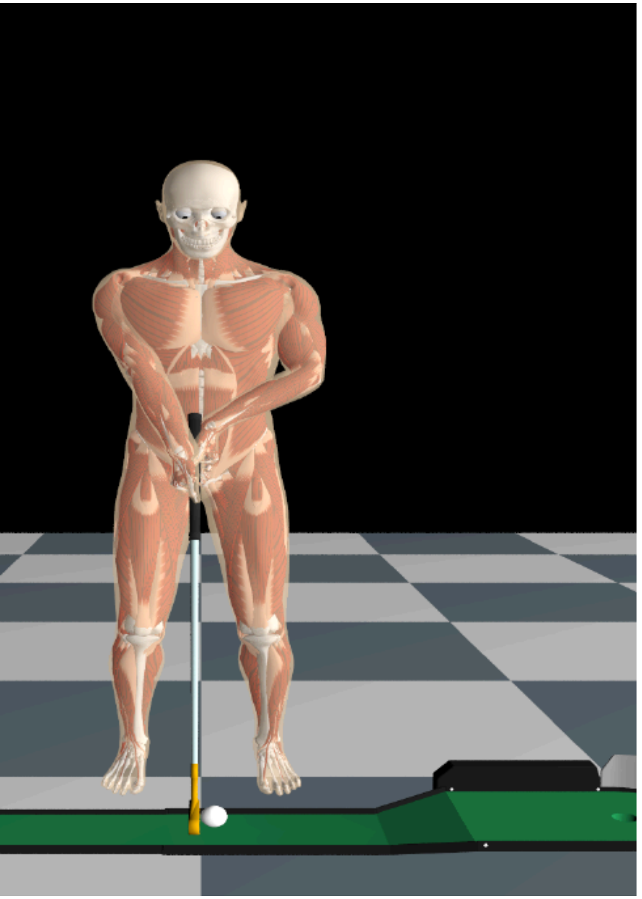
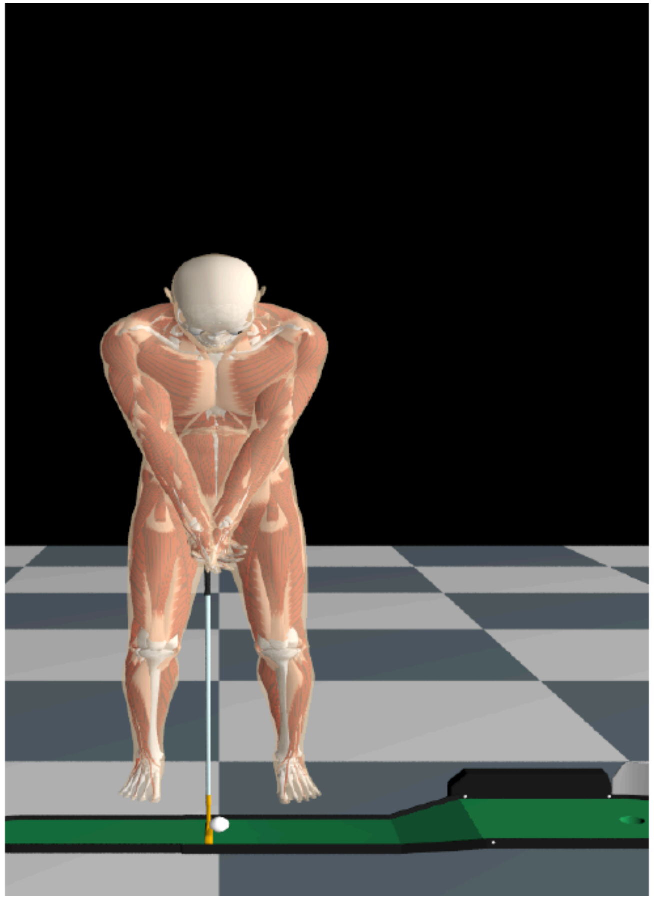
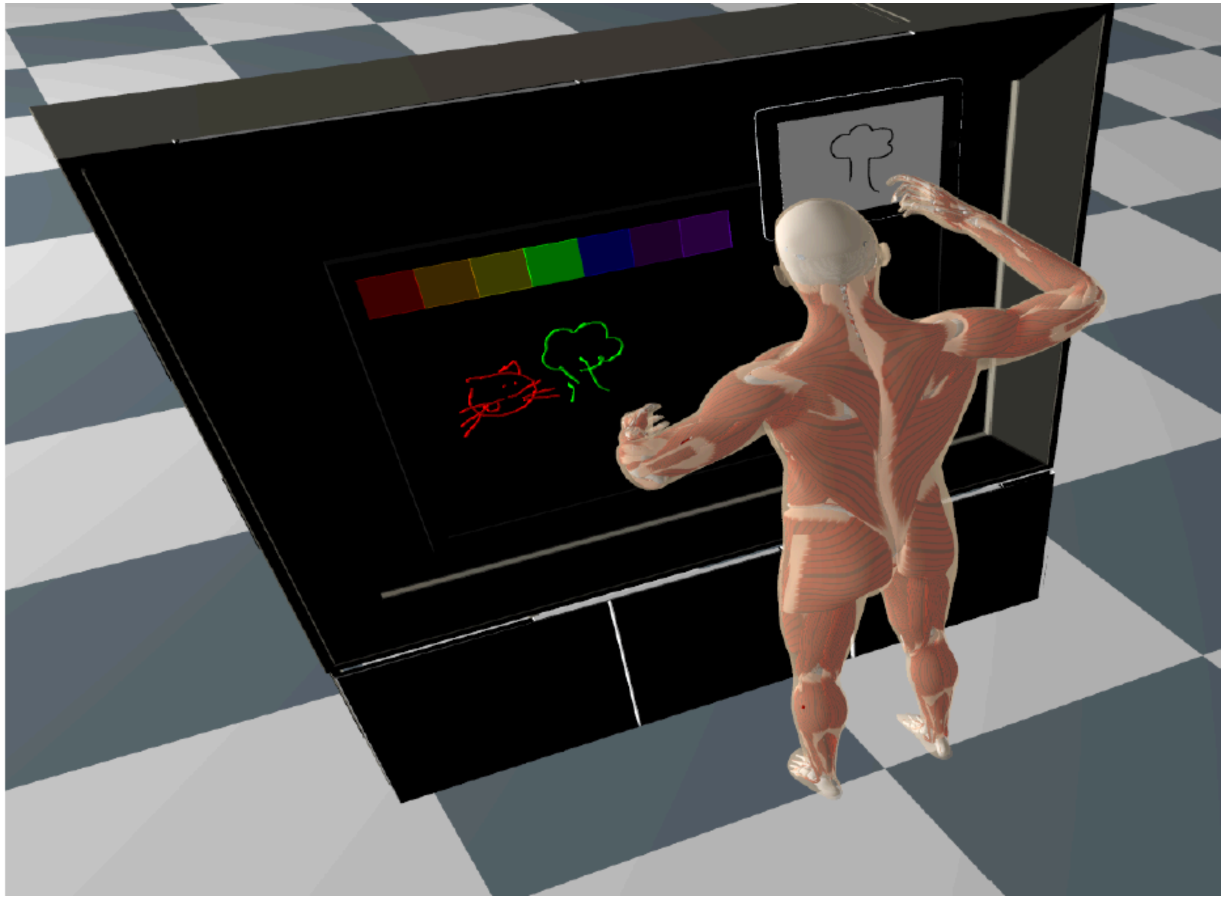
Core Training:

Learning Deep Neuromuscular Control of the Torso for Anthropomimetic Animation

Tao Zhou
Department of Computer Science
University of California, Los Angeles

Overview

- Related work
- Objective
- Biomechanical Human Musculoskeletal Model
- Neuromuscular Control System
- Experiments and Results
- Conclusion

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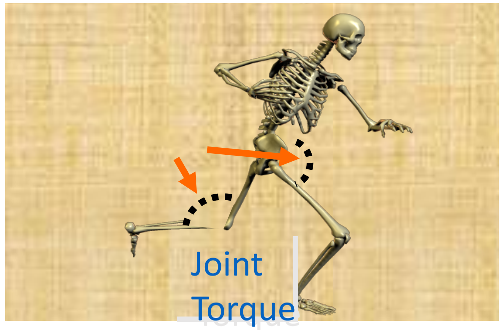
Human Motion

Related Work

Biomechanical Human Modeling

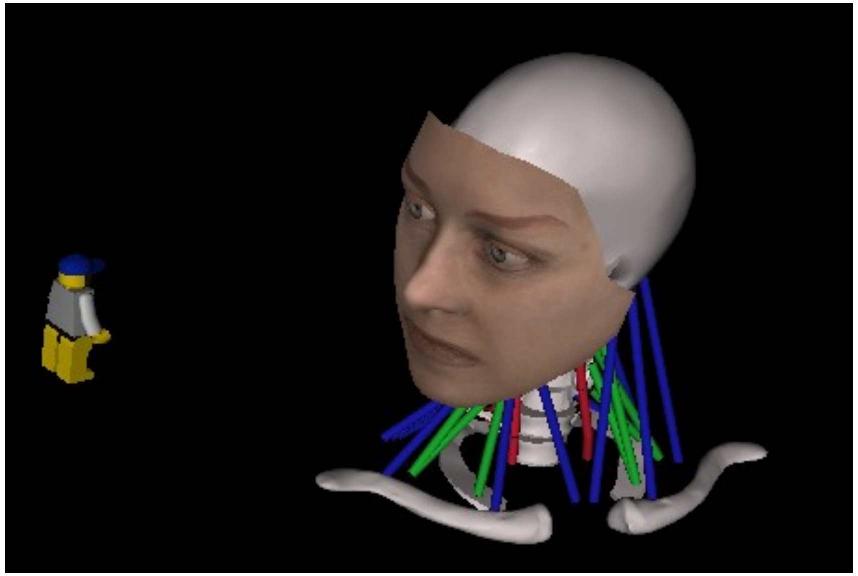
Hodgins et al.,1995

[Faloutsos et al., 2001]

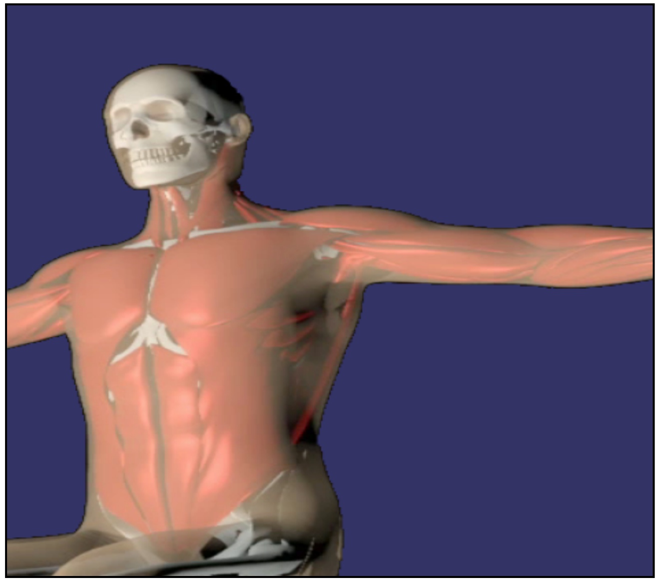


Neuromuscular Control for Musculoskeletal Human Animation from ***Prof. Terzopoulos group***

