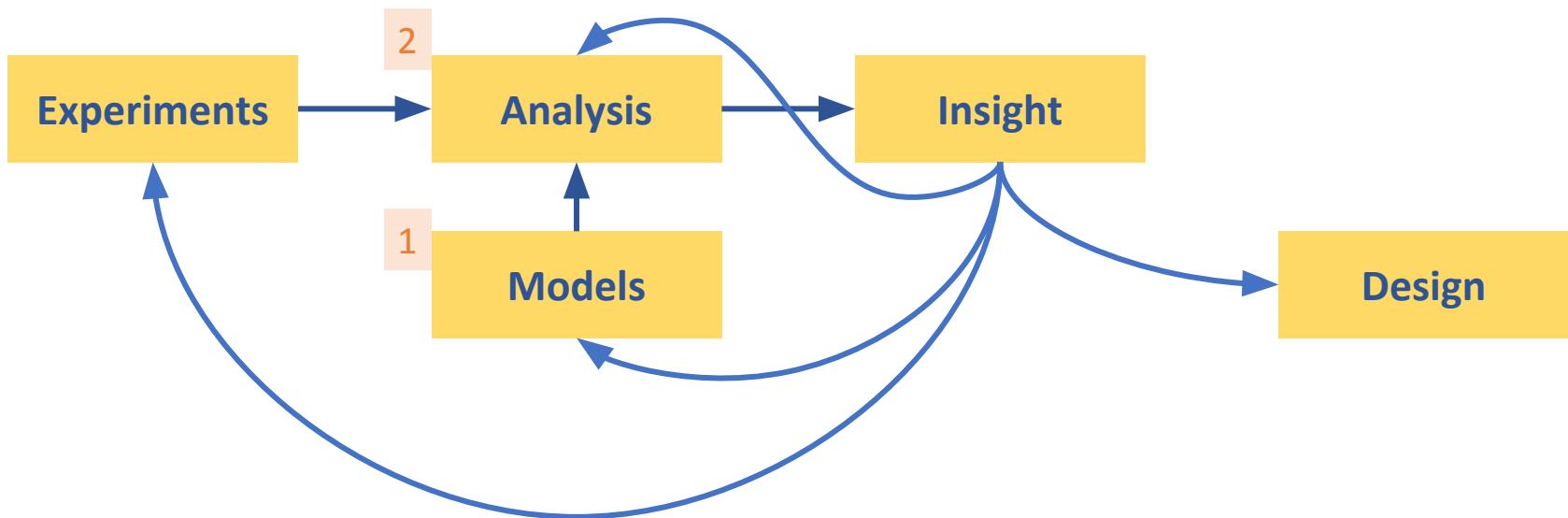
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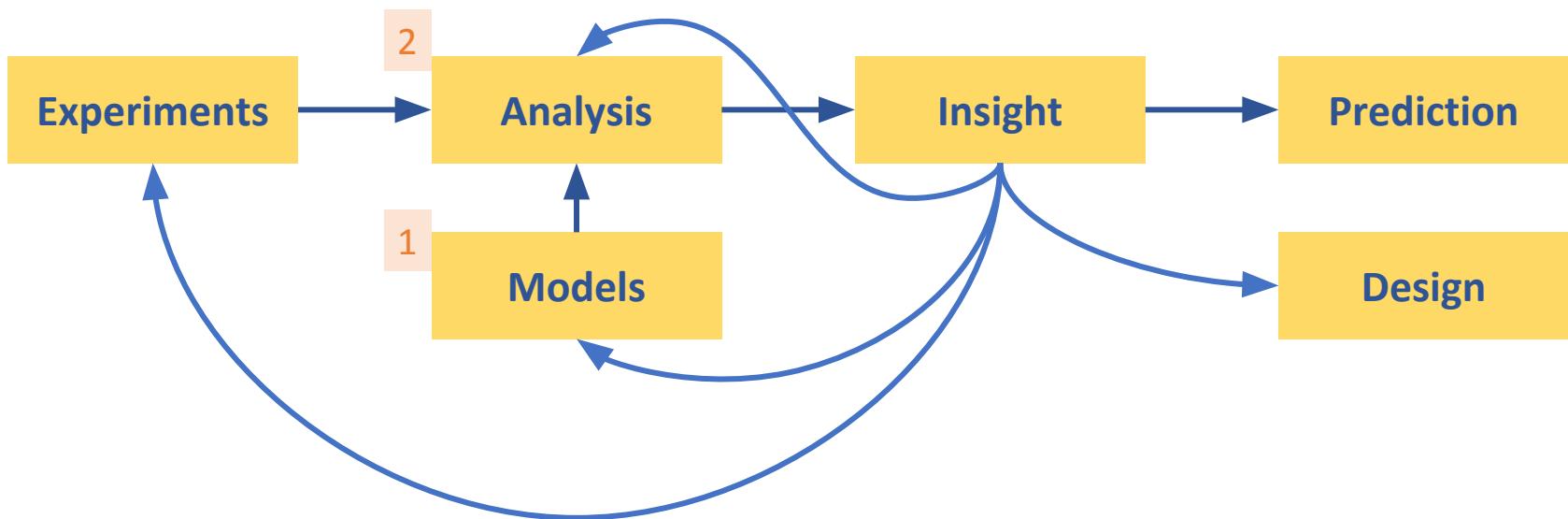
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Some questions about human movement

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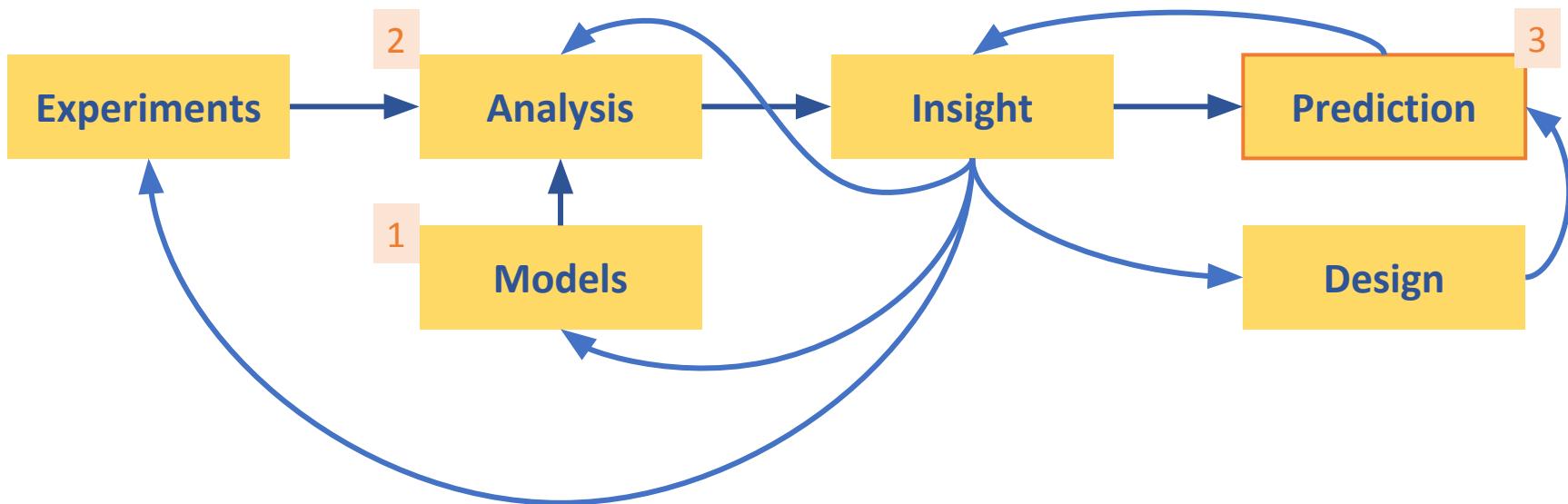
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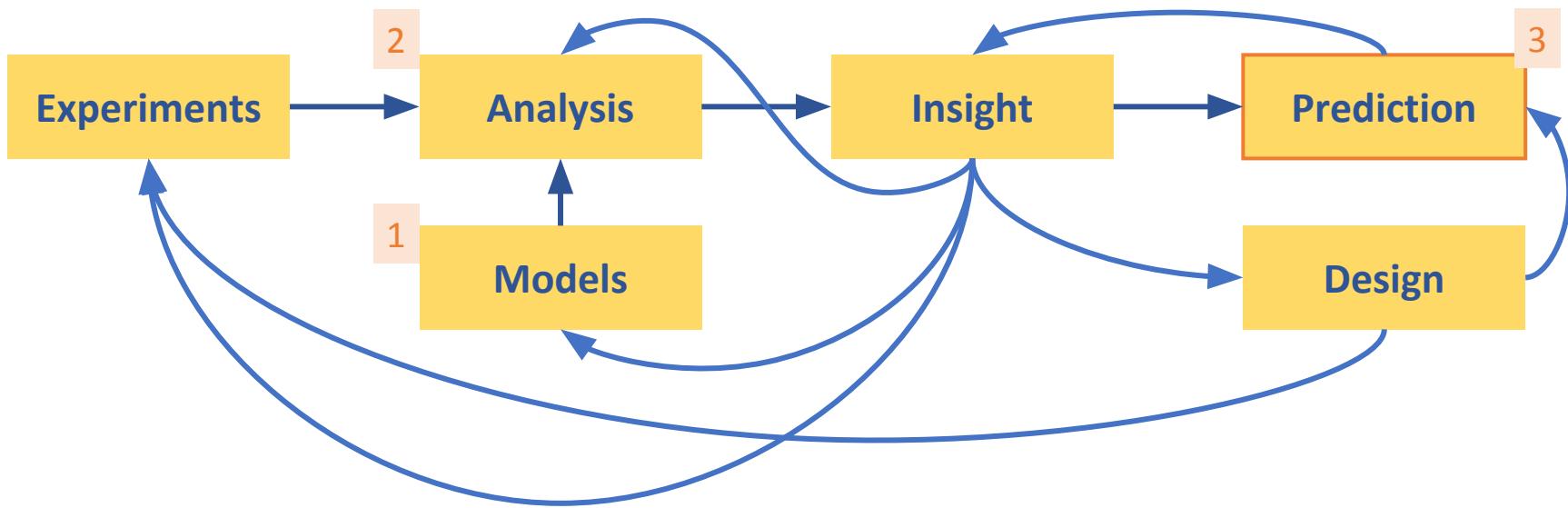
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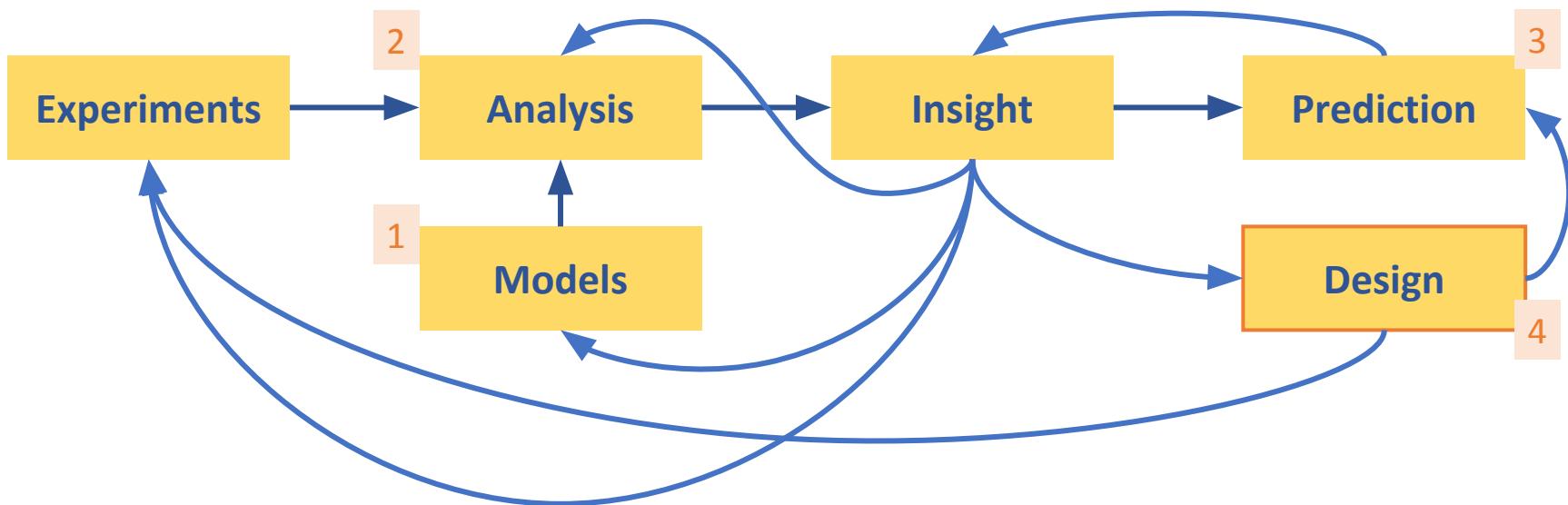
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Some questions about human movement

