Physics-Based Models for People Tracking: Biomechanics and Models of Locomotion

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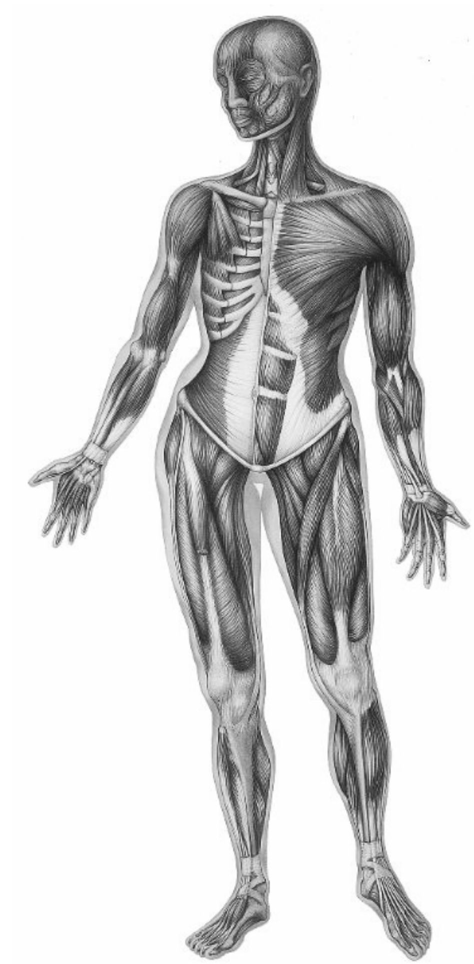
Biomechanics

Biomechanics studies motion of the body

- Structure of the body, bones and joints
- Size and mass properties of body parts
- Muscles
- Nature of locomotion