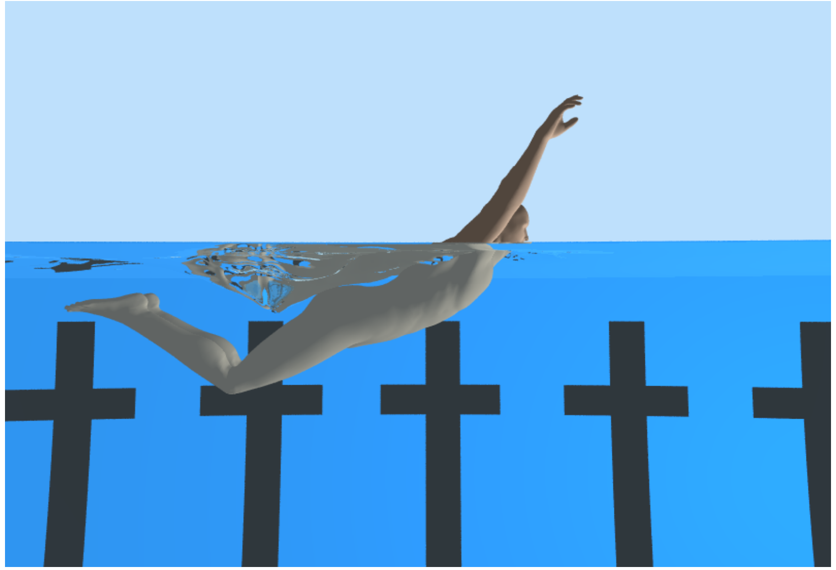
Lee, Terzopoulos 2006



Lee, Sifakis, Terzopoulos 2010



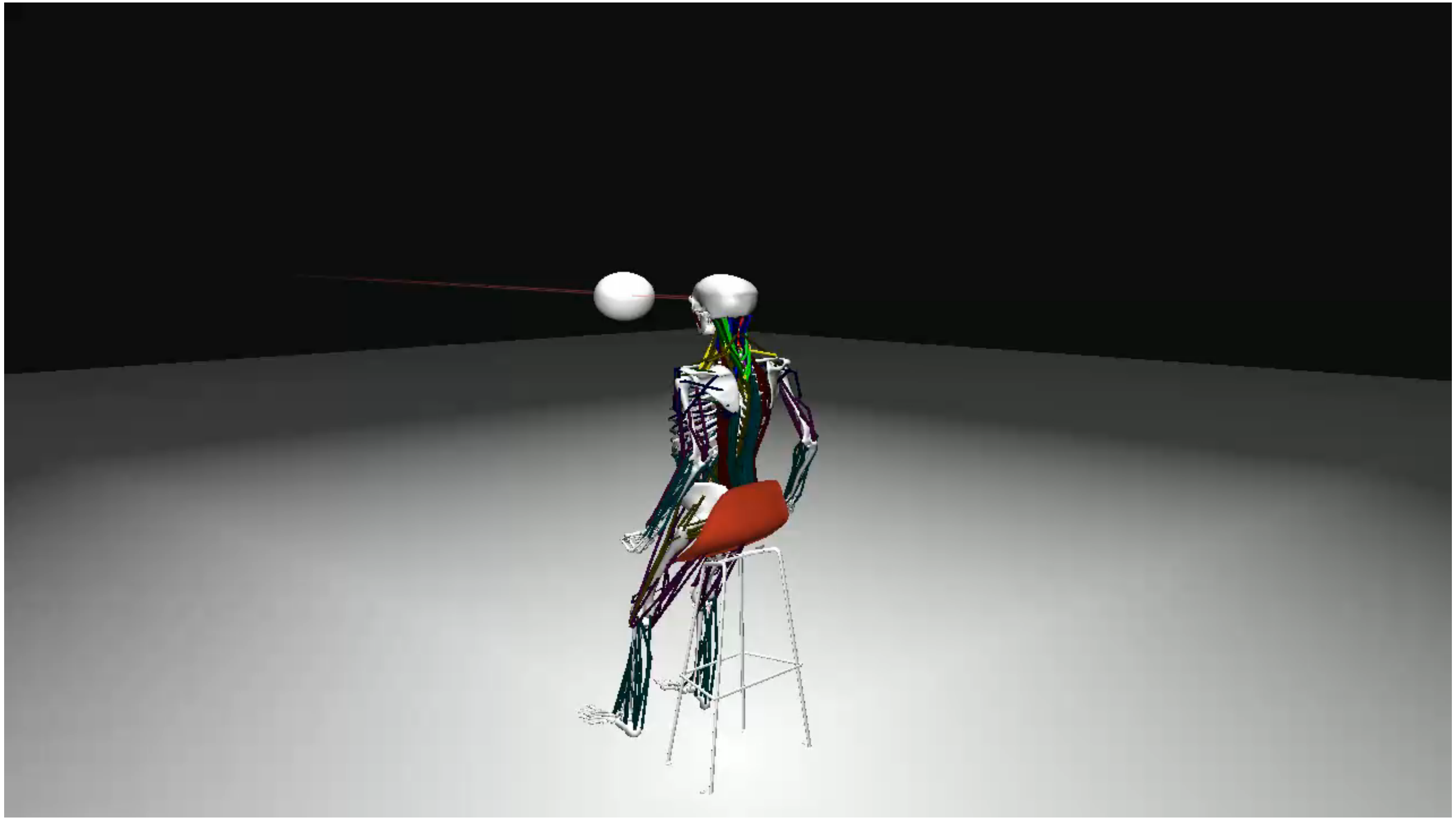
Si, Lee, Sifakis, Terzopoulos 2014

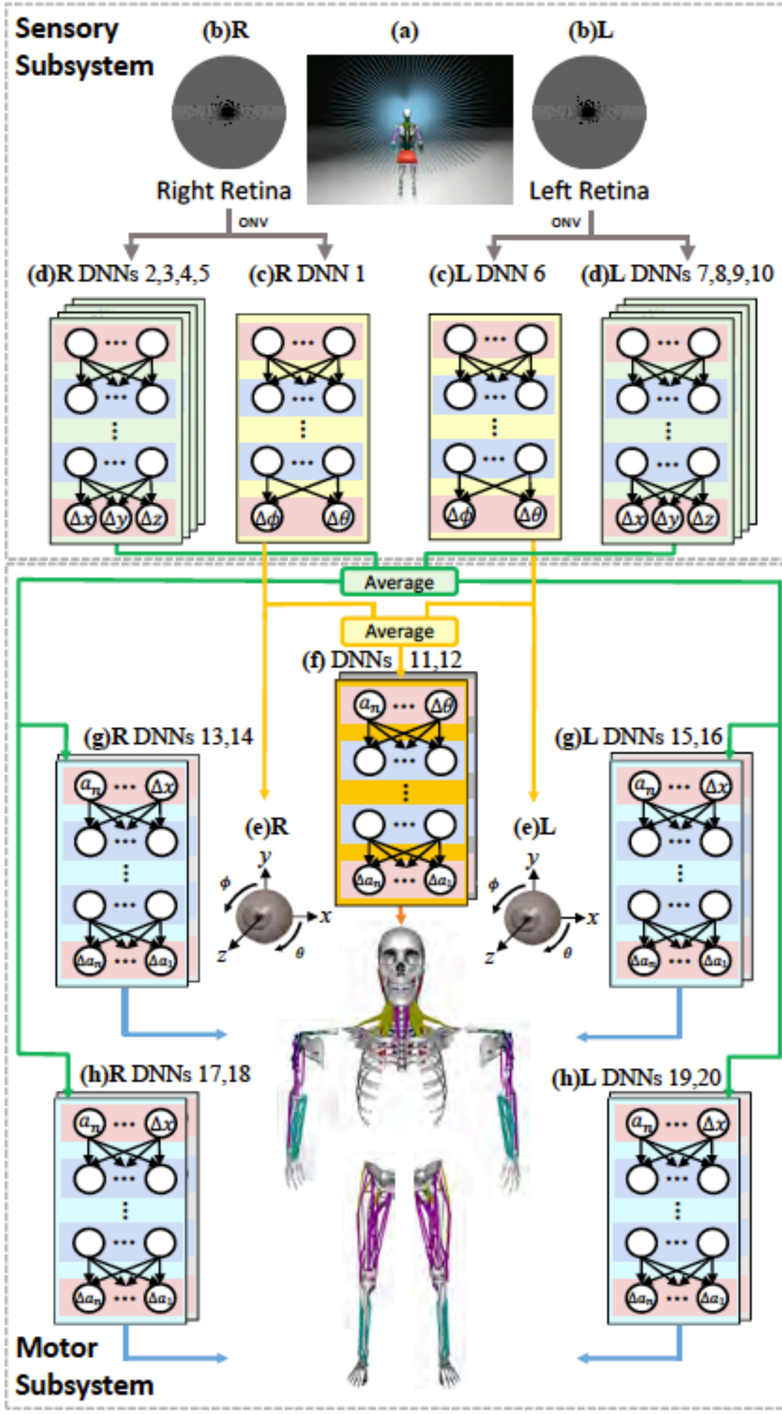


Deep Learning of Biomimetic Sensorimotor Control for Biomechanical Human Animation

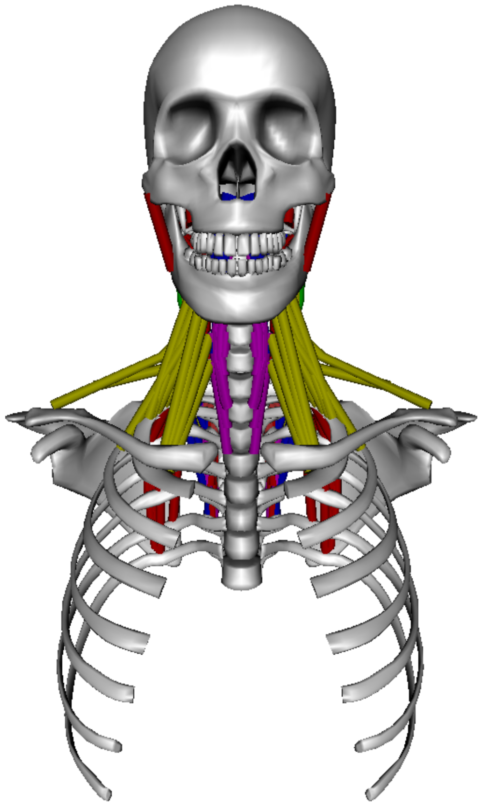
Masaki Nakada, ***Tao Zhou***, Honglin Chen, Tomer Weiss and Demetri Terzopoulos

Presented in SIGGRAPH 2018



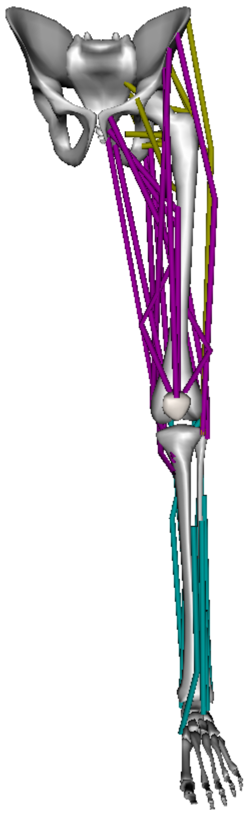


Nakada et. al SIGGRAPH 2018



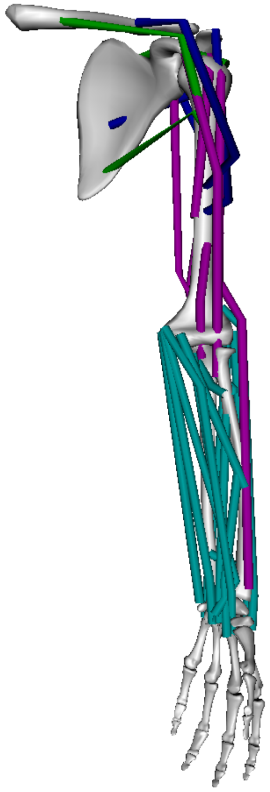
Cervicocephalic Complex

Root: T1
End effector: Skull
muscle #: 244



Leg Complex

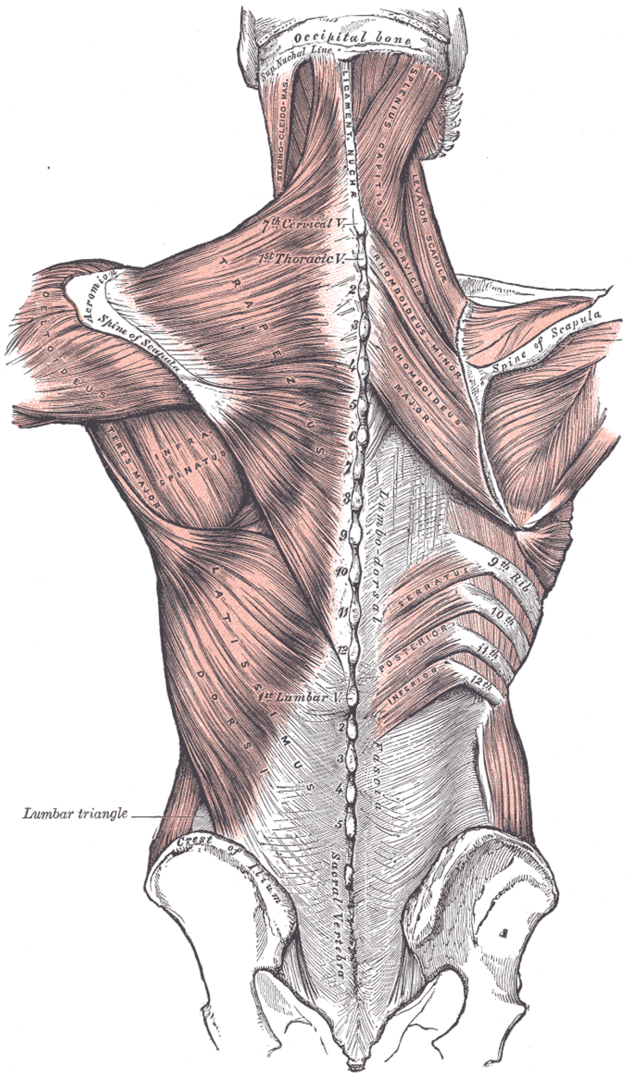
Root: Pelvis
End effector: Foot
muscle #: 39

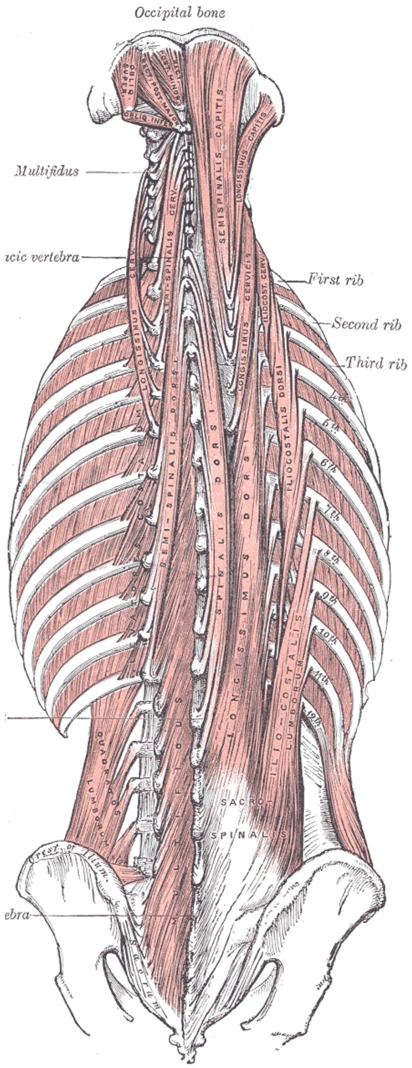


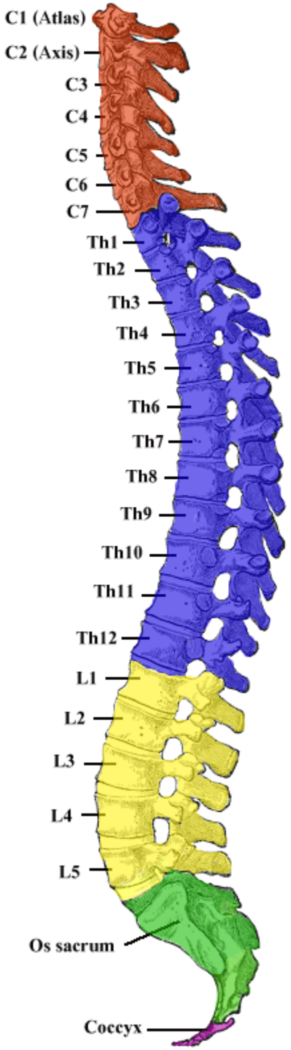
Arm Complex

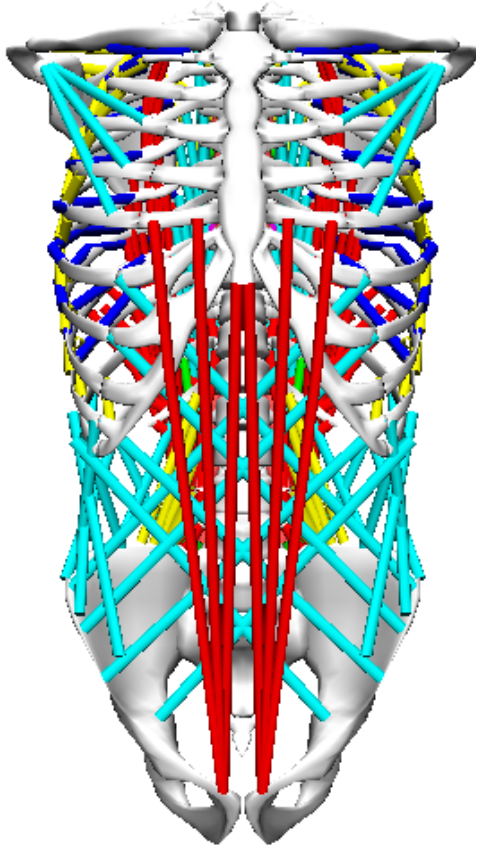
Root: Clavicle
End effector: Hand
muscle #: 29