What are the principles governing it?
What are the mechanisms causing it?

How can we “improve” it?
How can we imitate it?



The body is a robot!

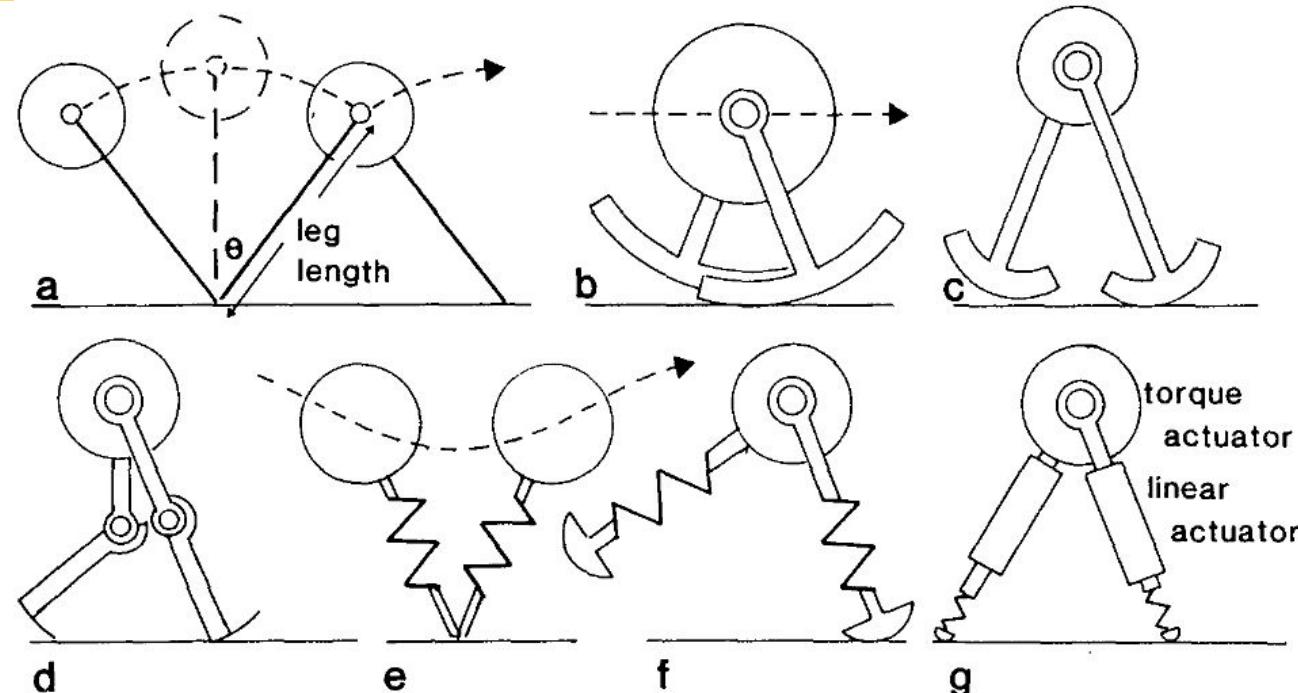
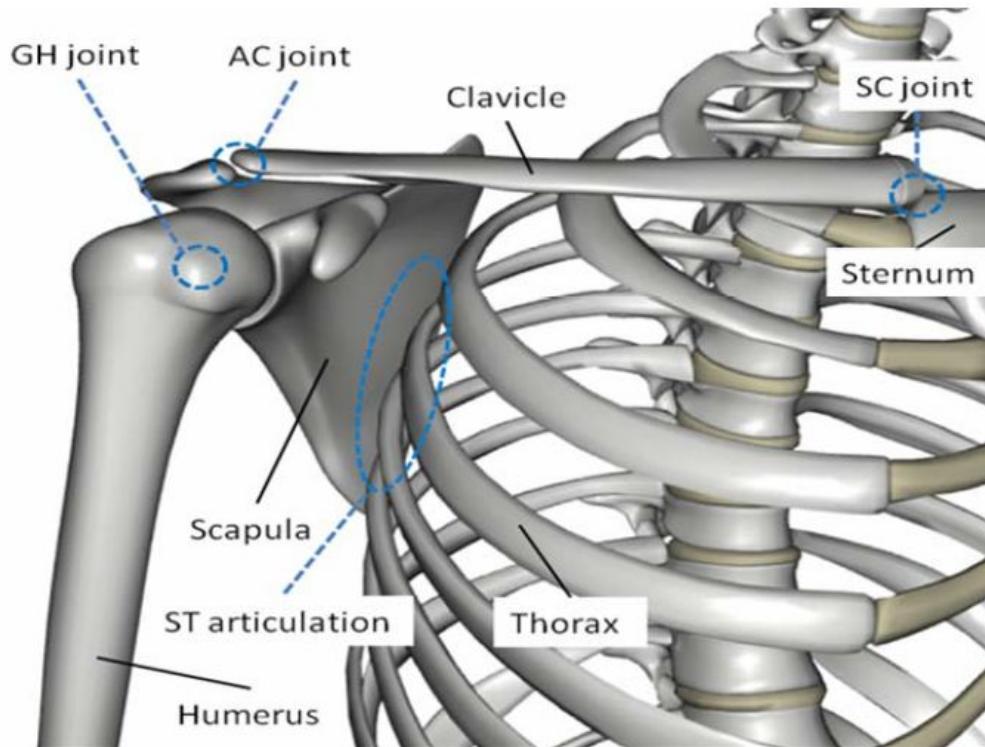


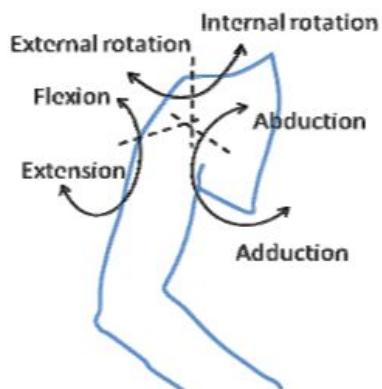
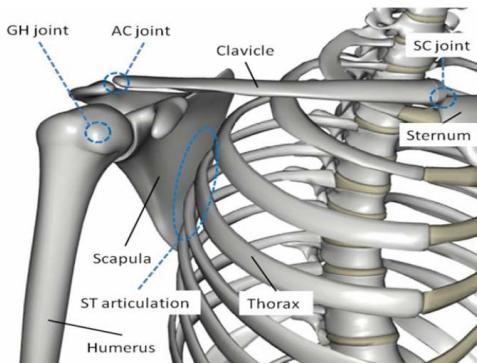
Fig 1. Models of walking and running: a) is the minimal biped; b) the synthetic wheel; c) McGeer's general two-dimensional biped; d) his knee-jointed biped; e) the mass-spring model; f) McGeer's passive running biped; and g) Alexander's force-controlled biped.

Example: modeling the shoulder (Yang *et al.*, 2010)



Models

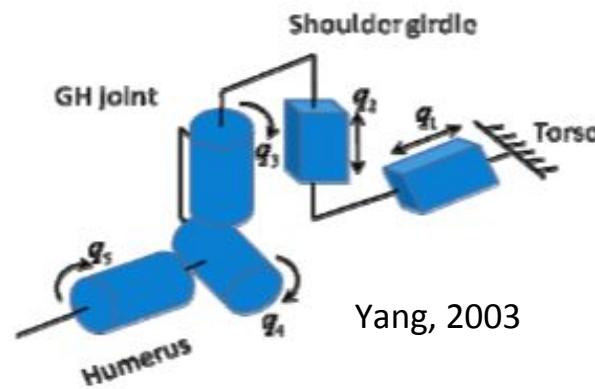
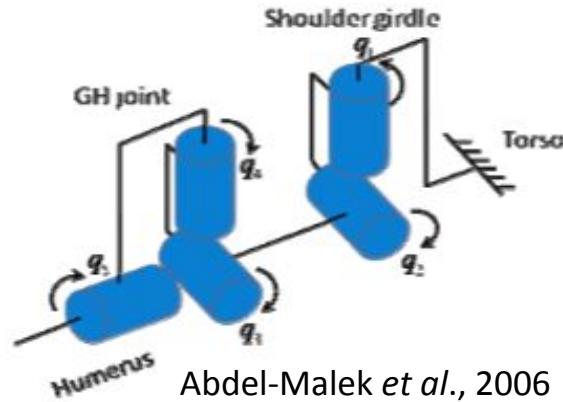
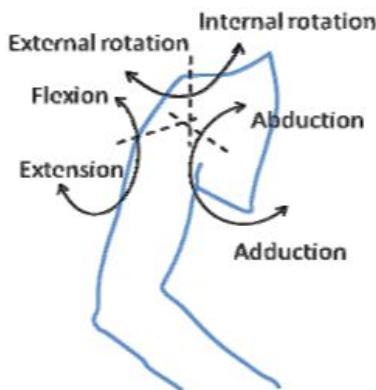
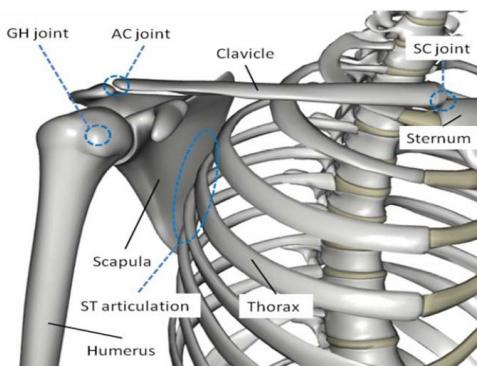
Example: modeling the shoulder (Yang *et al.*, 2010)