Clinical biomechanics studies both normal and pathological motion using…

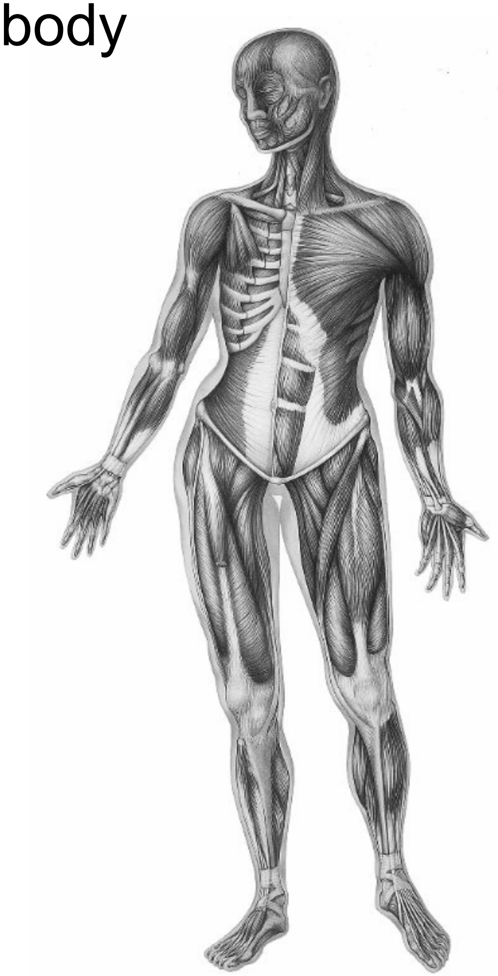
- Mocap
- Force plates
- EMG
- etc



Biomechanics: Body Segment Parameters

Anthropometrics and body segment parameters

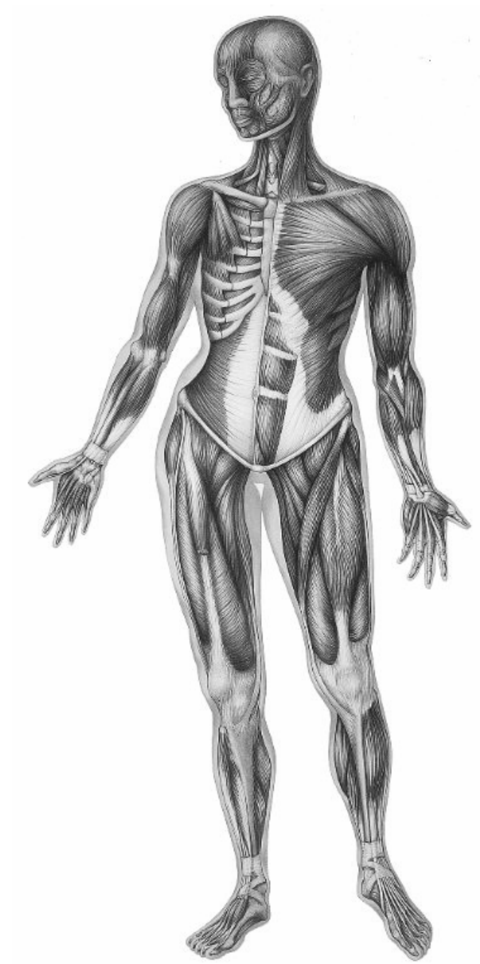
- Crucial for defining mass properties of body parts
- Several studies have measured mass, moments of inertia, length, etc



Biomechanics: Joint Kinematics

Joints are more complex than often thought

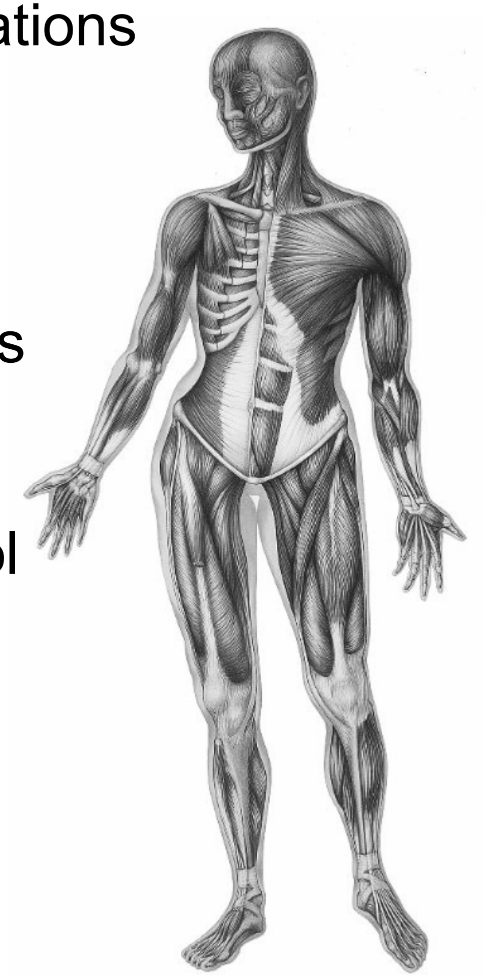
- Joints are not rigidly attached
- Axes of rotation for some joints are not fixed and may not be orthogonal
- Range of motion is often pose dependent
- E.G., knee has 3 rotational DoF, but close to only one at full extension