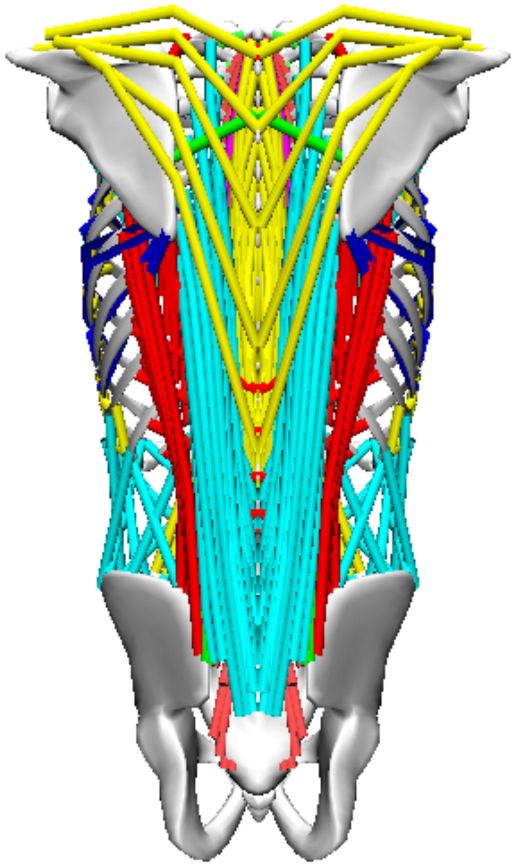
Torso Biomechanical Complex









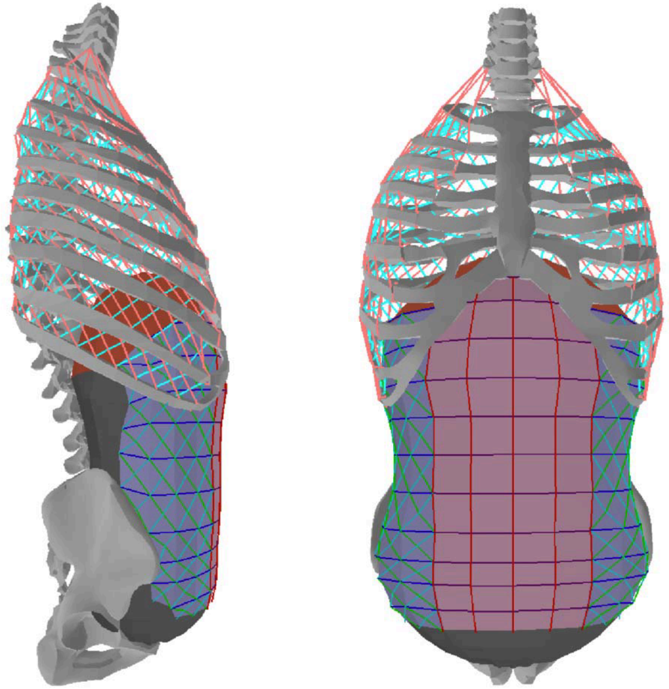


Root: Pelvis
End effector: T1
Bones #: 50
DoF: 112
muscle #: 443

Previous Torso Models

Monheit and Badler 1991

Zordan et al., 2006



Overview

Related work

Objective

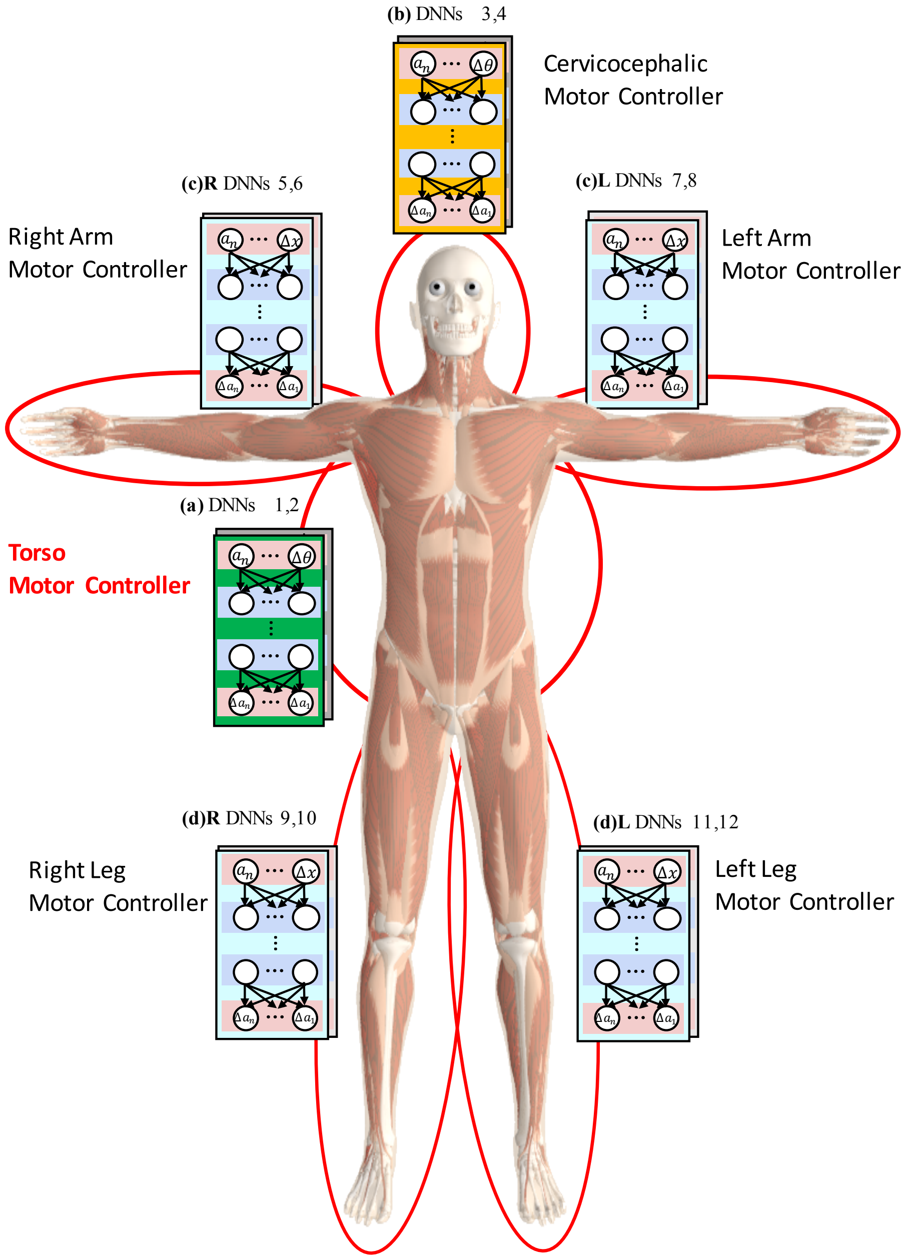
Biomechanical Human Musculoskeletal Model

Neuromuscular Control System

Experiments and Results

Conclusion

Goal: Learn deep neuromuscular control of the torso to enable full-body articulation



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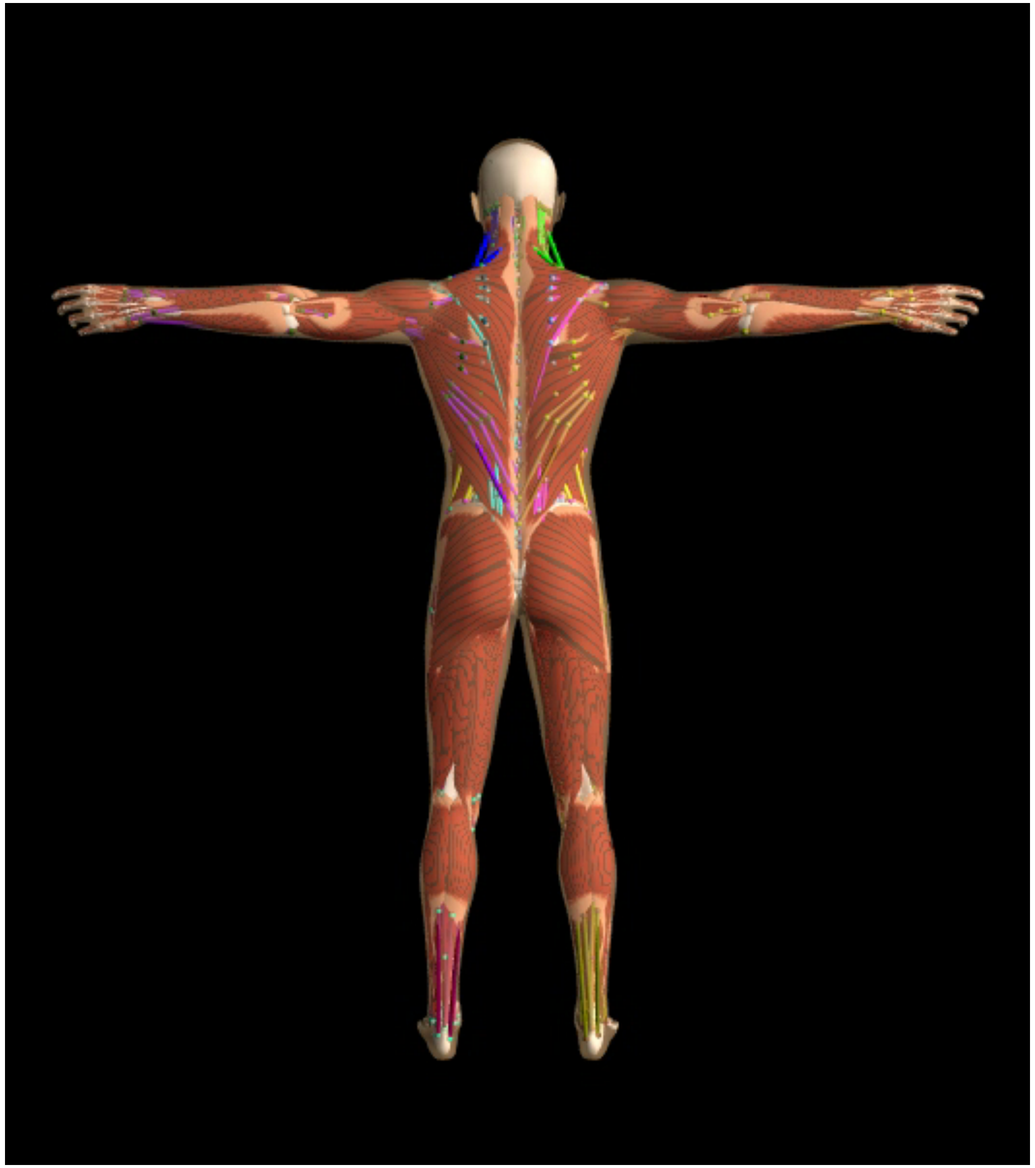
Musculoskeletal Human Model

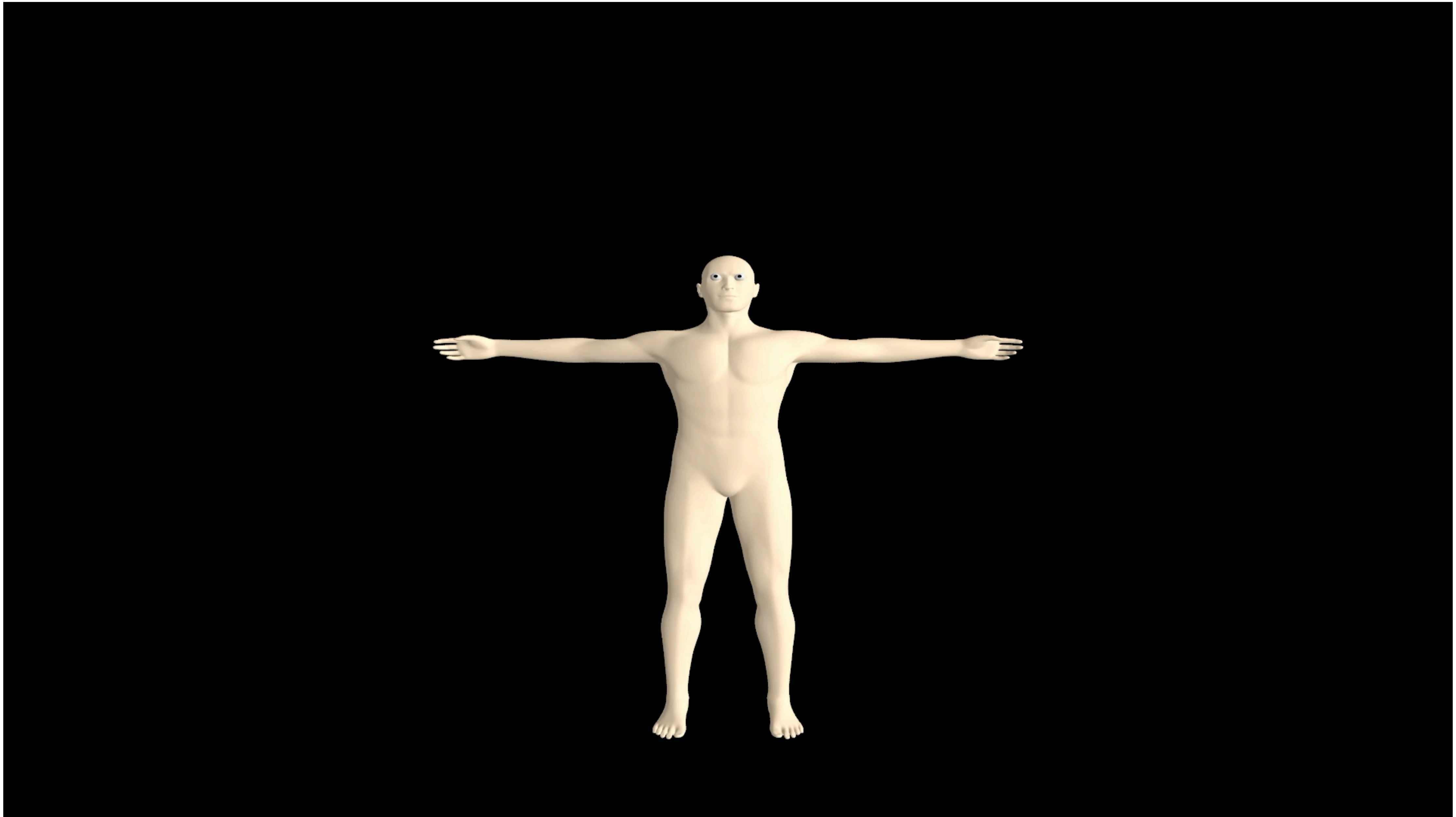
103 bones comprising 163 articular degrees of freedom