Images: Yang *et al.*, 2010

Models

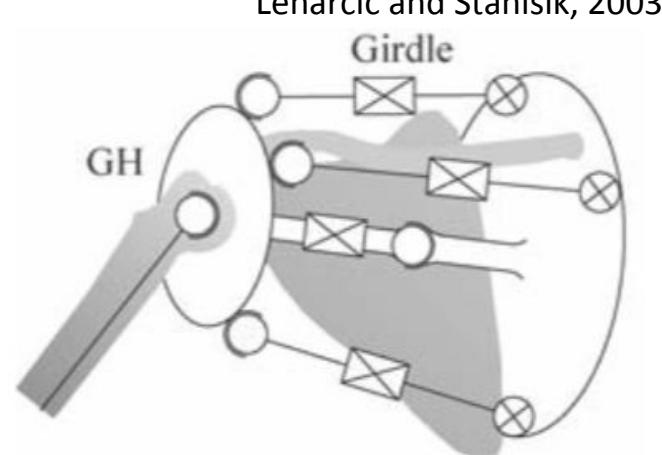
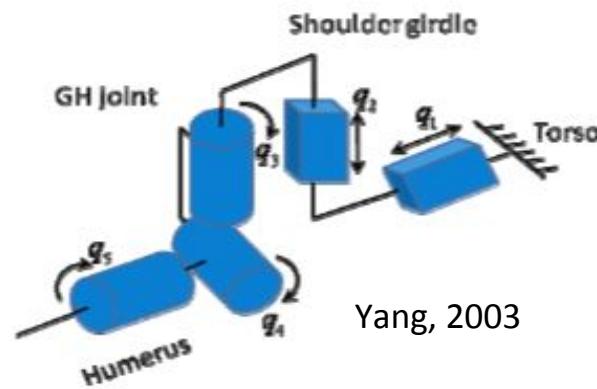
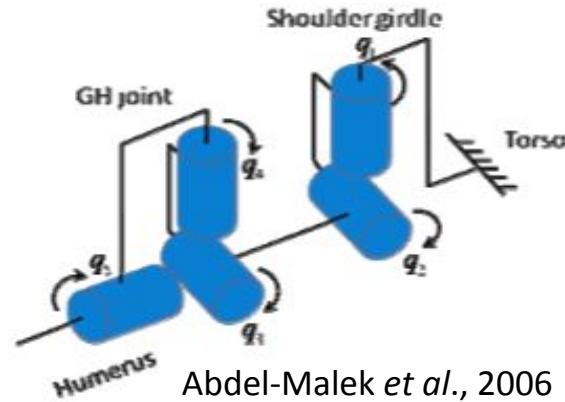
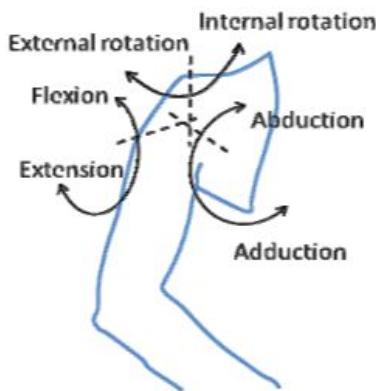
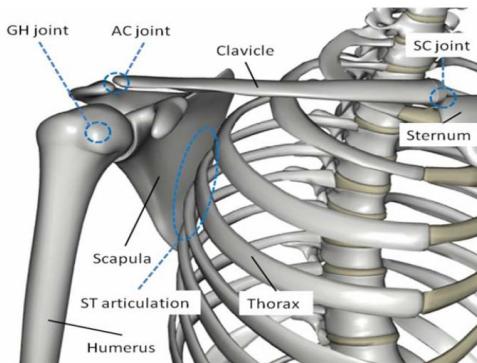
Example: modeling the shoulder (Yang *et al.*, 2010)



Images: Yang *et al.*, 2010

Models

Example: modeling the shoulder (Yang *et al.*, 2010)

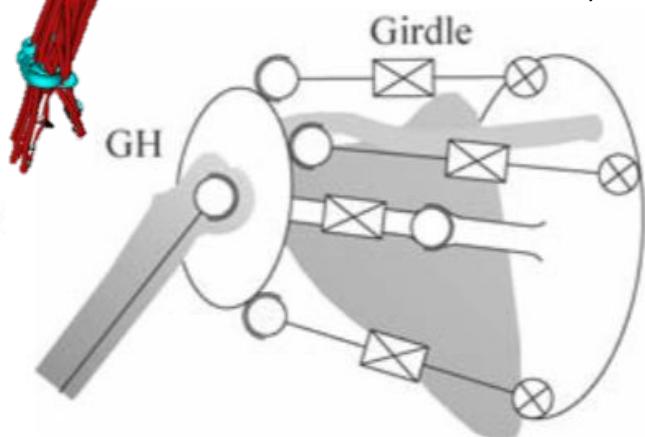
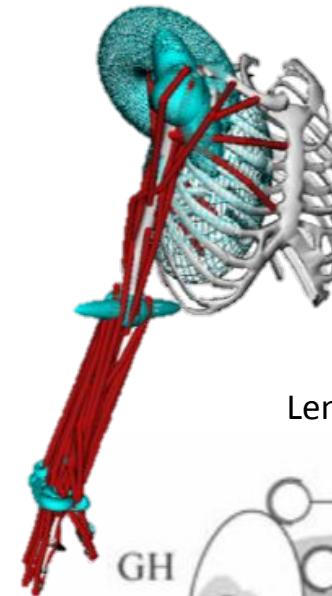
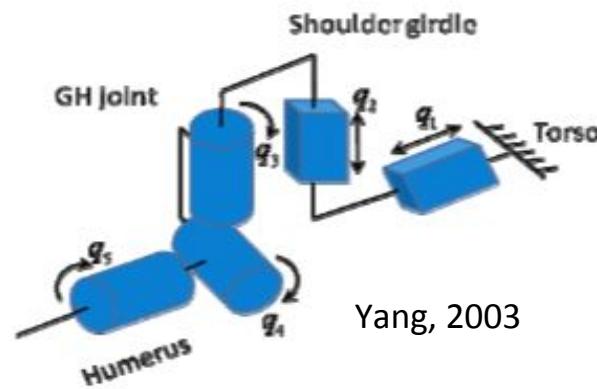
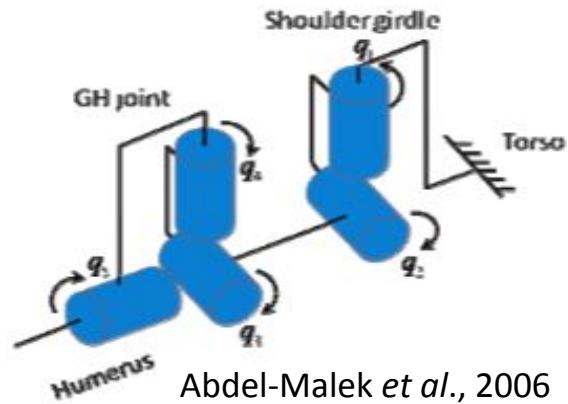
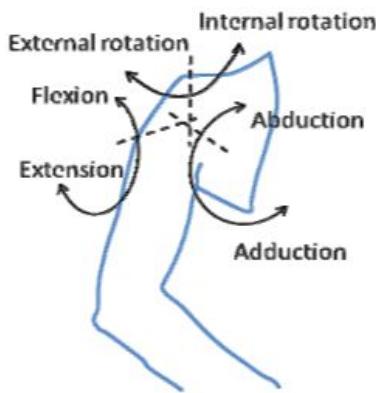
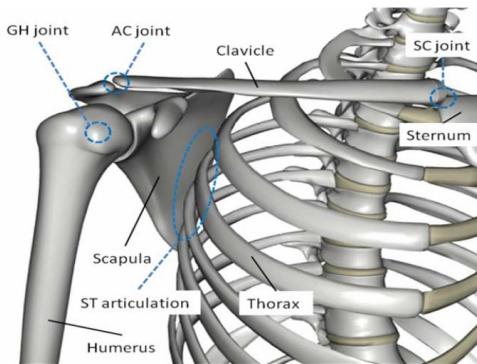


Images: Yang *et al.*, 2010

Lenarcic and Stanisik, 2003

Models

Example: modeling the shoulder (Yang *et al.*, 2010)



Images: Yang *et al.*, 2010

Analysis

How do we generate motion?