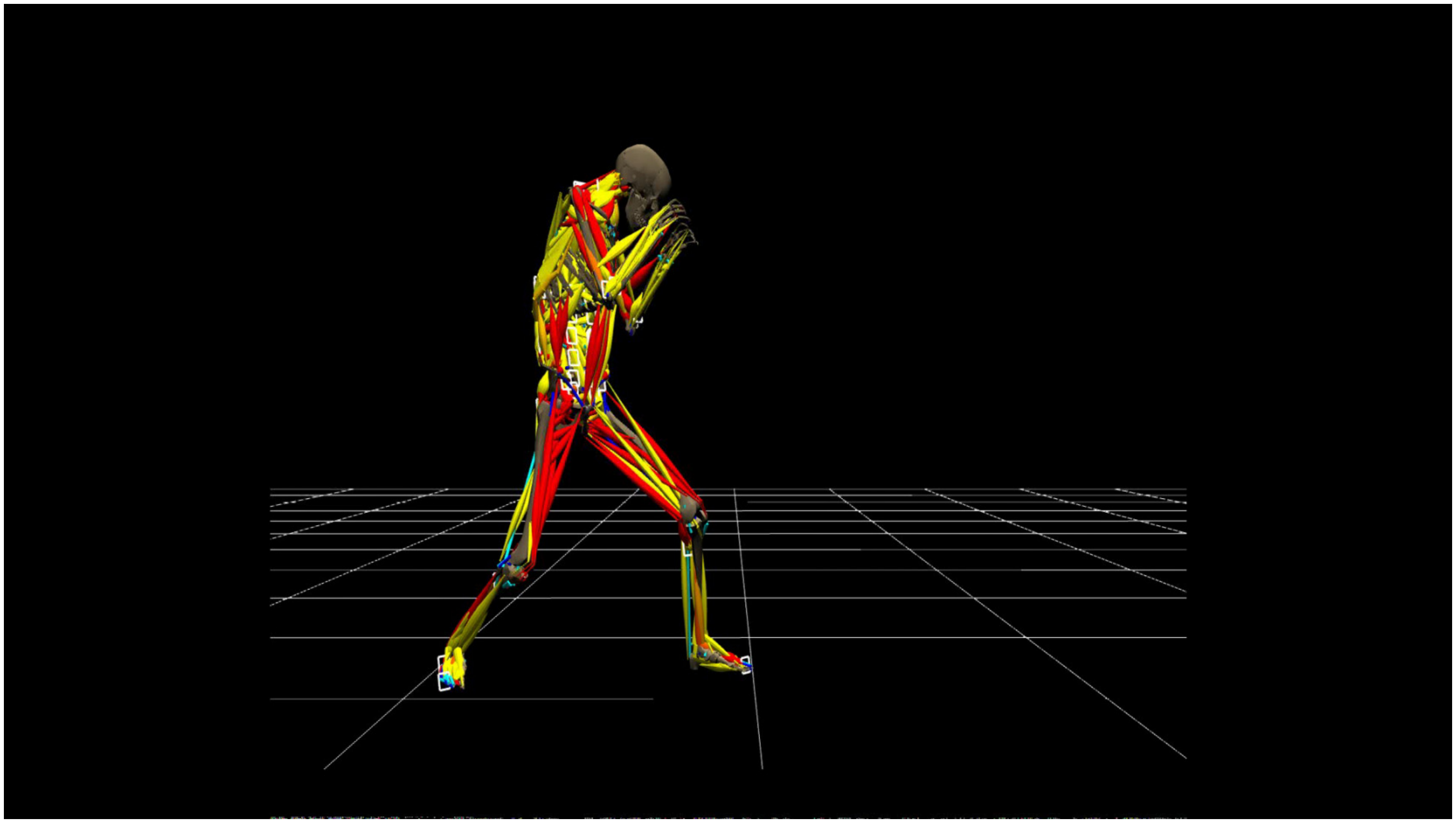
Biomechanics: Dynamics

Dynamics of muscles and neural control

- Net torques at joints are gross simplifications
- Pose dependent muscle forces
- Temporal dynamics of muscles
- Muscles and tendons as passive springs
- Biarticular muscles
- Signal dependent noise in neural control