A total of 823 Hill-type contractile muscle actuators

With deforming flesh and muscles



Musculoskeletal Human Model

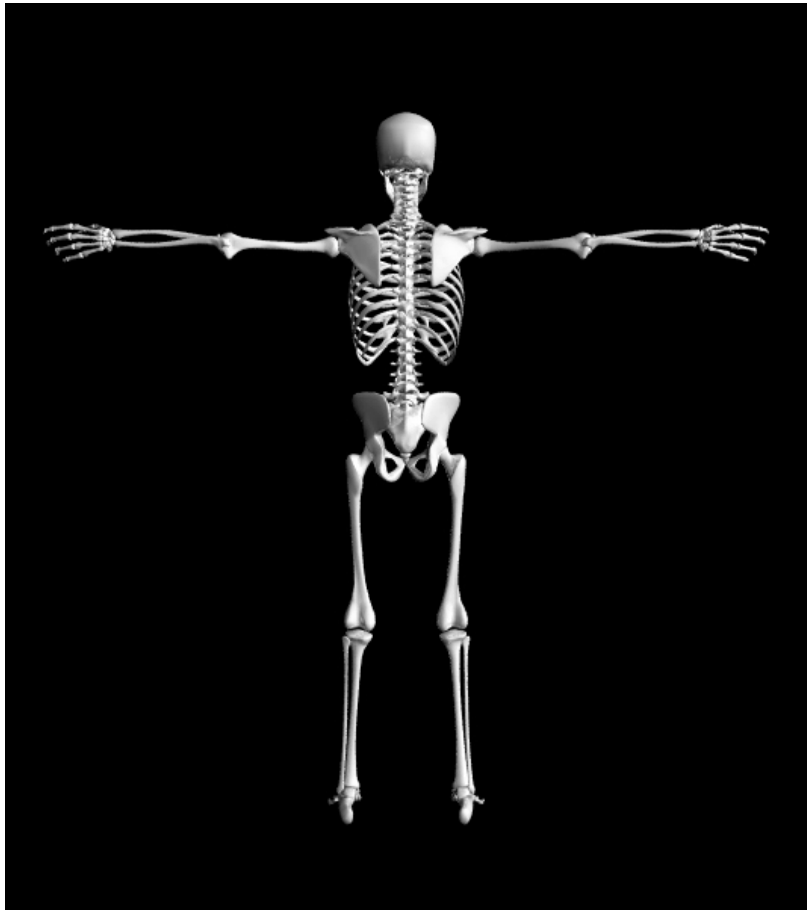


Skeletal system

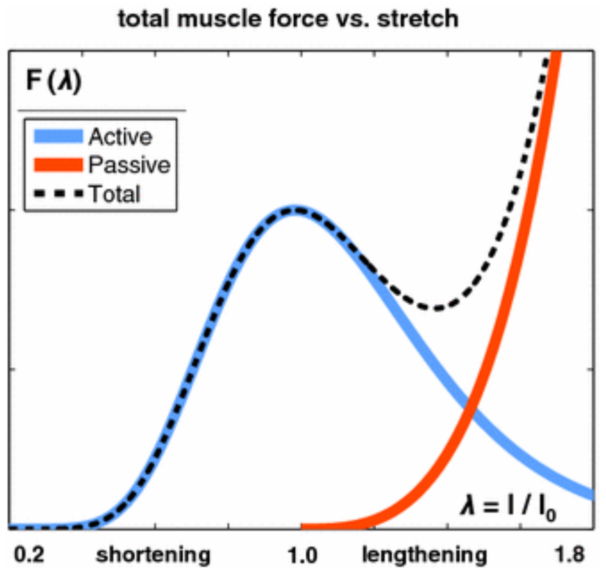
- The equation of motion.
  - q_m : Muscle driven joints.
  - q_p: Passive joints
  - M: Mass matrix
  - C : Forces from connecting tissues, Coriolis forces and centrifugal forces
  - J: Transform the applied external force to the joint space
  - P: Momentum arm matrix to map the contractile force to joint torque

- Numerically integrate the equations of motion through time

$$M(q)\begin{bmatrix}\ddot{q}_m\\ \ddot{q}_p\end{bmatrix}+C(q,\dot{q})=\begin{bmatrix}P(q)f_c\\ 0\end{bmatrix}+J^Tf_e \quad (1)$$



Muscle system



Hill-type muscle model

- (1) f_P is a passive element which passively produces restoring force due to the material elasticity to the deformation.
  - k_s and k_d are the stiffness and damping coefficient
  - e is muscle strain and $\dot{e}$ is strain rate

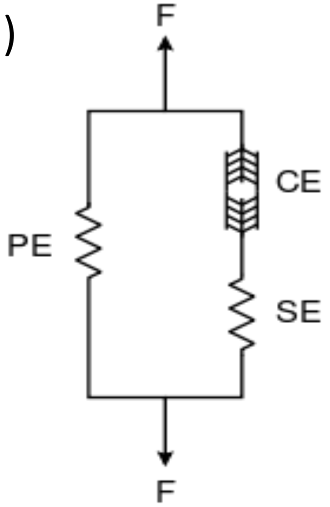
$$f_P = \max(0, k_s(\exp(k_c e) - 1) + k_d \dot{e}) \quad (1)$$

- (2) f_C is a contractile element which actively generate the contractile force by activating the muscle
  - a is the muscle activation
  - F_l is the force-length relation and f_v is the force velocity relation

$$f_C = aF_l(l)F_v(\dot{l}) \quad (2)$$

- (3) The force is the combination of two components. $f_m = f_P + f_C$.

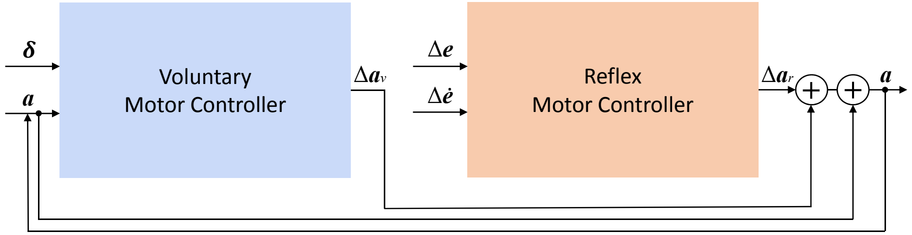
$$f_m = f_P + f_C \quad (3)$$



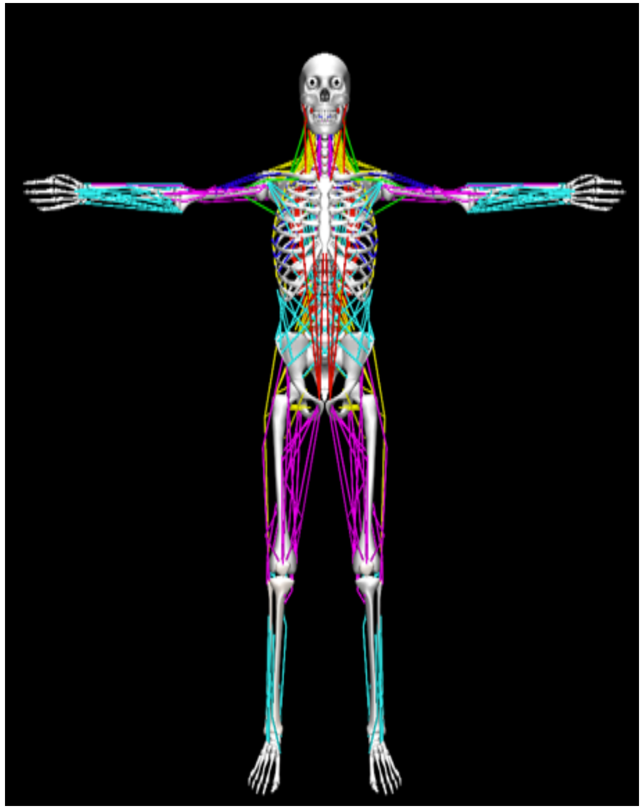
*SE is a force by tendons. The stiffness is very high, so it has very small effect and can be neglected

Overview

Voluntary + reflex
Muscle control



Muscle System

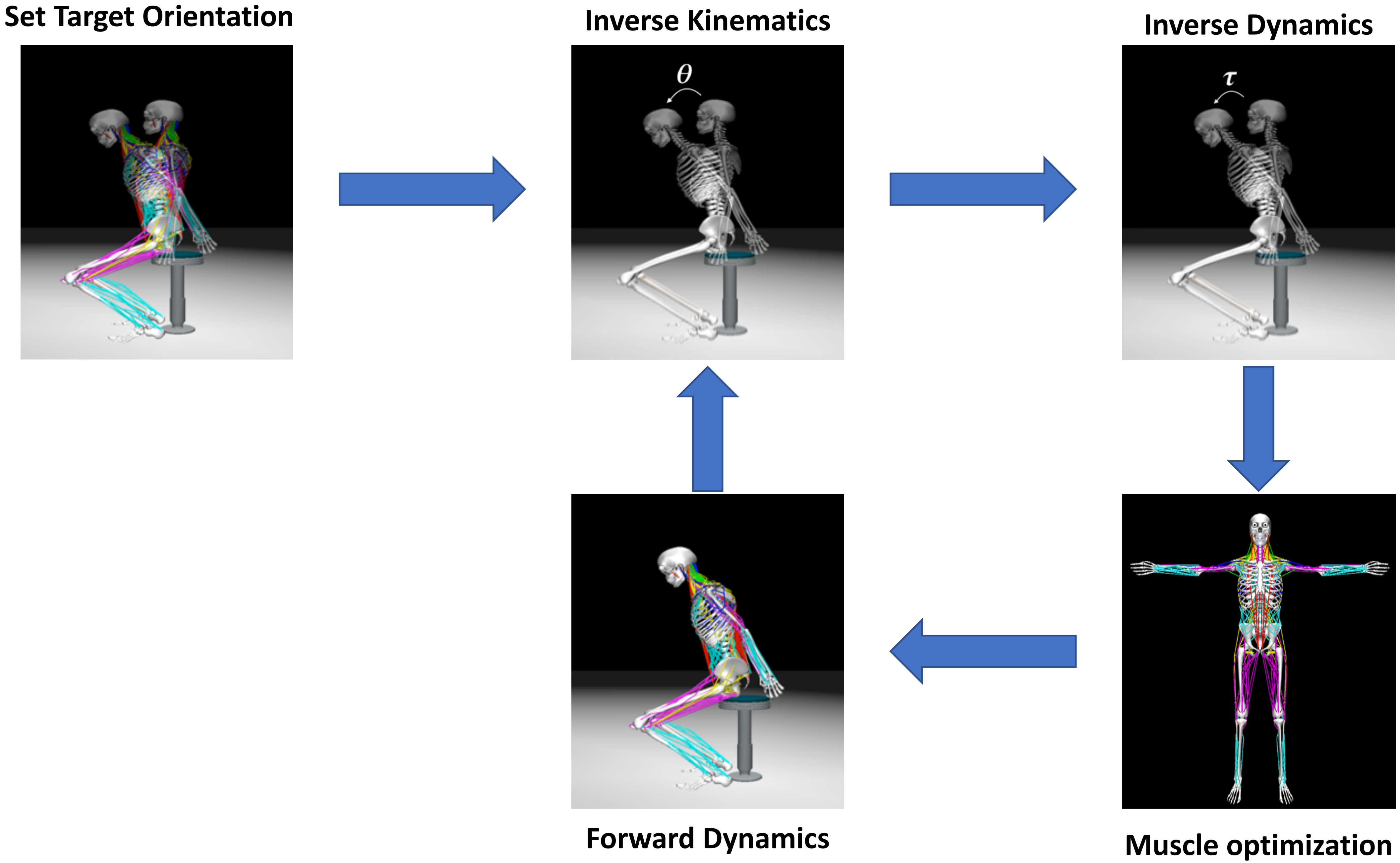


Proprioceptive Feedback

External Force

Gravity or Perturbation

Training data synthesis for voluntary motor DNN



Reflex control

Stabilizes the musculoskeletal system

- (1) compute the reflex control signal by comparing current and desired muscle strain and strain rate

$$a_b = s(k_p(e - e_d) + k_d sat_m(\dot{e} - \dot{e}_d)) \quad (1)$$

$$sat_m(x) = \begin{cases} x & |x| < m \\ m\,\mathrm{sgn}(x) & \text{otherwise} \end{cases}$$

  - k_p and k_d are the proportional and derivative gains
  - e and $\dot{e}$ are muscle strain and strain rate
  - e_d and $\dot{e}_d$ are the desired strain and strain rate, which are generated by setpoint signal generator.
  - sat(x) is to limit the maximum of the derivative gain.

- (2) Add the reflex control signal to the voluntary signal. Limit the range to be $0 \leq x \leq 1$

$$a = \min(1, \max(0, a_f + a_b)) \quad (2)$$

Challenge

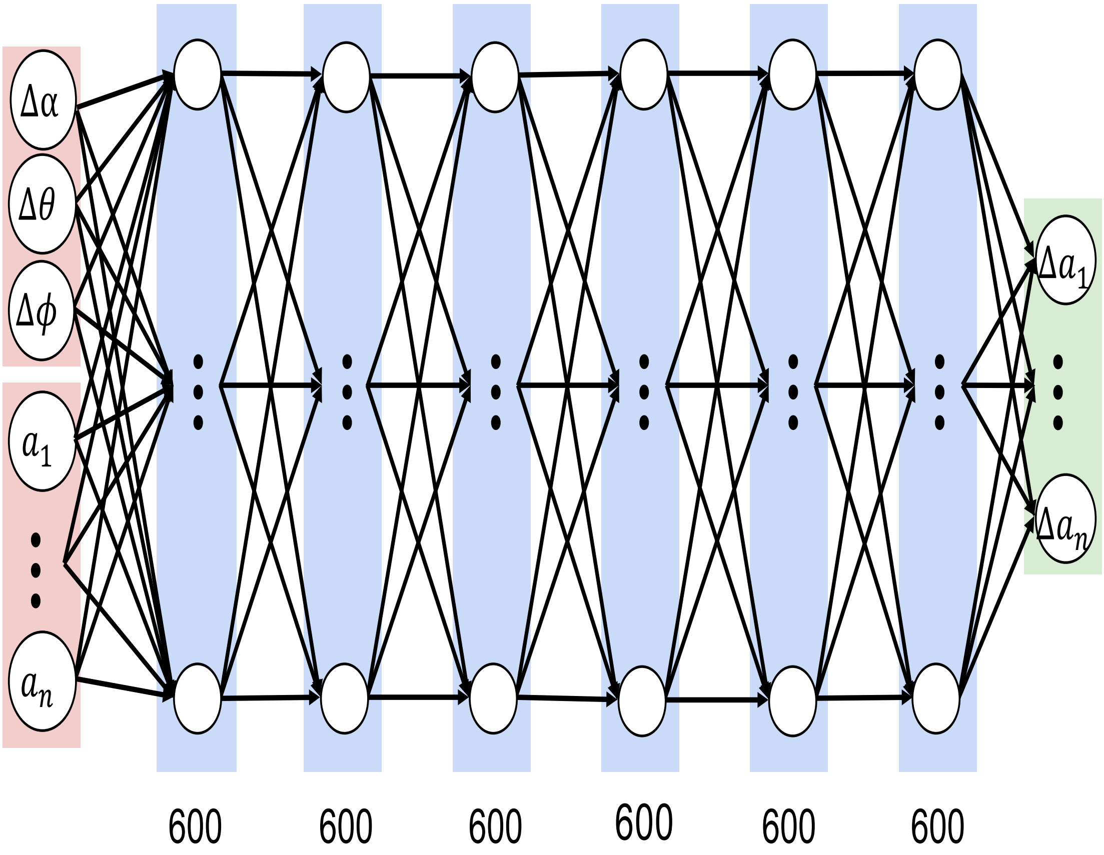
- The articulated biomechanical skeletal structure remains connected while moving.
- Each of the musculoskeletal complexes of the extremities include multiple significant muscles that attach to major bones in the torso.