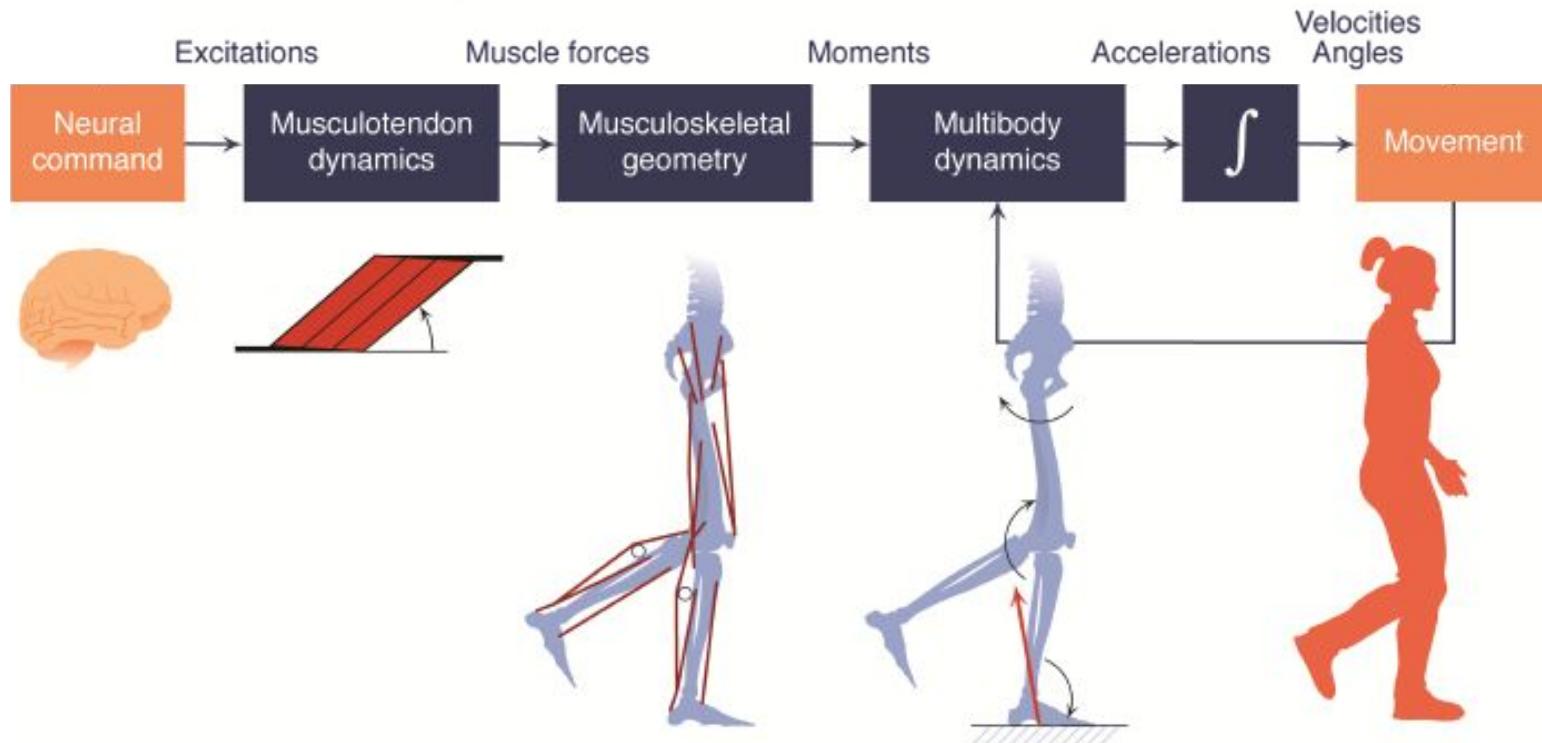
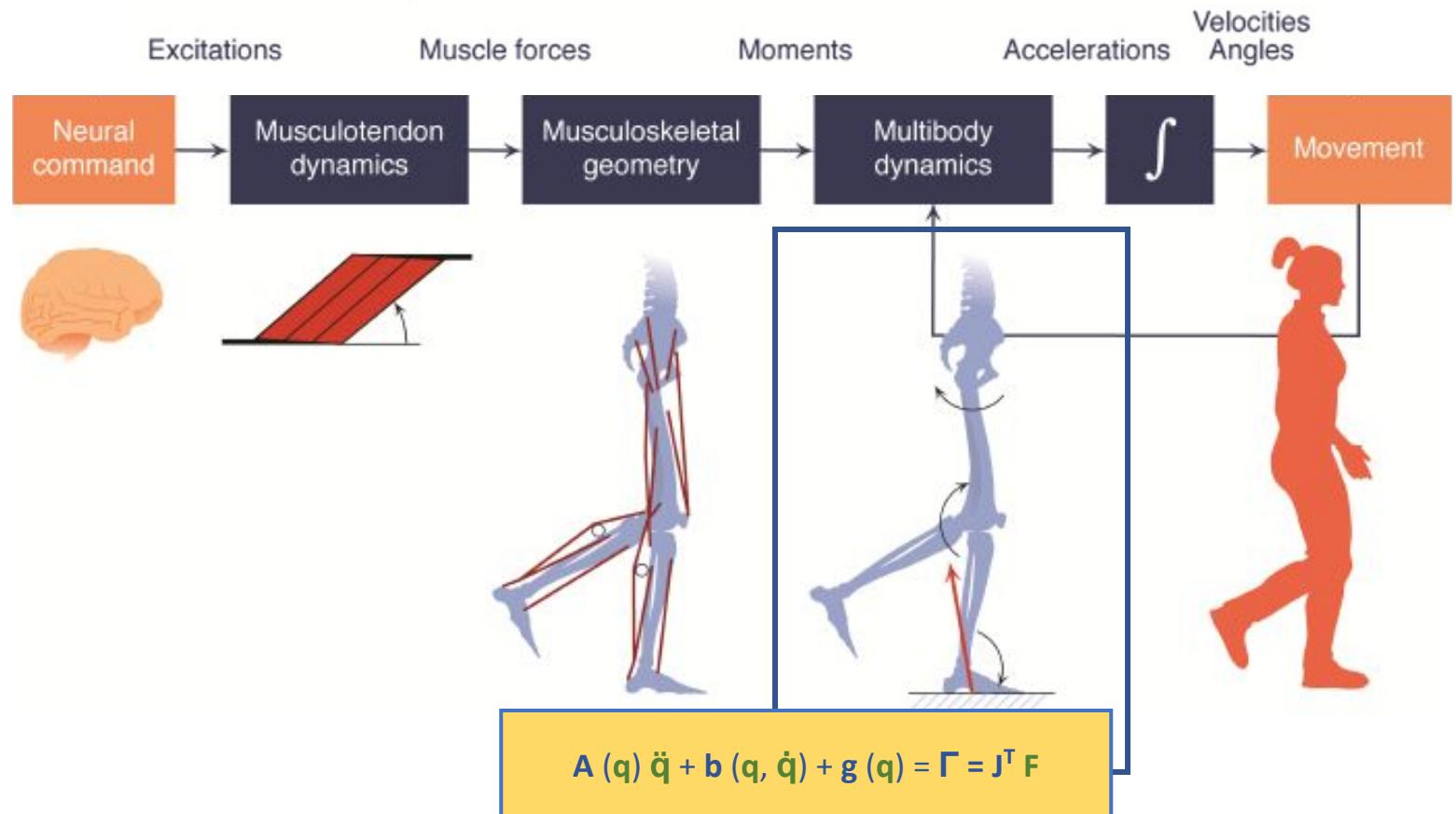
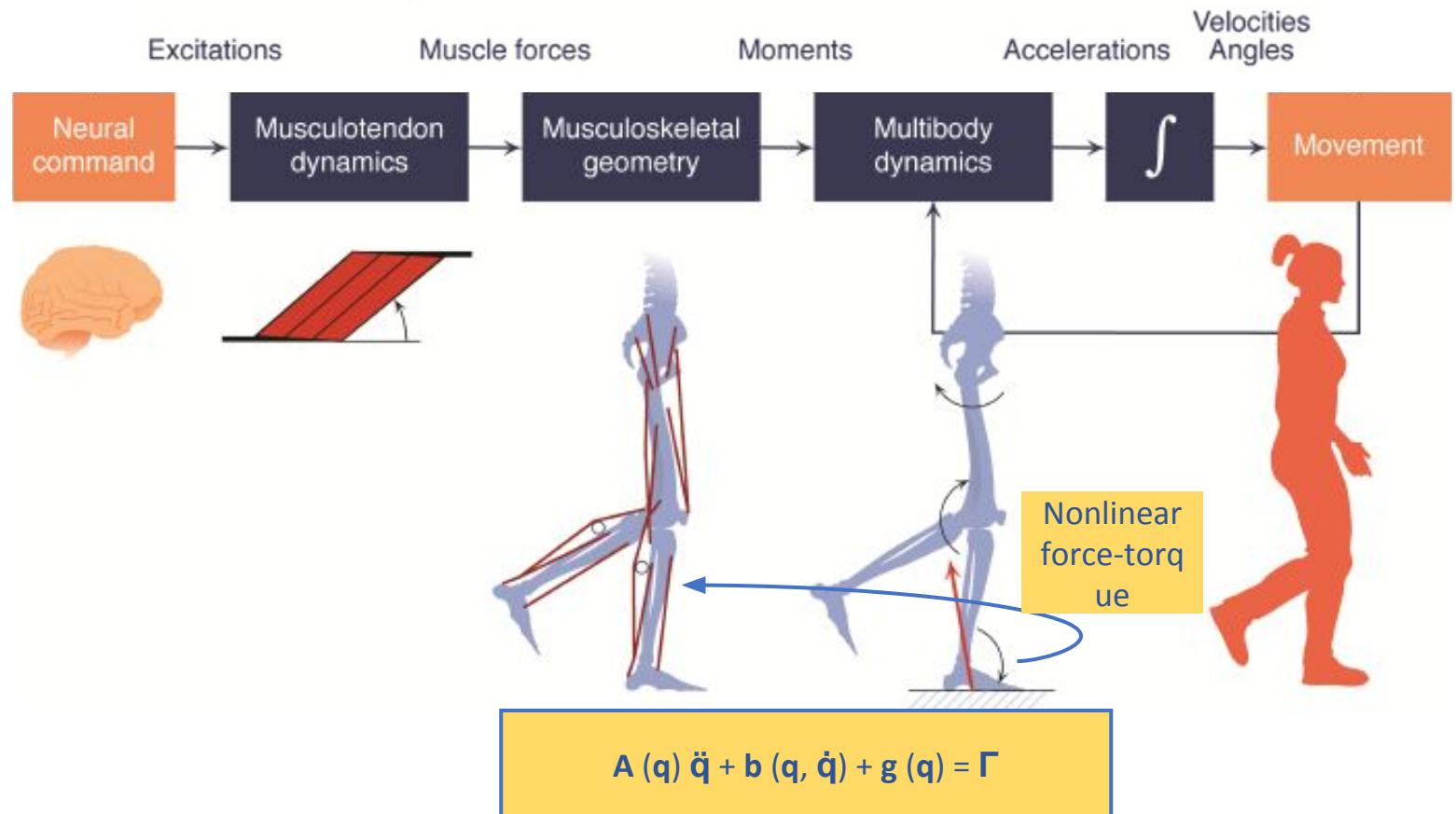
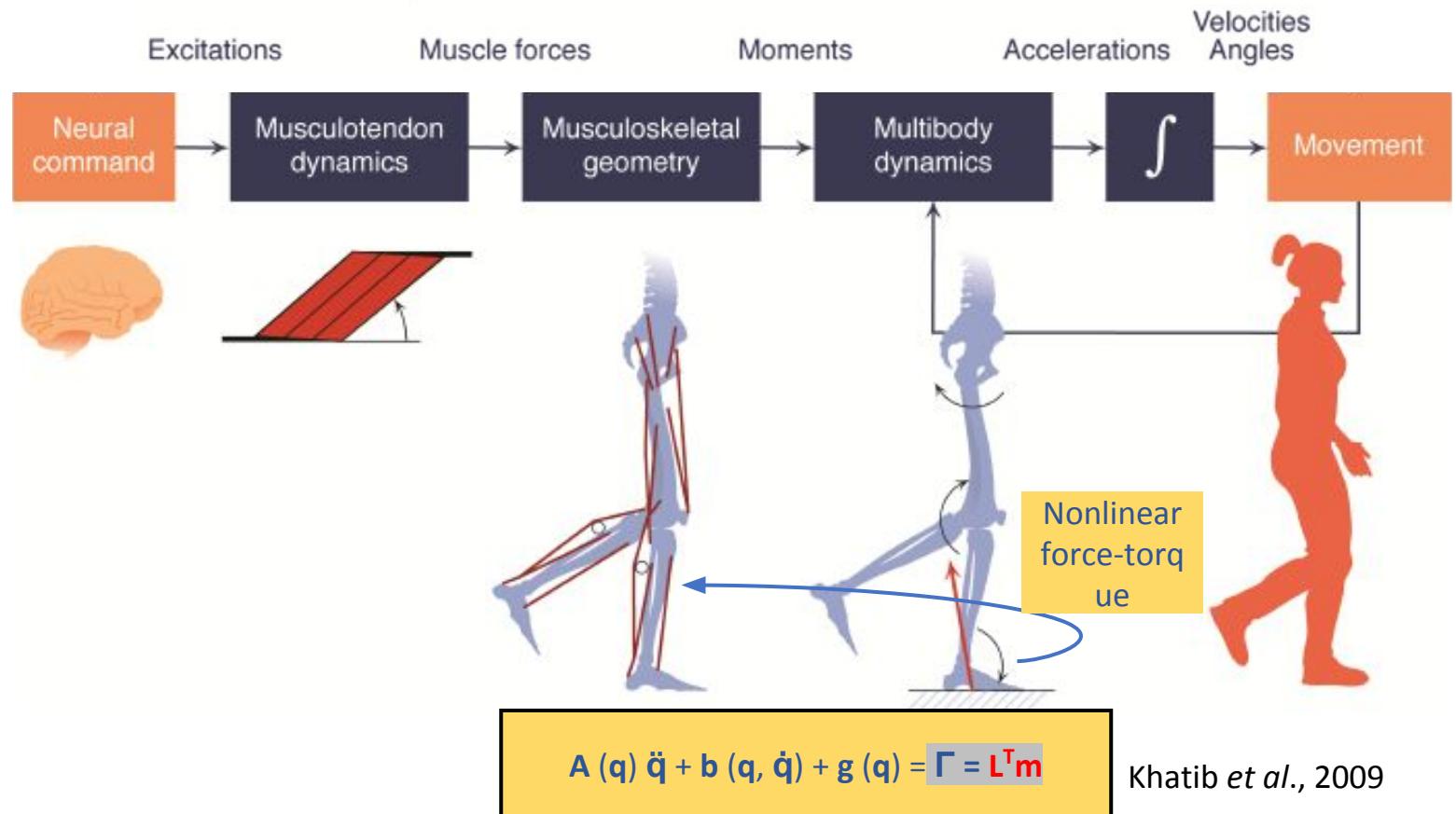