Solution

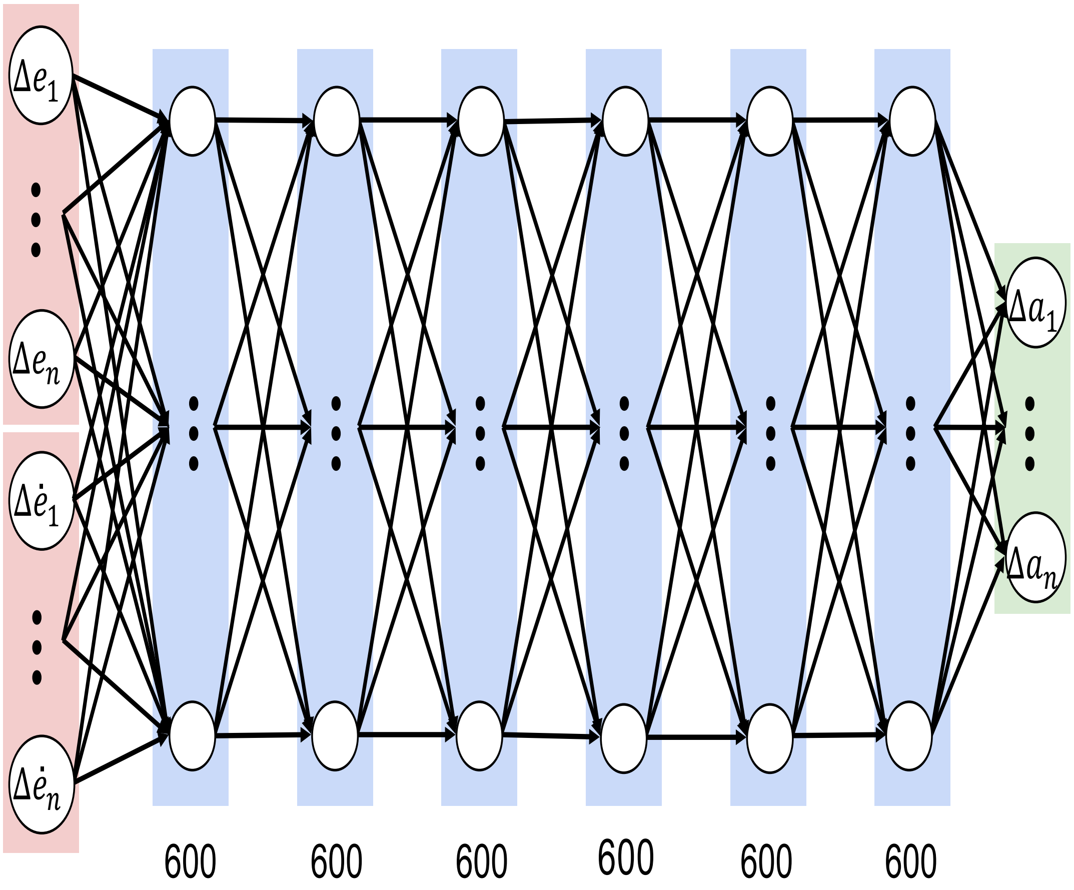
- For viable core training, we must regard the whole-body model as a unified system.
- Introduce random forces from the extremities onto the torso, such that the torso neuromuscular controller learns the consequences of forces derived from the extremities
- To learn balance, if COP comes to the margin of the support polygon, the biomechanical model is reset to an upright posture

Network Structure

Voluntary Controller

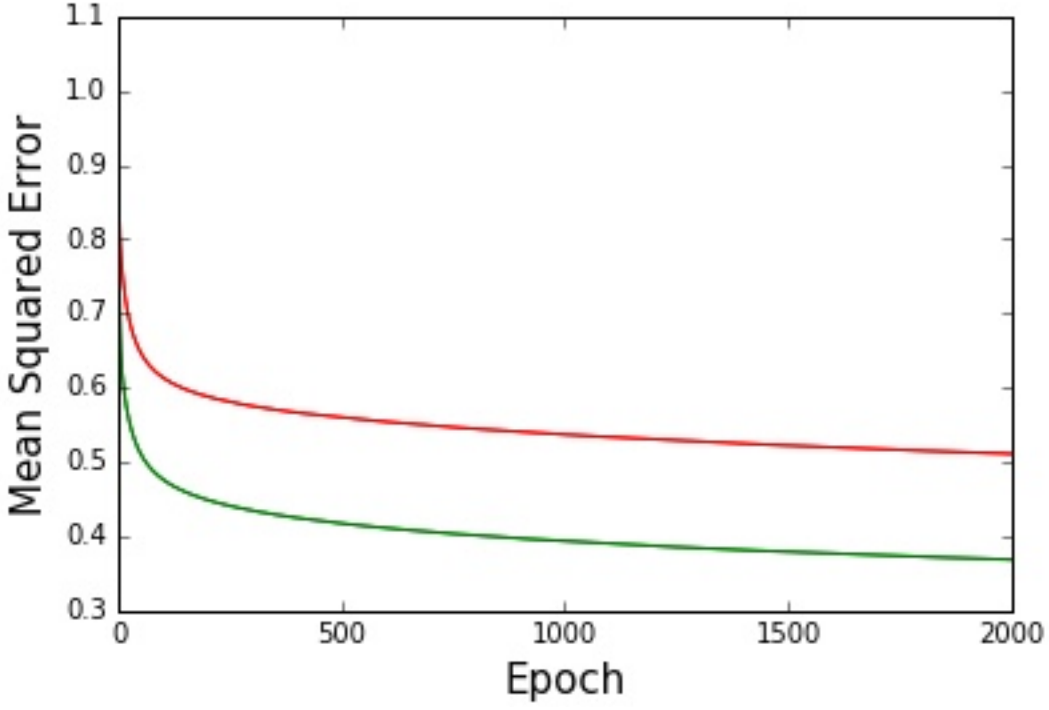


Reflex Controller

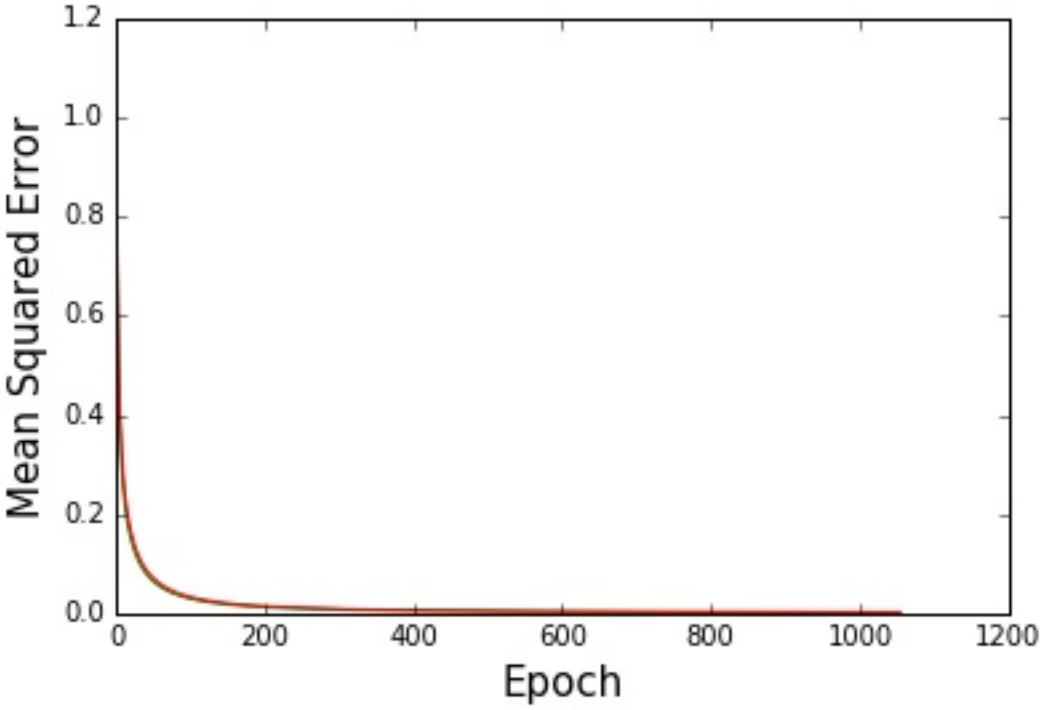


Training Progress

Torso Voluntary Controller

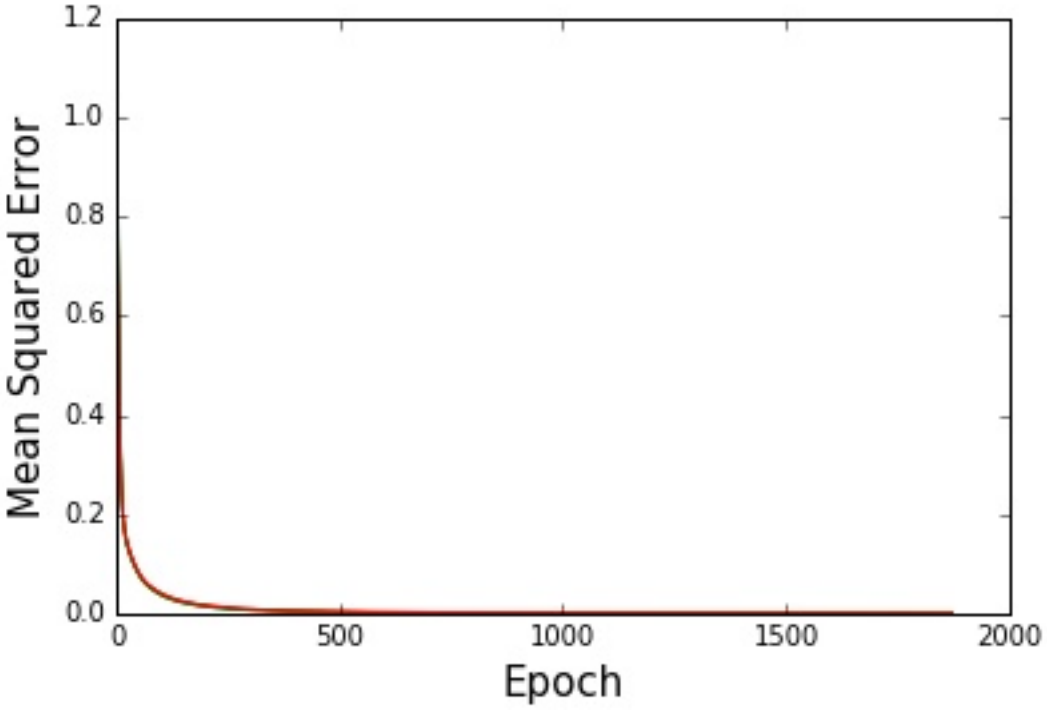


Torso Reflex Controller

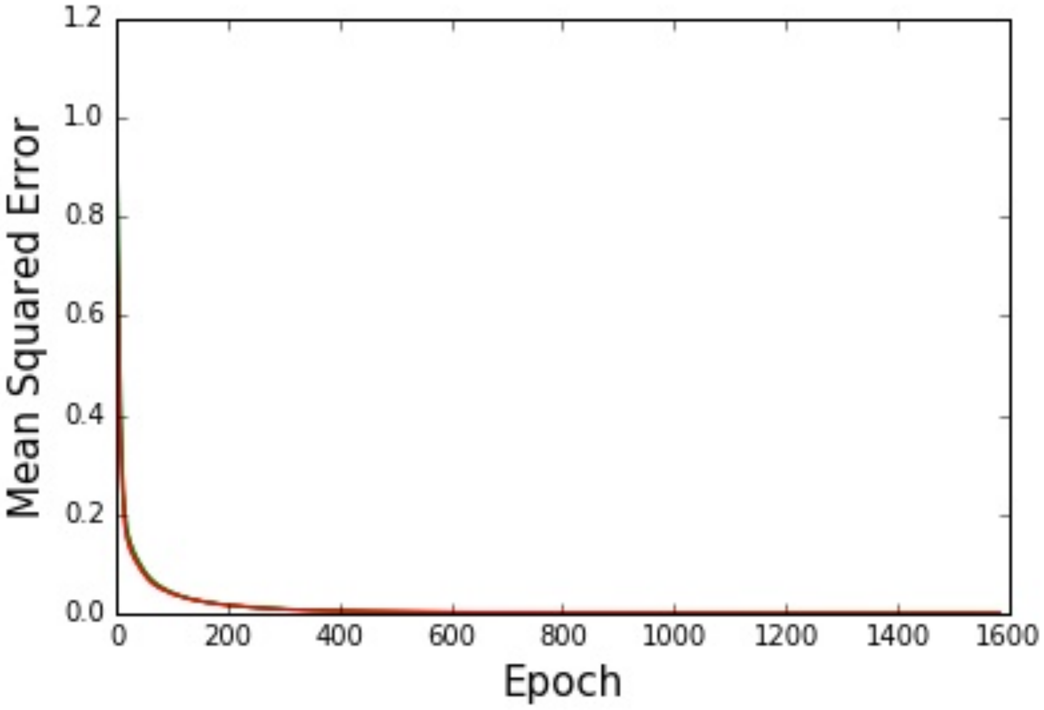


Passive Posture Stabilization (Leg reflex)

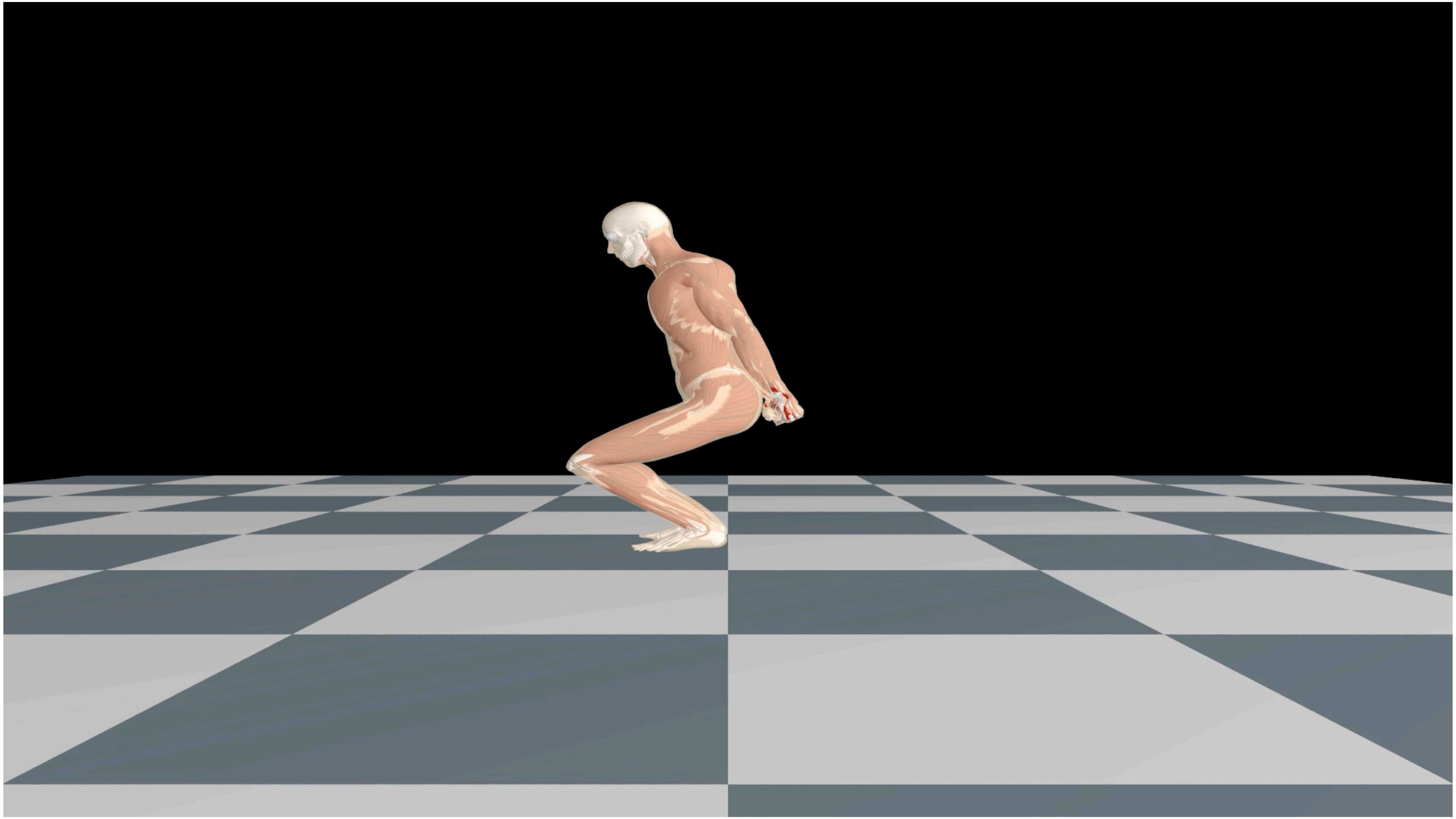
Left Leg Reflex



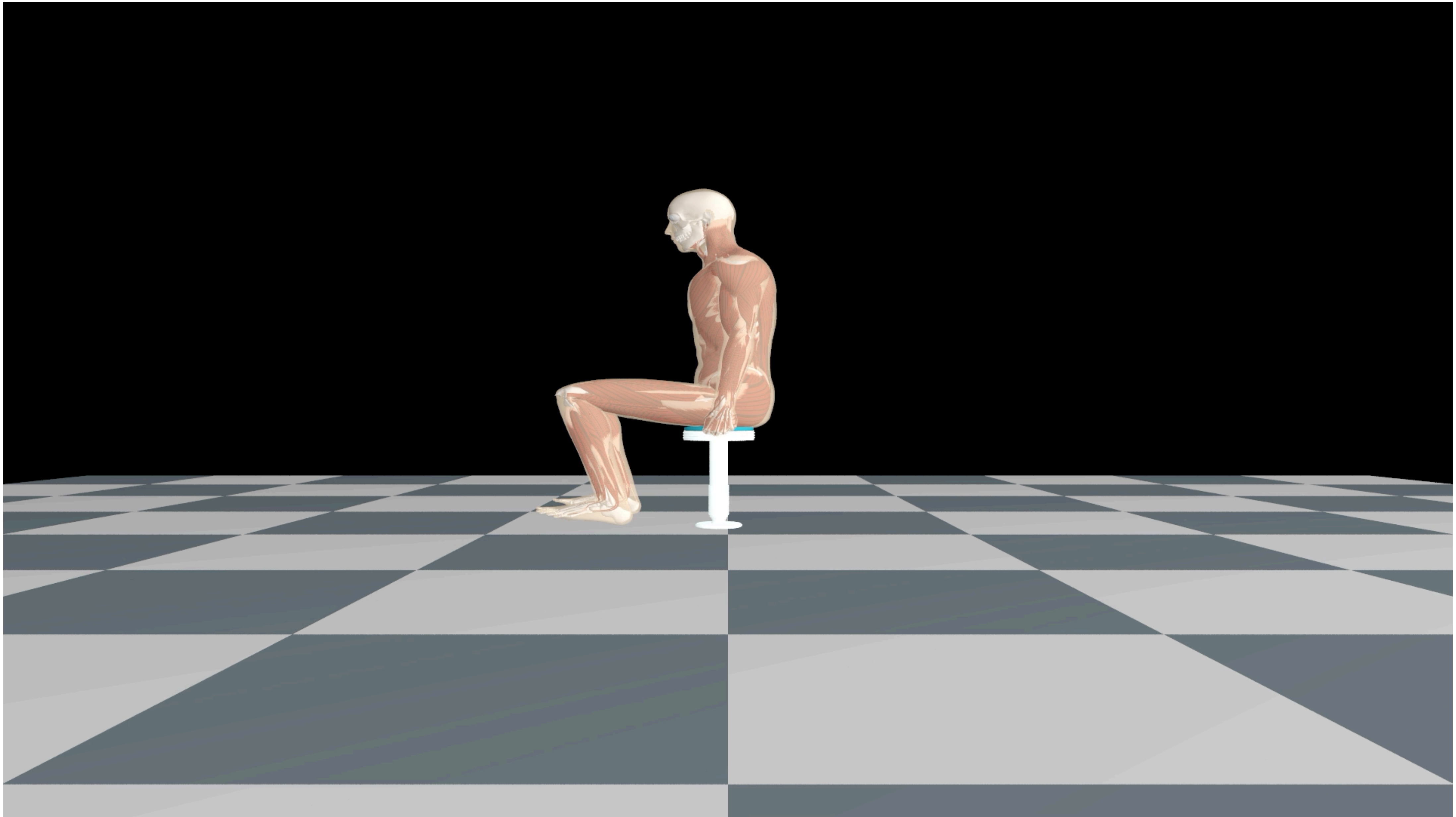
Right Leg Reflex



Progress of Neuromuscular Controller Training



Standing up after 1000 epochs training



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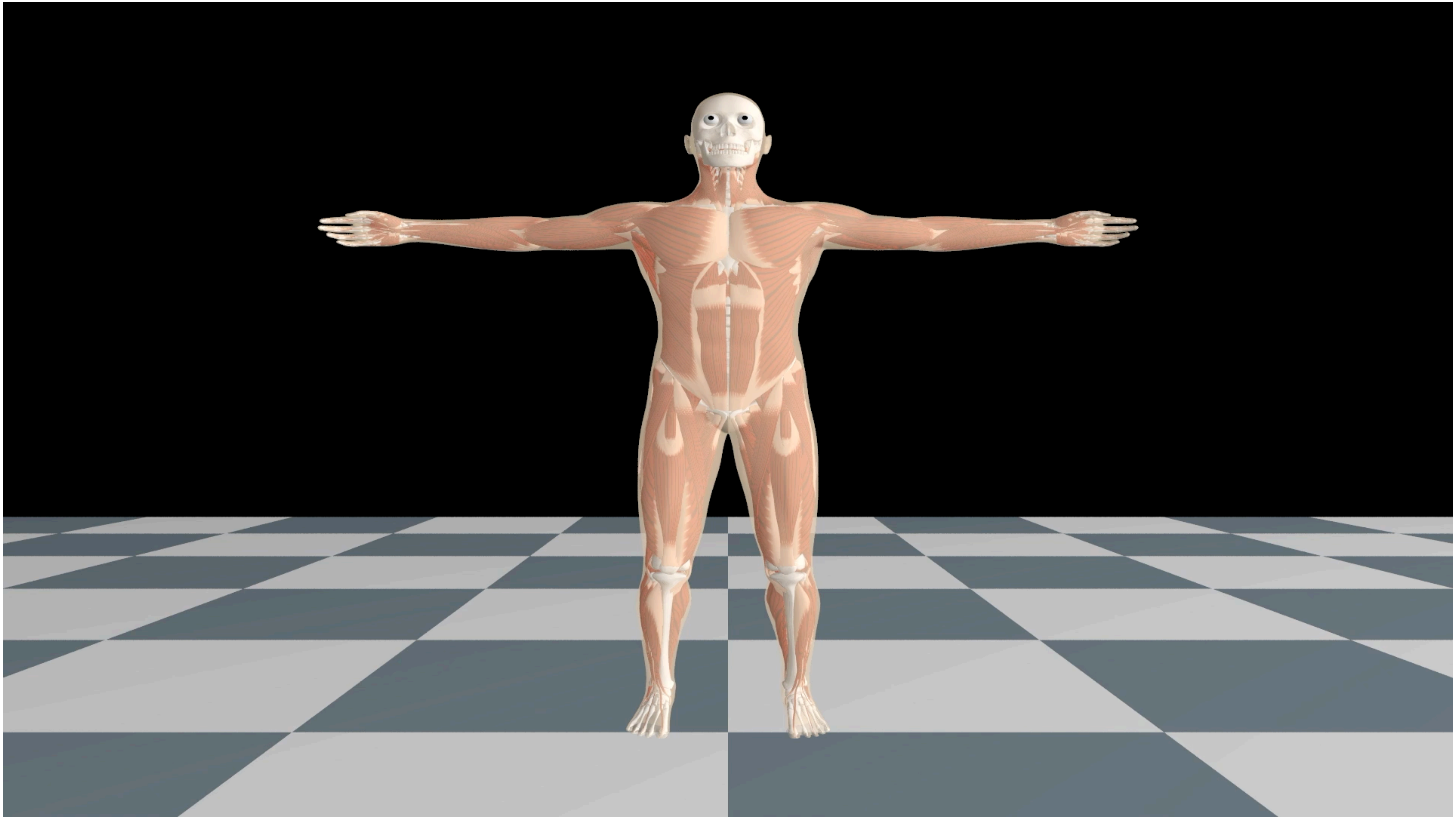
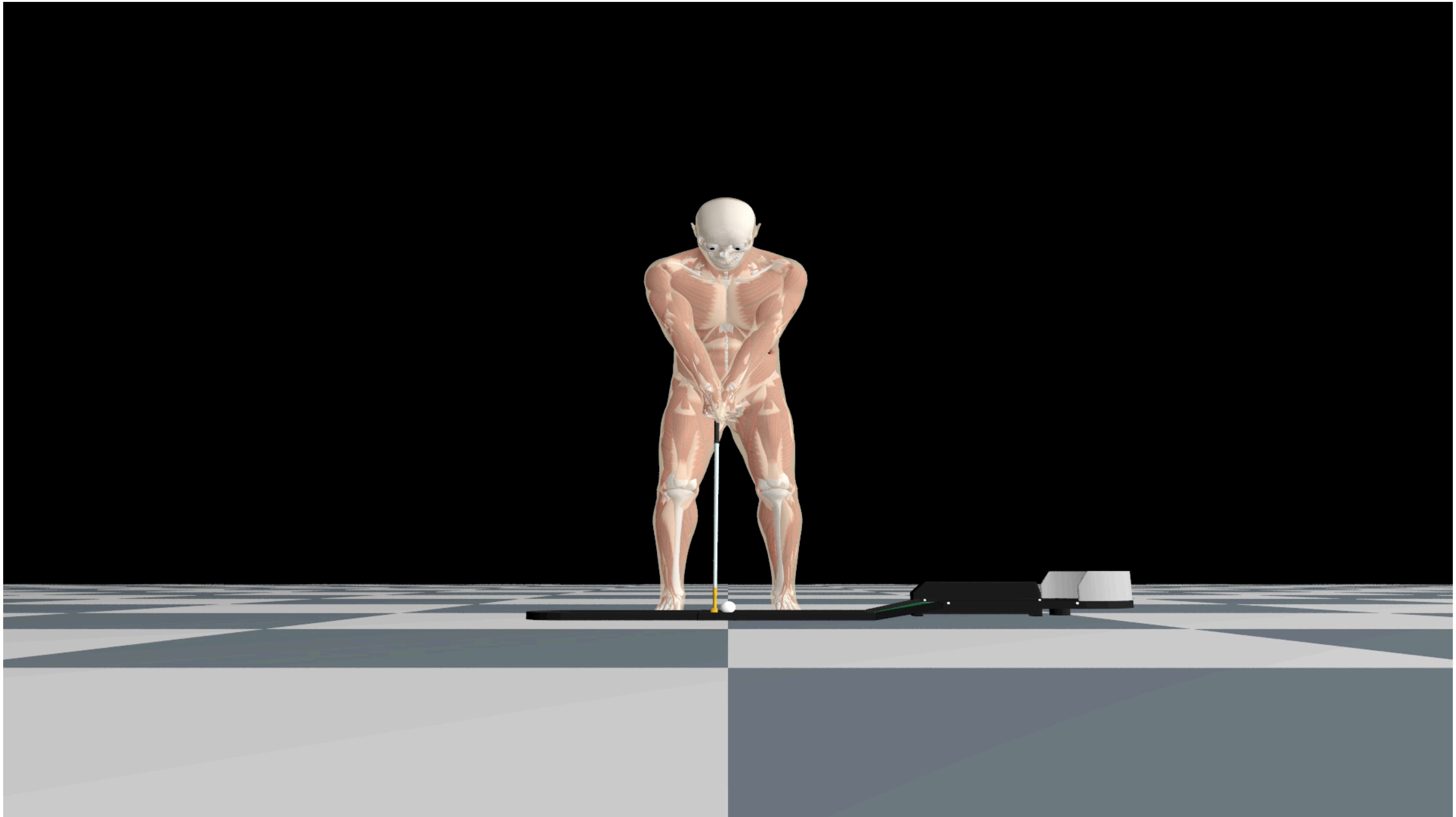
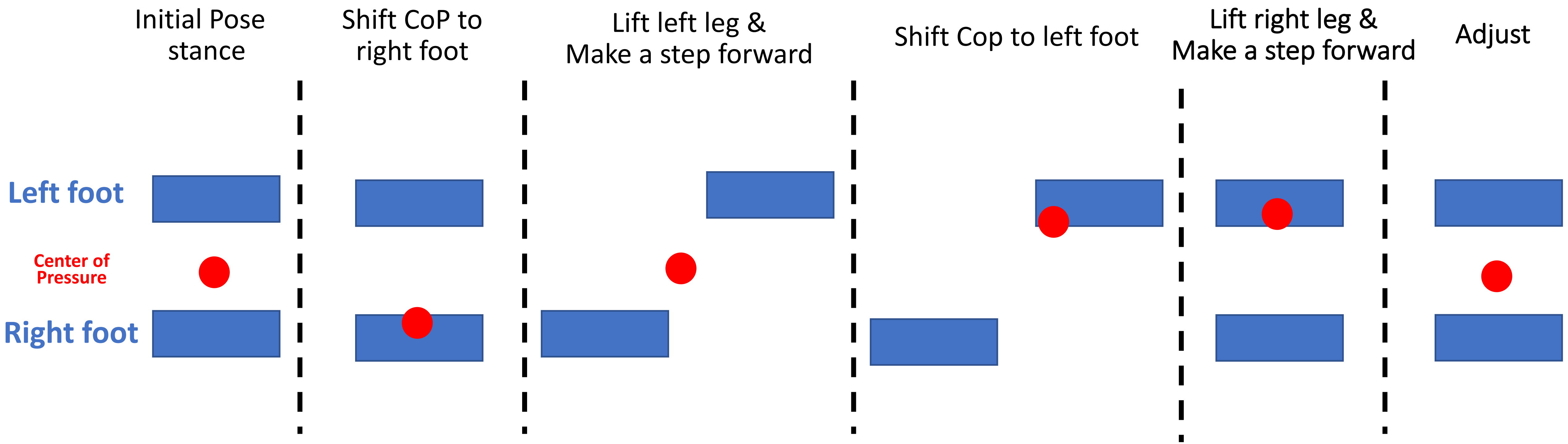
Calisthenic exercises