Image adapted from: Seth *et al.*, 2018







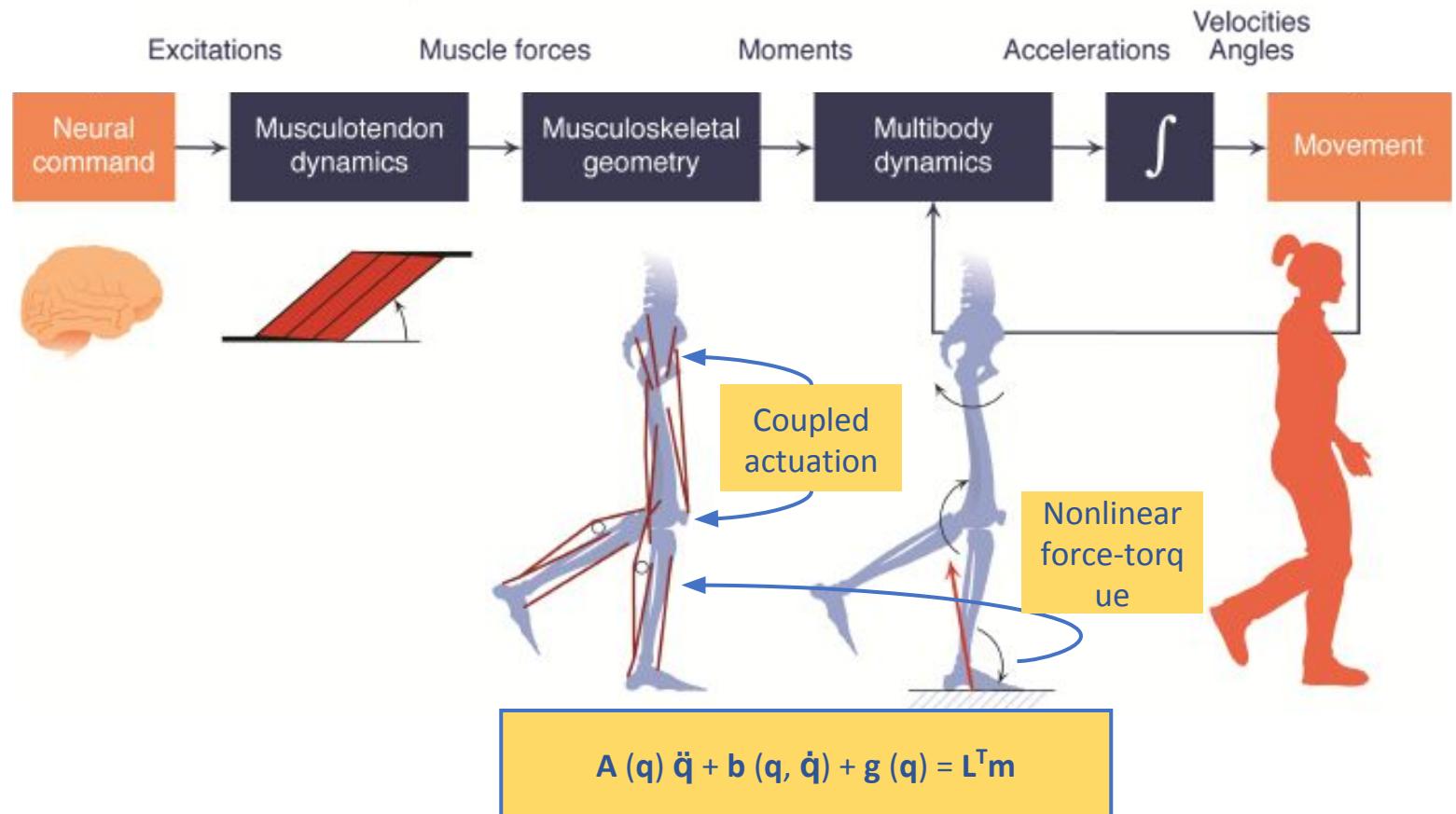
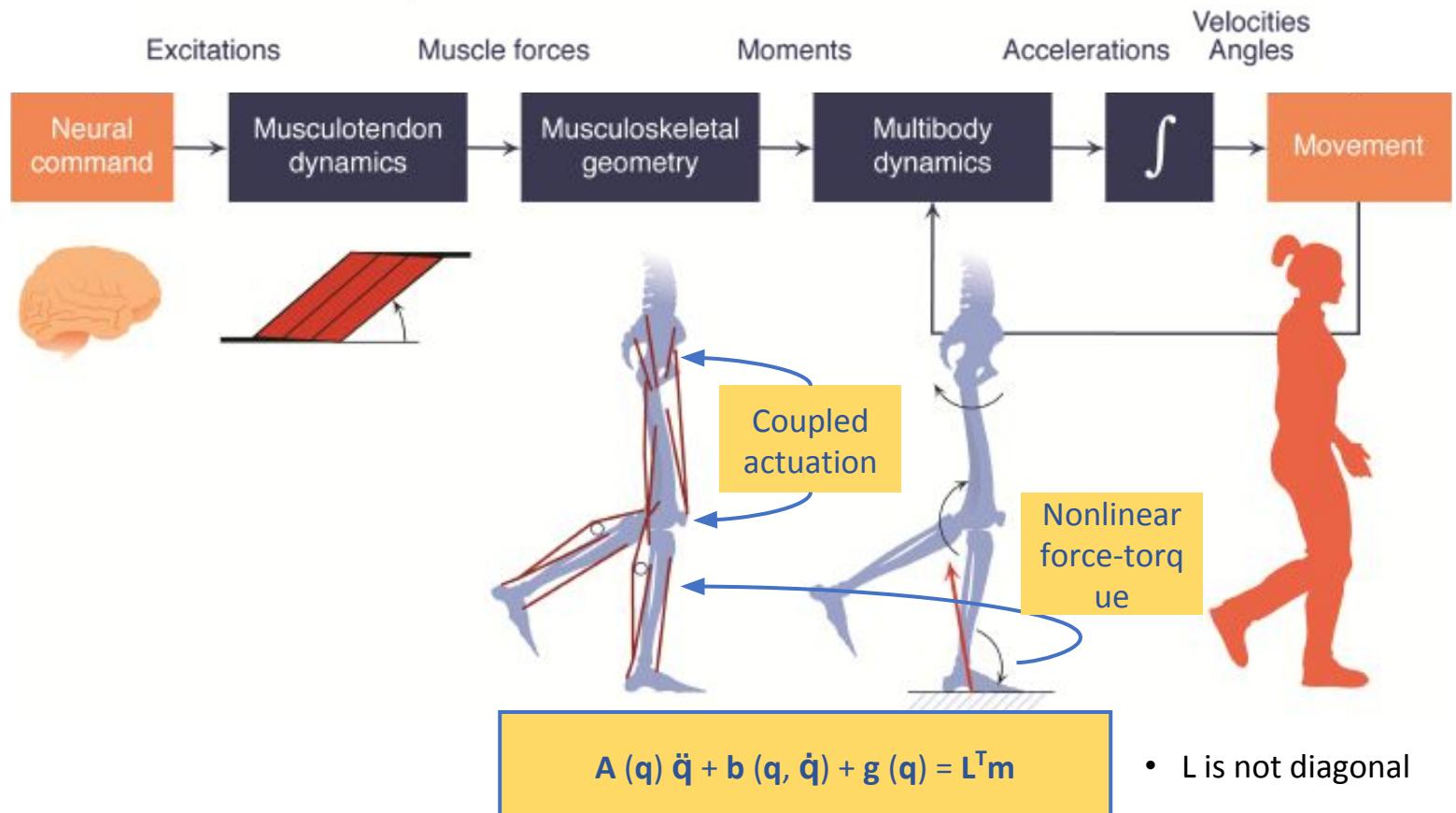
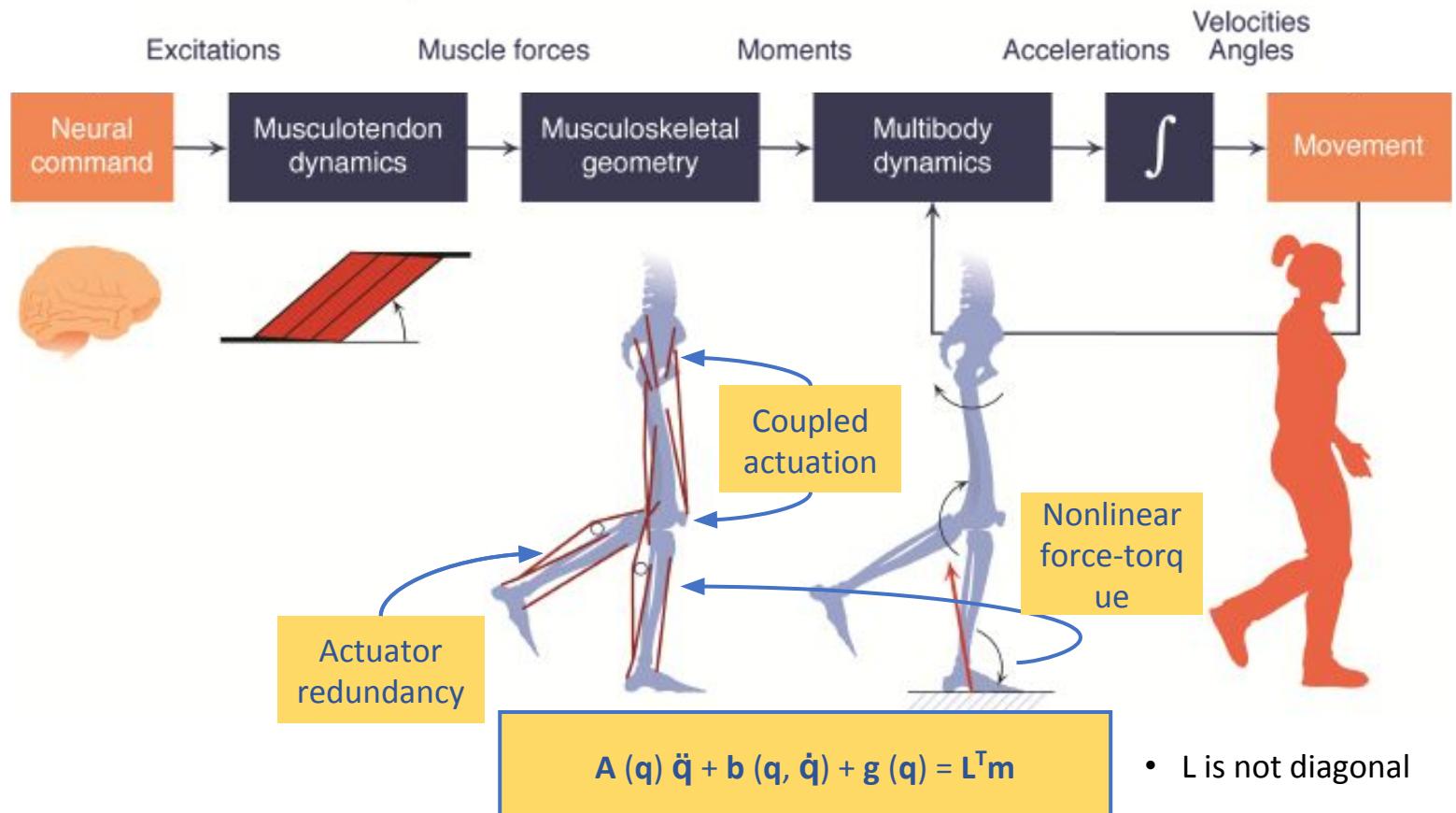