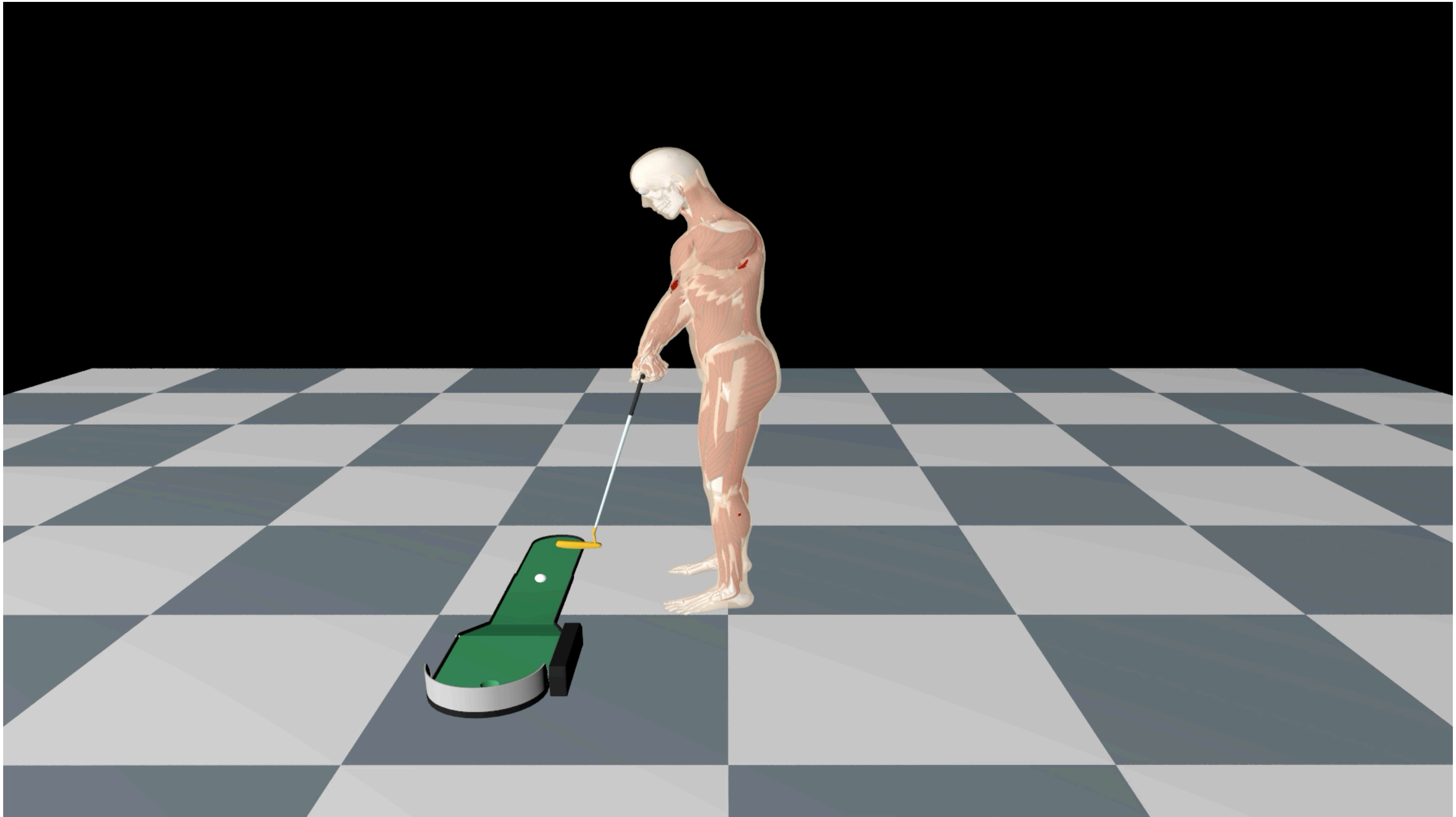
Golf (front view)



Stepping

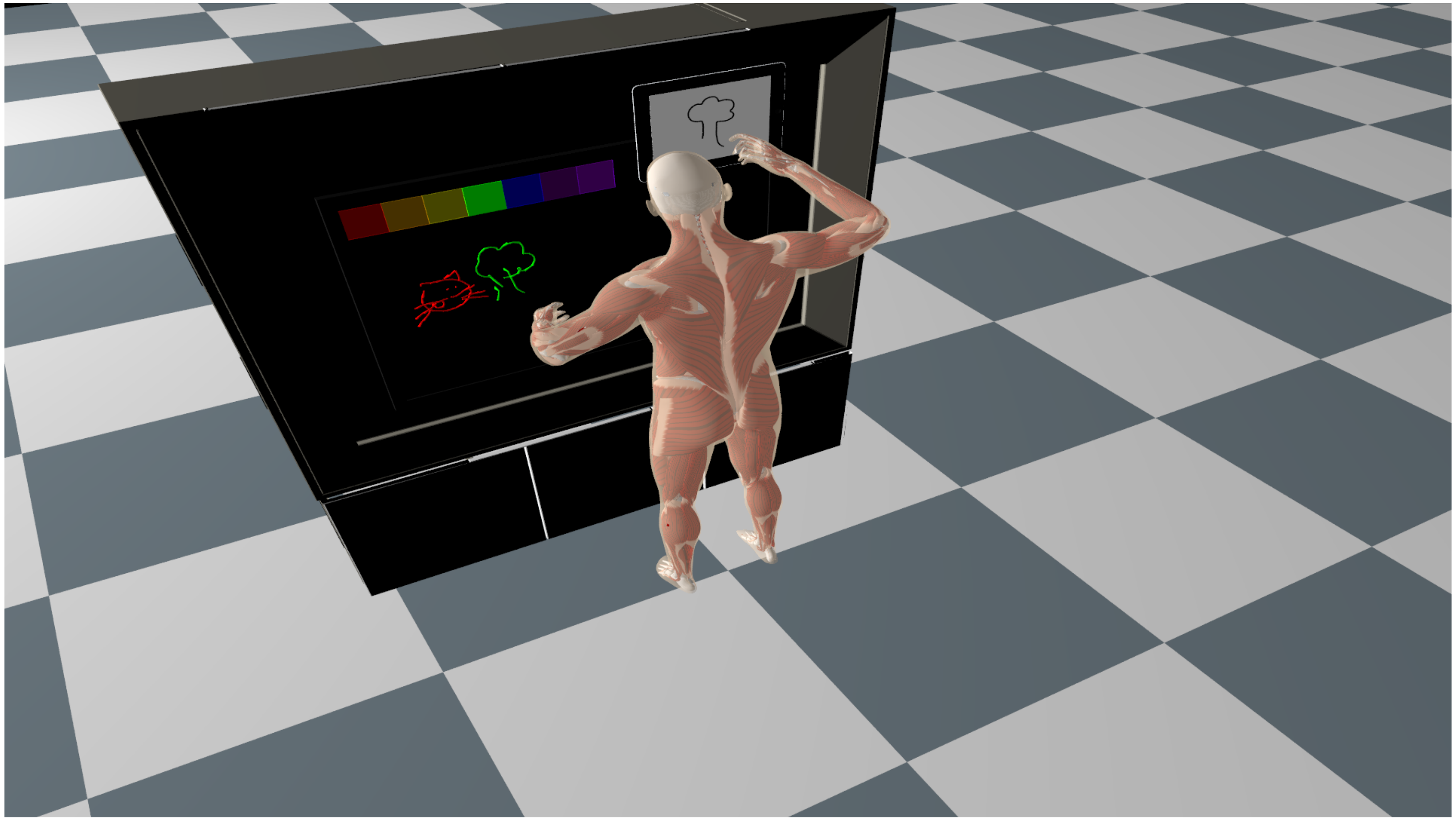

Initial Pose stance
Shift CoP to right foot
Lift left leg & Make a step forward
Shift Cop to left foot
Lift right leg & Make a step forward
Adjust
Left foot
Center of Pressure
Right foot

Stepping and golf (side view)



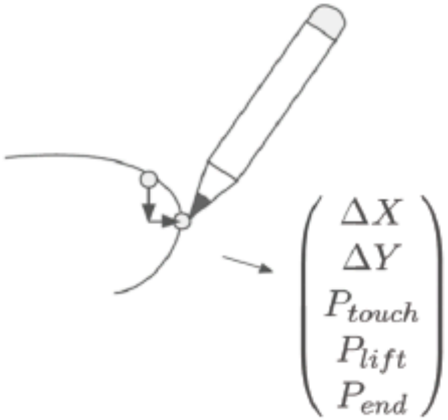
AN APPLICATION TO SENSORIMOTOR CONTROL: SKETCHING

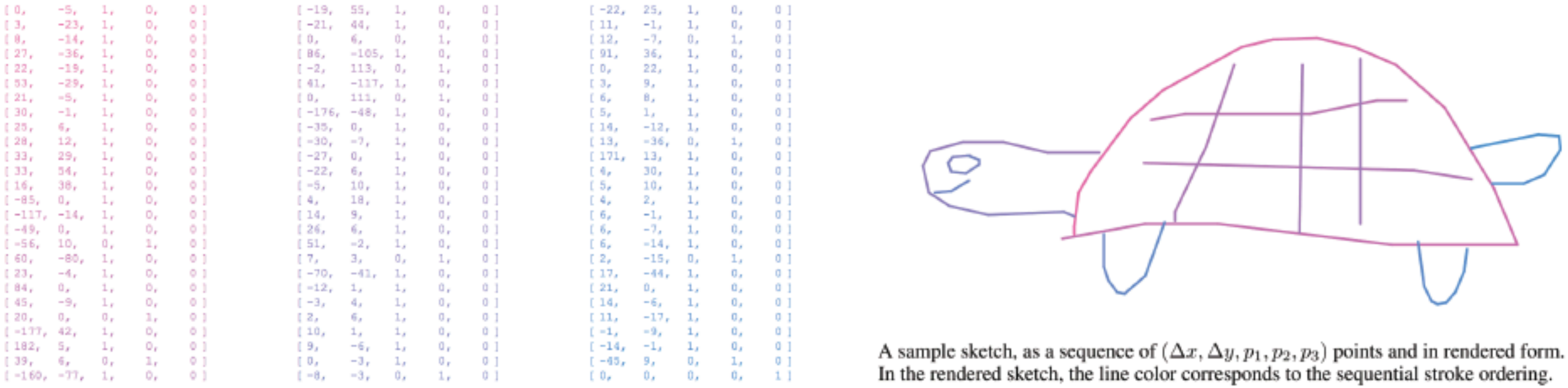
Motivation: Humans, do not understand the world as a grid of pixels, but develop abstract concepts to represent what we see. We learn to express a representation of an image as a short sequence of strokes.



Quick, Draw! Dataset

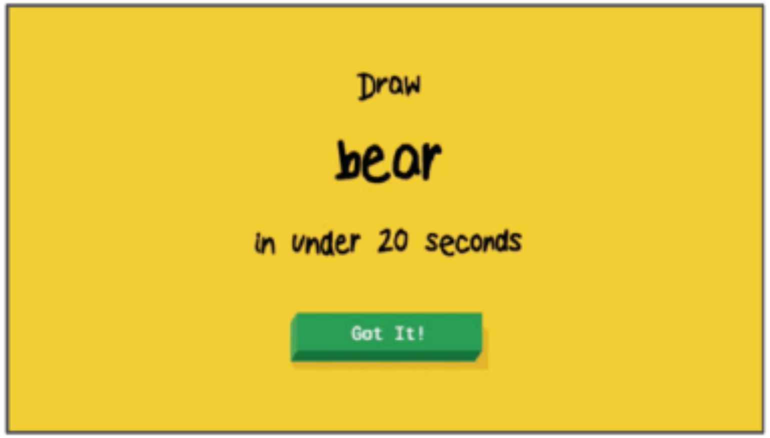
quickdraw.withgoogle.com/data

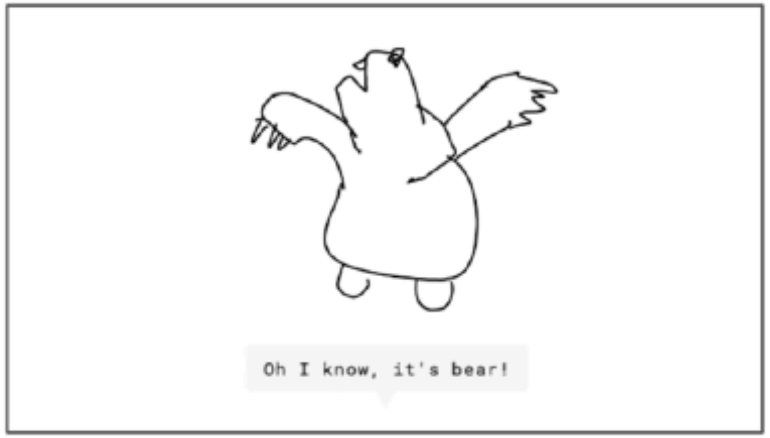




A sample sketch, as a sequence of $(\Delta x, \Delta y, p_1, p_2, p_3)$ points and in rendered form. In the rendered sketch, the line color corresponds to the sequential stroke ordering.