Image adapted from: Seth *et al.*, 2018





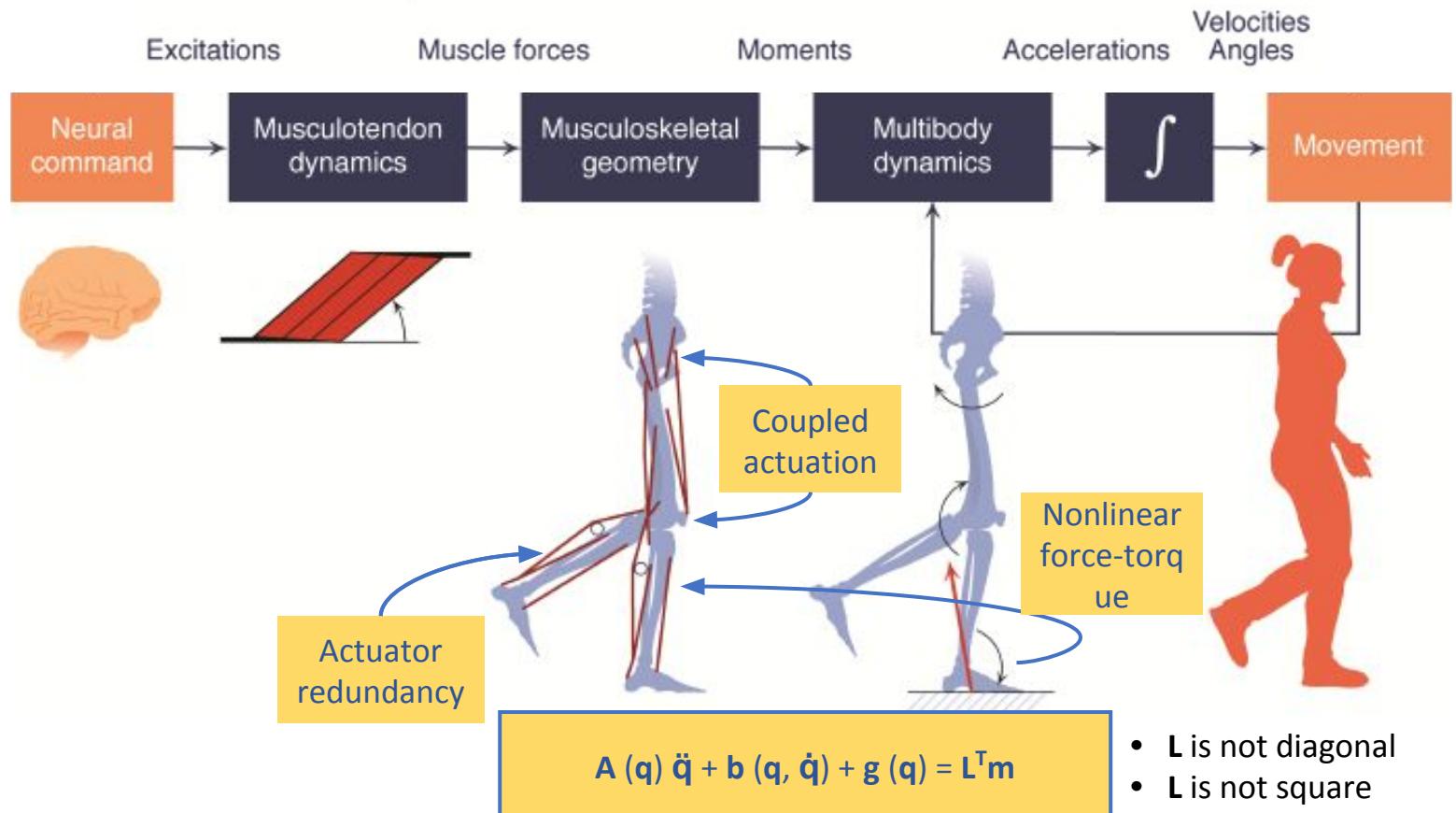


Image adapted from: Seth *et al.*, 2018

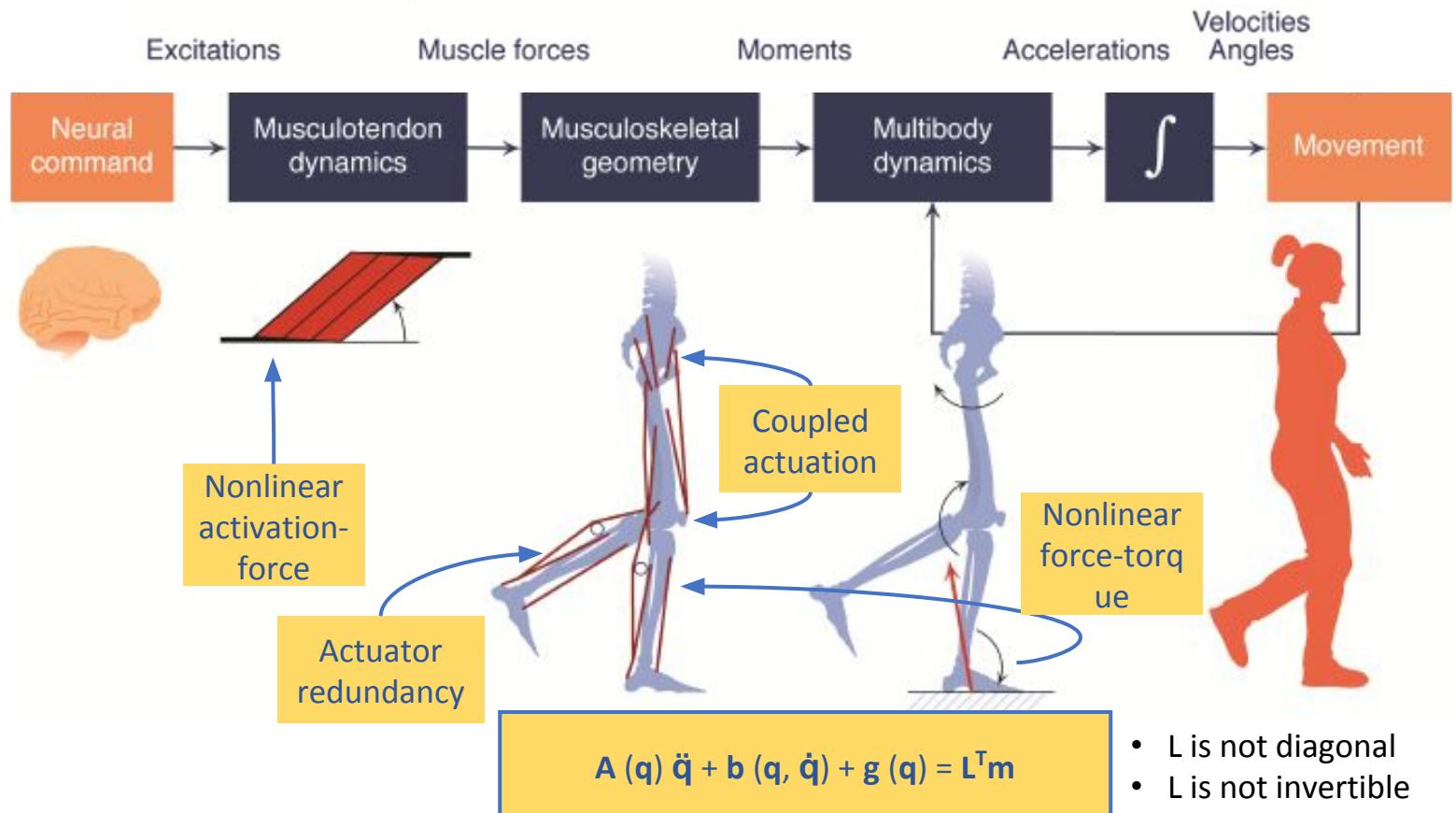
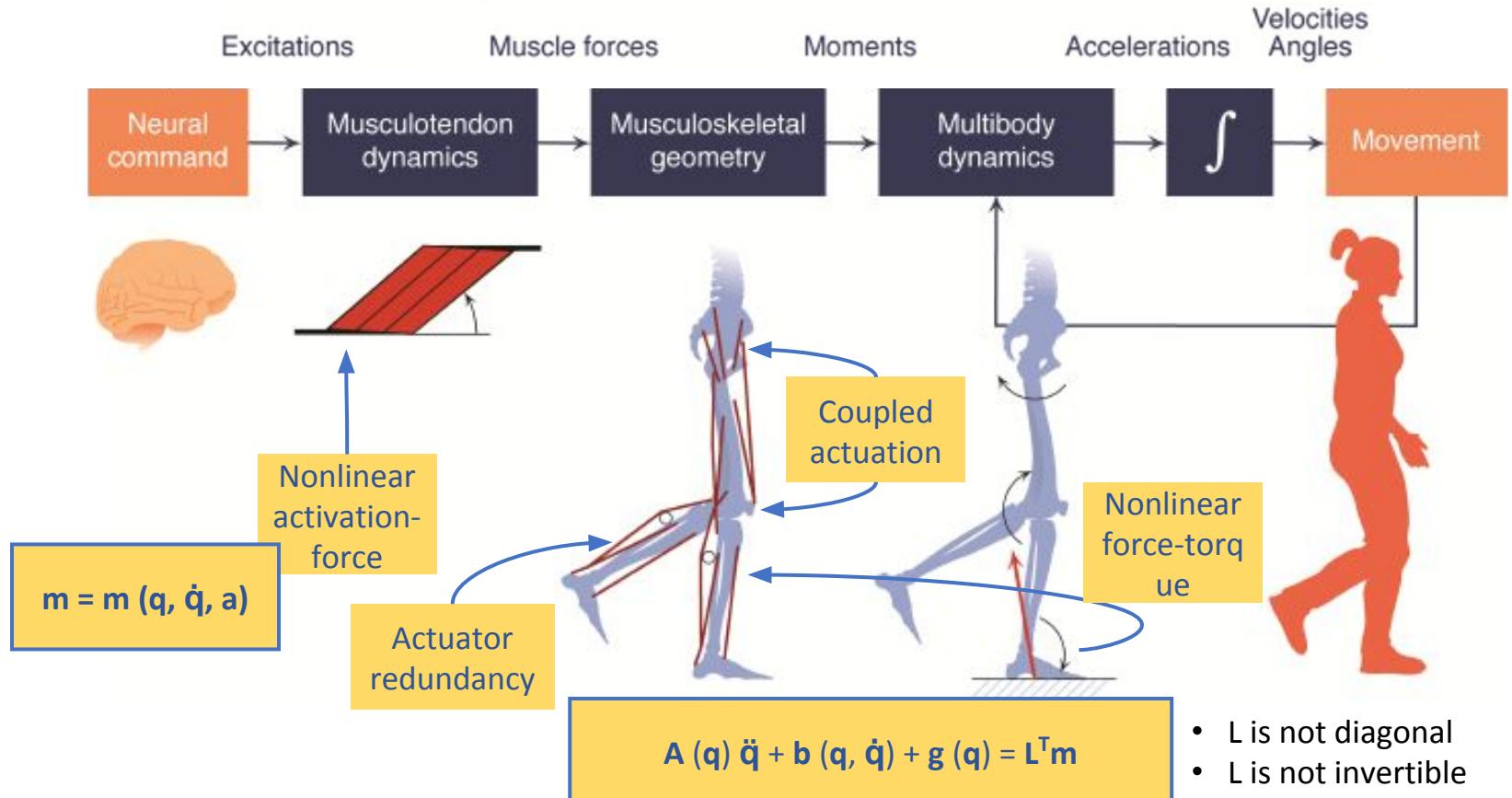