Sketches are represented as a sequence of motor actions controlling a pen.
Open sourced dataset of 50M doodles, collected from *Quick, Draw!* game.





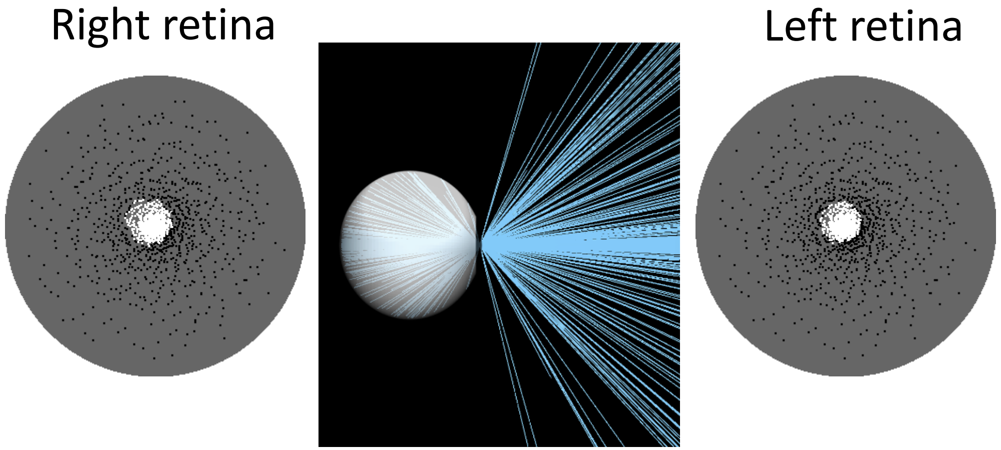
Example sketch drawings from `QuickDraw` dataset.

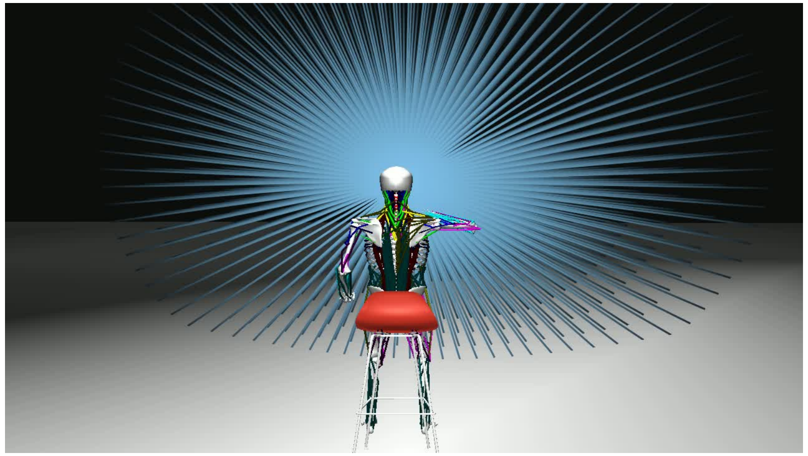
Google Creative Lab

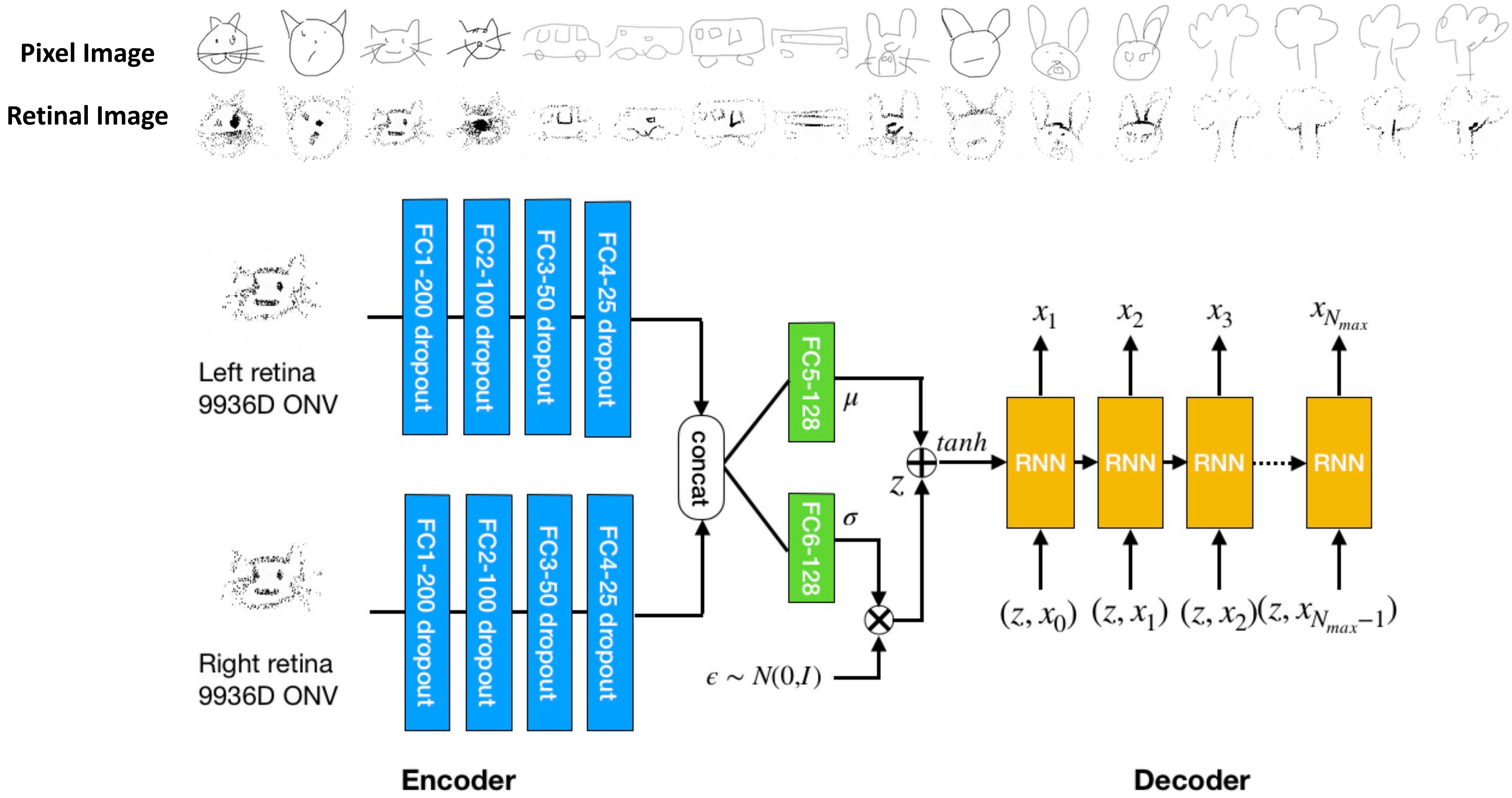
Eye Model

$$\mathbf{d}_k = e^{\rho_j} \begin{bmatrix} \cos\theta_i \\ \sin\theta_i \end{bmatrix} + \begin{bmatrix} \mathcal{N}(\mu, \sigma^2) \\ \mathcal{N}(\mu, \sigma^2) \end{bmatrix}$$

- Modeled as a sphere of radius of 12 mm
- Fields of view : 167.5 degrees
- Optic: Ideal pinhole camera
- Photoreceptors are distributed with Log-polar distribution with a IID Gaussian noise
- 9,936 photoreceptors are placed







Pixel Image
Retinal Image
Left retina
9936D ONV
Right retina
9936D ONV
FC1-200 dropout
FC2-100 dropout
FC3-50 dropout
FC4-25 dropout
FC1-200 dropout
FC2-100 dropout
FC3-50 dropout
FC4-25 dropout
concat
FC5-128
FC6-128
μ
σ
z
tanh
$\epsilon \sim N(0,I)$
RNN
RNN
RNN
RNN
x_1
x_2
x_3
$x_{N_{max}}$
(z, x_0)
(z, x_1)
(z, x_2)
$(z, x_{N_{max}-1})$
Encoder
Decoder

Training

We model (Δx , Δy) as a Gaussian mixture model

$$p(\Delta x, \Delta y) = \sum_{j=1}^{m} w_j \mathcal{N}(\Delta x, \Delta y | \mu_{x_j}, \mu_{y_j}, \sigma_{x_j}, \sigma_{y_j}, \rho_{xy_j}),$$

W_j, a categorical distribution, are the mixture weights of the Gaussian mixture model.

The objective function is a reconstruction loss L, which is the sum of L_S

$$L = L_s + L_p.$$

$$L_s = -\frac{1}{N_{max}} \sum_{i=1}^{N_{max}} log(p(\Delta x, \Delta y))$$

$$L_p = -\frac{1}{N_{\max}} \sum_{i=1}^{N_{\max}} \sum_{k=1}^{3} p_{k\,i} \log(q_{k\,i}),$$

N_{MAX} is the total sequence length

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Contributions

- (1) We developed the first neuromuscular motor control system for the spine and torso.
- (2) We demonstrated that our control framework for the core musculoskeletal complex can work in concert with neuromuscular controllers specialized to the five extremities—the cervicocephalic, two arm, and two leg musculoskeletal complexes.
- (3) We showed how the six neuromuscular motor controllers, which included twelve Deep Neural Networks (DNNs) can form the motor subsystem of a whole-body sensorimotor control system, and demonstrated its robust online operation in carrying out several skillful (non-locomotive) motor tasks.

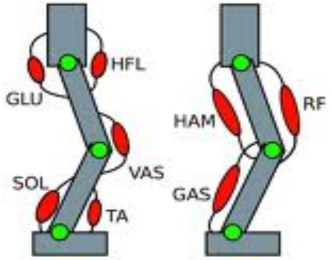
Future Work

1) Biomechanical hand model

Sueda et al, 2008

2) Bipedal locomotion

Wang et al., 2012



3) Continuous online learning

Acknowledgement

Prof. Demetri Terzopoulos, Prof. Song-Chun Zhu, Prof. Guy Van den Broeck, Prof. Joseph Teran

Masaki Nakada, Arjun Lakshmipathy, Alan Litteneker, Sung-Hee Lee, Si Weiguang

Tomer Weiss, Chenfanfu Jiang, Sharath Gopal, Garett Ridge, Xiaowei Ding, Gergely Klar, Andre Pradhana, Abdullah-Al-Zubaer Imran, Ziran Lin, Yajun Shi, Yingyue Qiu, Hao Ding.

Adobe Gift Funding

Thank you & Questions!

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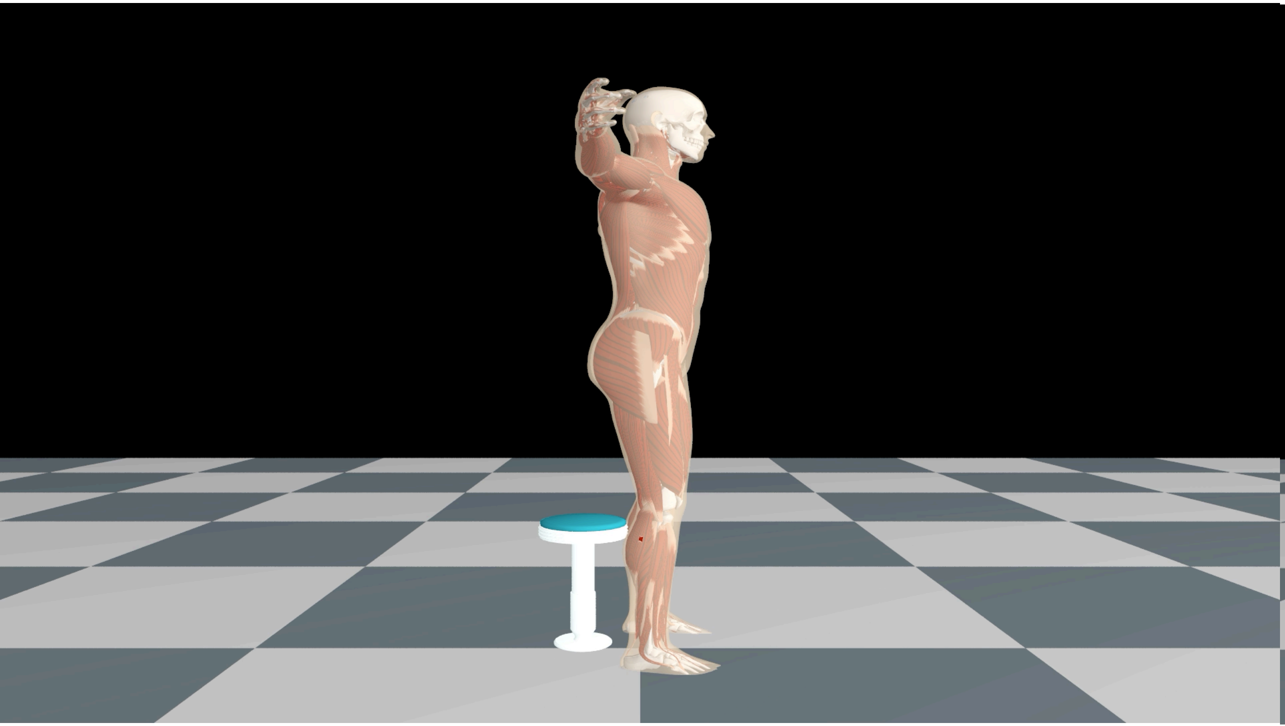
SIGGRAPH Asia 2019 Technical Paper Submission #322

Flesh Deformation Demo

Sit with Flesh Deformation



Sit w/o Flesh Deformation