Image adapted from: Seth *et al.*, 2018



Analysis

$$A(q) \ddot{q} + b(q, \dot{q}) + g(q) = L^T m(q, \dot{q}, a)$$

How do we deal with underdetermined systems in robotics?

Analysis

$$A(\mathbf{q}) \ddot{\mathbf{q}} + b(\mathbf{q}, \dot{\mathbf{q}}) + g(\mathbf{q}) = L^T m(\mathbf{q}, \dot{\mathbf{q}}, \mathbf{a})$$

How do we deal with underdetermined systems in robotics?

Static optimization methods

- Minimize $E = \sum c_i m_i^2$ (*Khatib et. al, 2009*)
- Minimize $f = \sum c_i a_i^2$ *
- Minimize $g = \sum \sigma_i^2$ *

* For examples, see *Erdemir et. al, 2007*

Analysis

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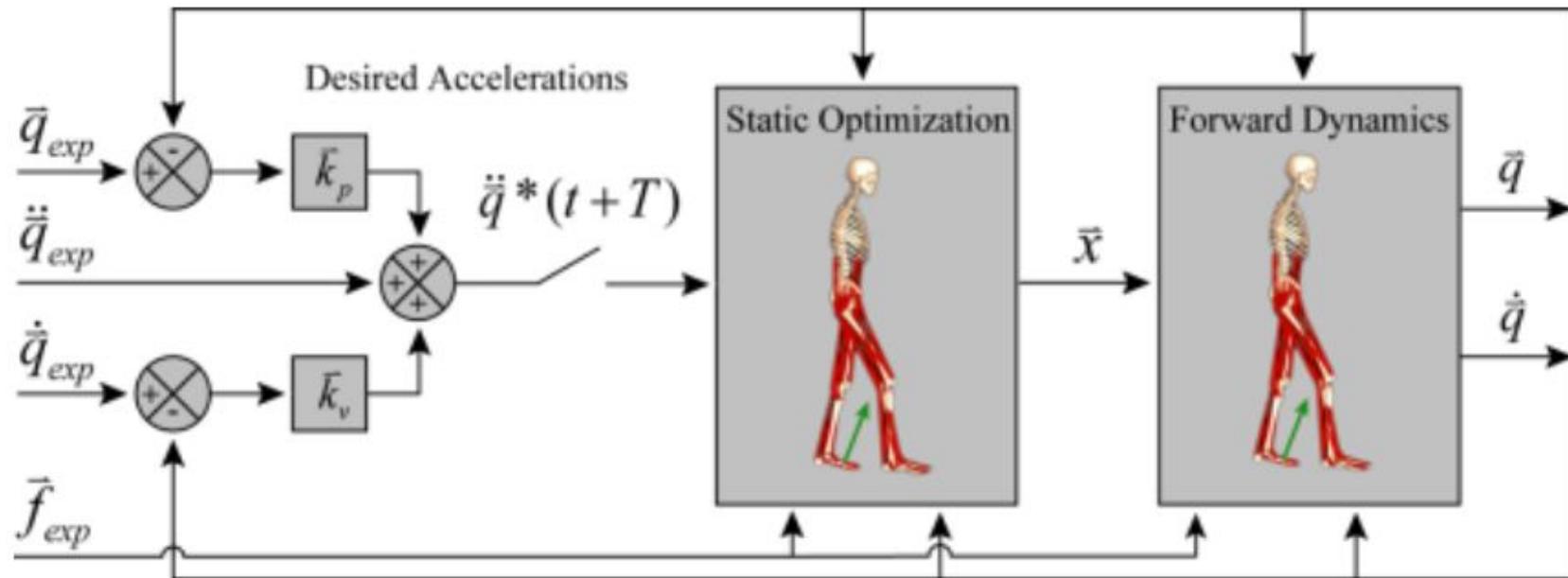
* For examples, see *Erdemir et. al, 2007*

Dynamic optimization methods

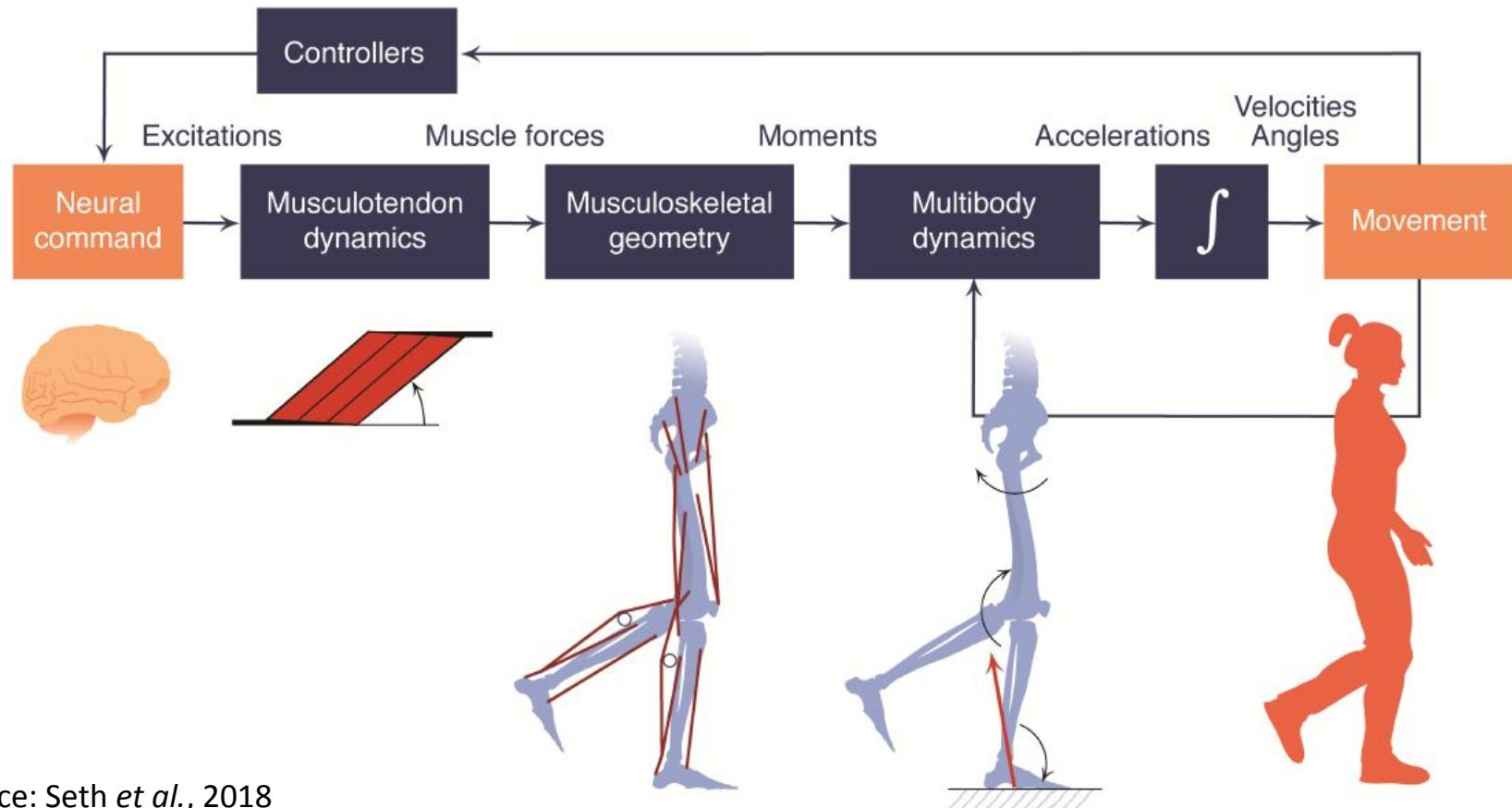
- Minimize $\int E(t) dt$
- Minimize $\int f(t) dt$
- Minimize $\int g(t) dt$

and so on (see *Dembia et. al, 2019*)

Analysis

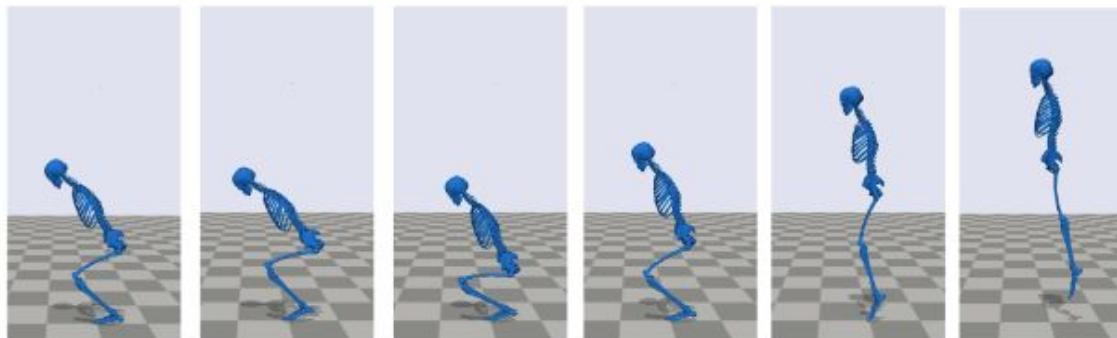
Extending Computed Torque Control to Computed Muscle Control
(Thelen *et al.*, 2003)

Prediction



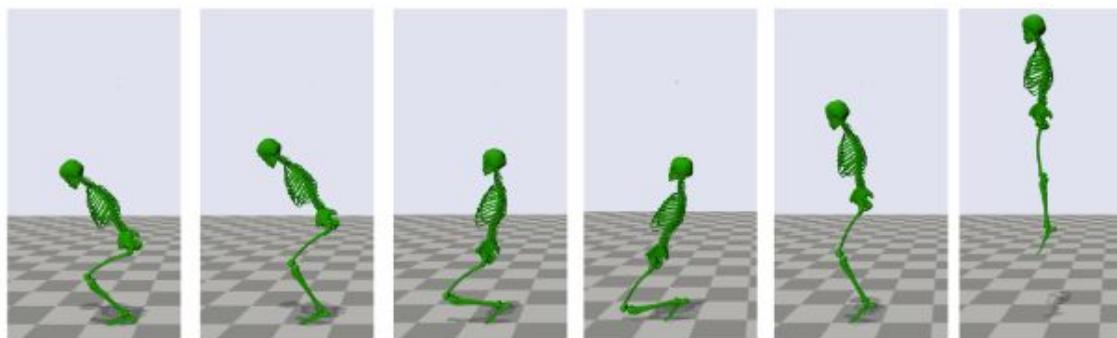
Prediction

If the objective functions are known, we can do predictive simulation



Jiang *et al.*, 2019

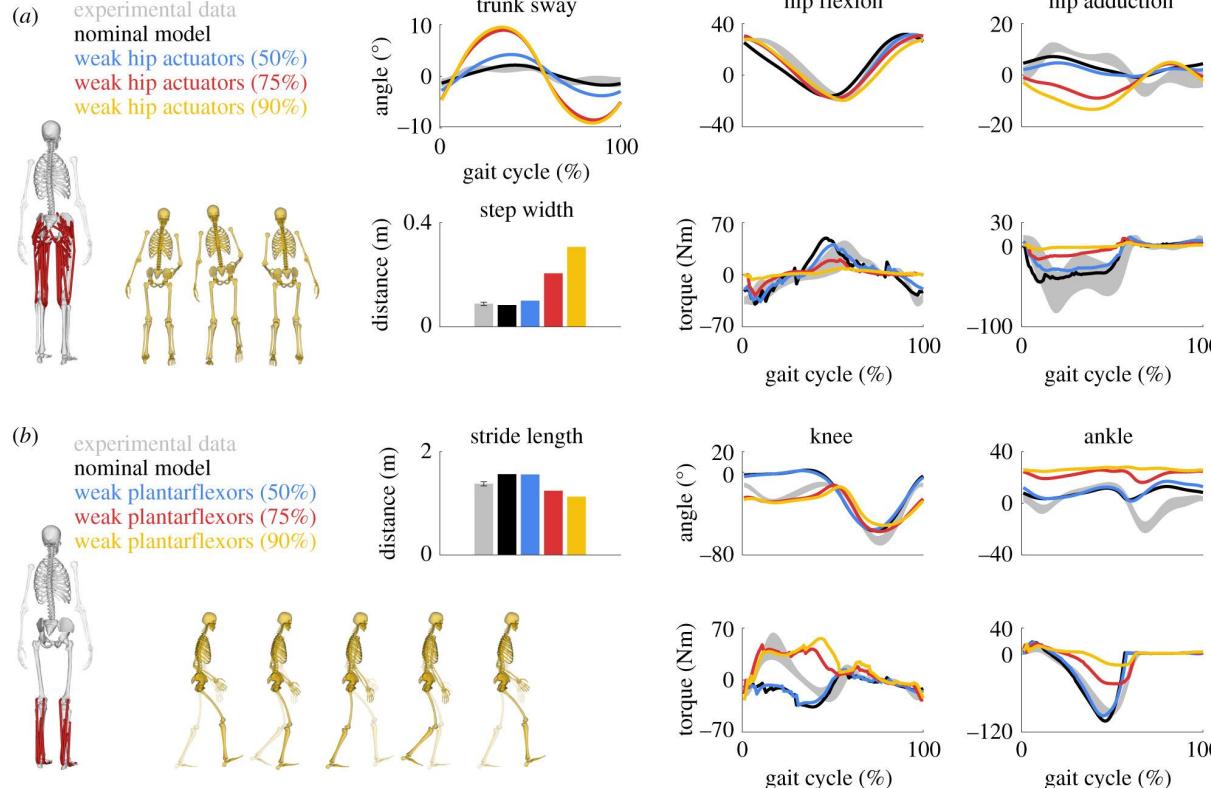
Maximize jump height with joint-torque control by learning pose-torque relationships



Compared to using torque limits that are independent of pose

Prediction

If the objective functions are known, we can do predictive simulation

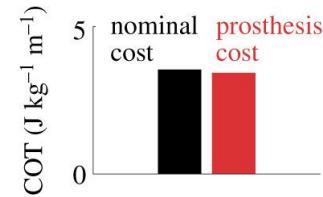
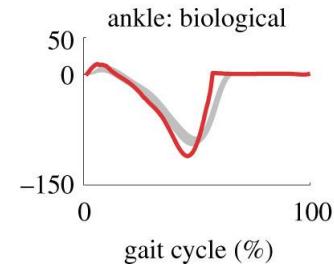
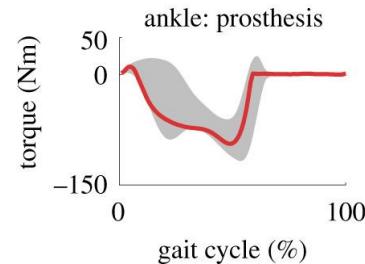
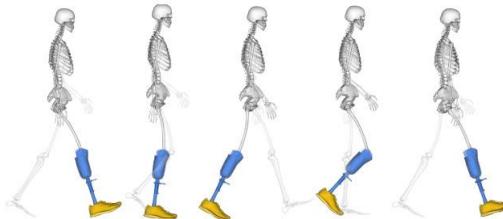


Falisse *et al.*, 2019

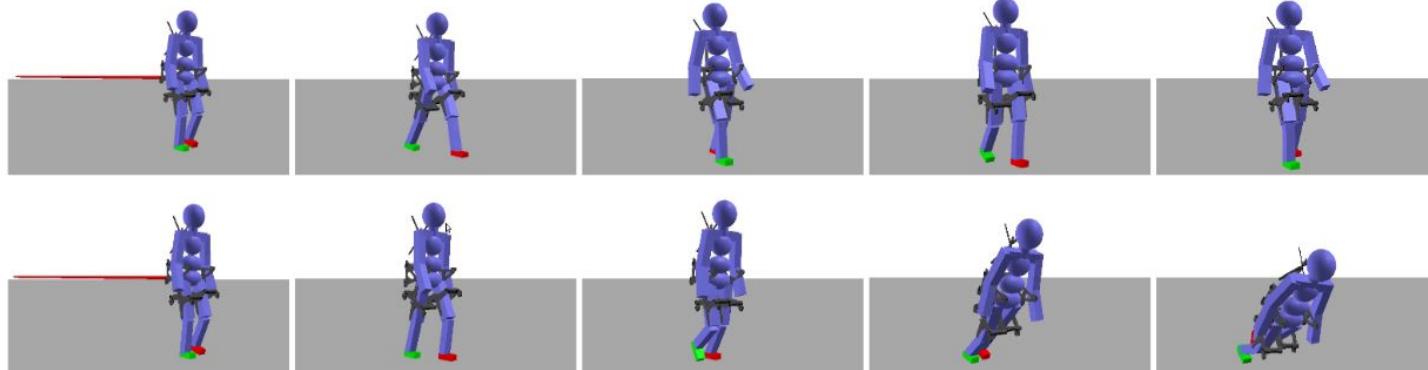
Minimize

- Metabolic energy expenditure
 - Muscle activity
 - Joint accelerations
 - Passive torques
 - Arm excitations
- to predict walking

Design



Falisse *et al.*, 2019

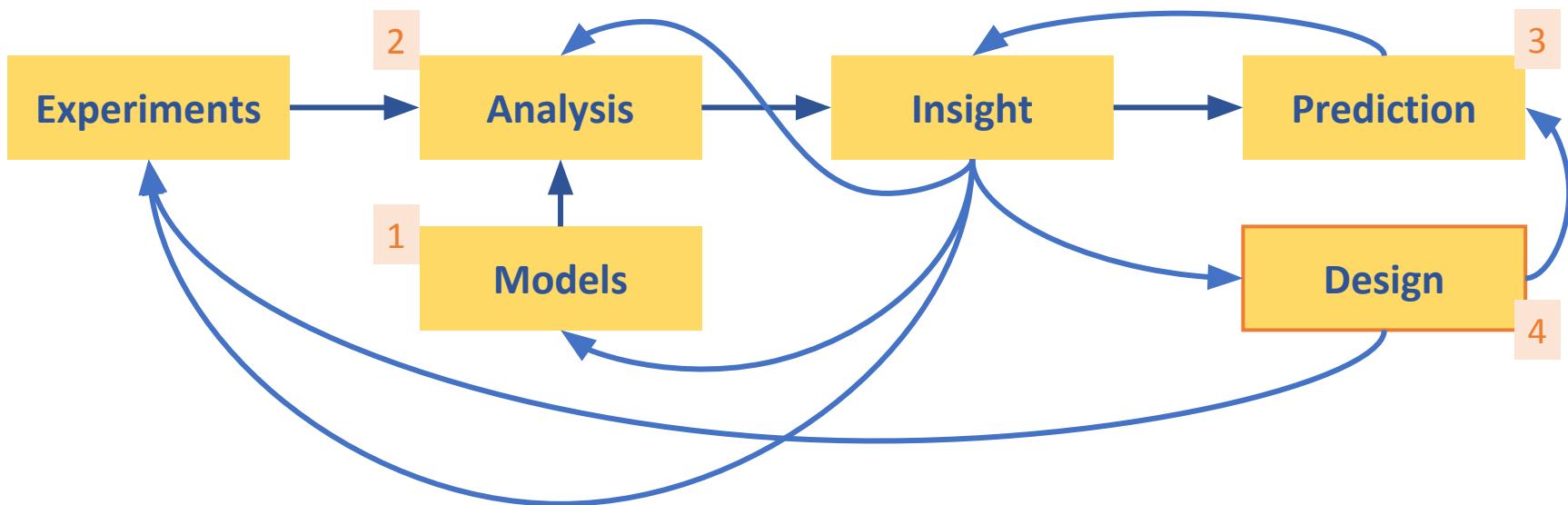


Kumar *et al.*, 2019

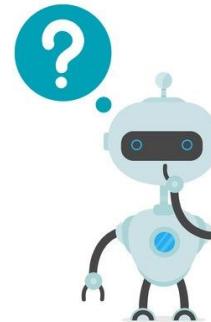
Some questions about human movement

What are the principles governing it?
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Thank you
Questions?



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Record of the discussion for future reference

Comment from Oussama:

Humans are slow at closing the sensing loop but good at prediction,

Comment from Gabriela

Motion primitives can help get there

Comment from Oussama

Yes like playing tennis