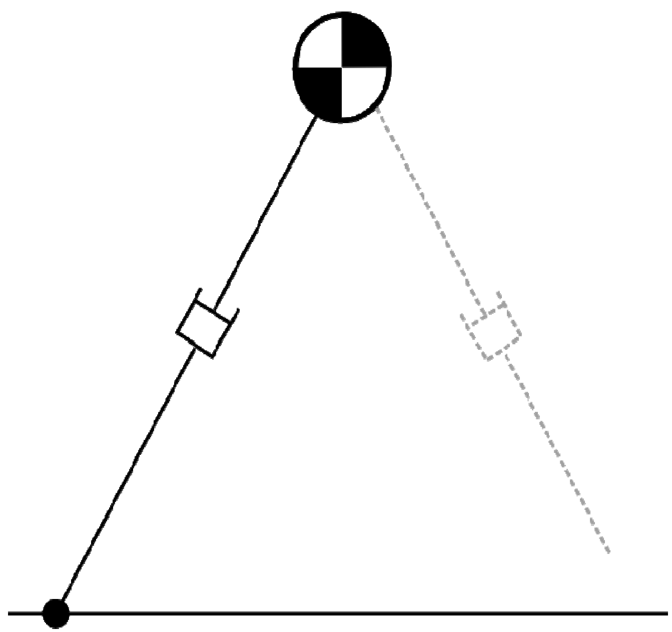
Biomechanics: Musculo-skeletal models



[*Nakamura, Yamane, Suzuki, Fujita, ‘03 /’04*]

Models of Human Locomotion: The Monopode

Monopode

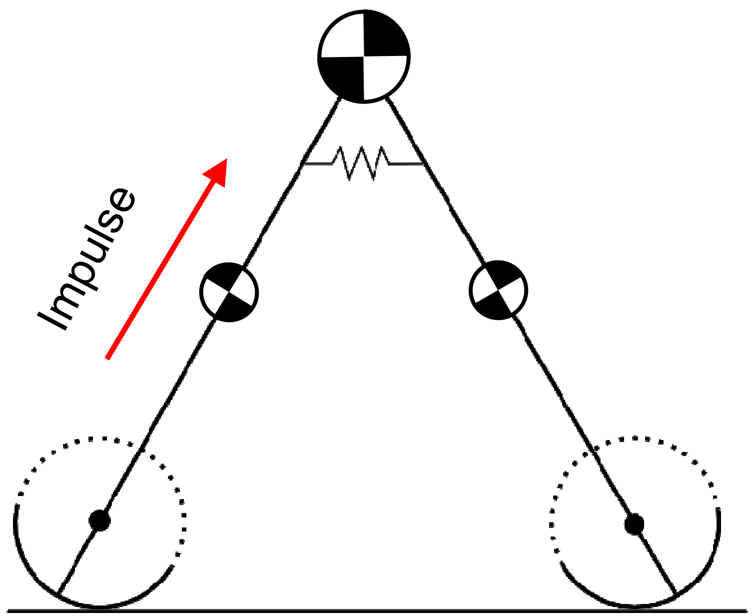


[*Blickhan & Full 1993*; *Srinivasan & Ruina 2000*]

- point-mass at hip, mass-less legs with a prismatic joint
- inverted pendular motion
- models walking and running in humans and other animals
- …uninformative

Models of Human Locomotion: Anthropomorphic Walker

Anthropomorphic Walker



[*McGeer 1990; Kuo 2001,2002; Brubaker et al CVPR 2006*]

- point mass for torso and rigid bodies for legs
- forces due to torsional spring between legs and an impulsive toe-off
- wide range of cyclic gaits can be found by varying spring stiffness and impulse
- Matlab code available to simulate and find cyclic gaits

Models of Human Locomotion: Anthropomorphic Walker

Speed: 6.7 km/hr; Step length: 0.875m

Models of Human Locomotion: Anthropomorphic Walker

Speed: 5.4 km/hr; Step length: 0.875m

Models of Human Locomotion: Anthropomorphic Walker

Speed: 4.0 km/hr; Step length: 0.875m

Models of Human Locomotion: Anthropomorphic Walker

Speed: 4.0 km/hr; Step length: 0.625m

Models of Human Locomotion: Anthropomorphic Walker

Speed: 2.7 km/hr; Step length: 0.875m

Models of Human Locomotion: Anthropomorphic Walker

Speed: 2.7 km/hr; Step length: 0.625m

Models of Human Locomotion: Anthropomorphic Walker

Speed: 2.7 km/hr; Step length: 0.375m

Models of Human Locomotion: Passive dynamics

Much of walking is essentially passive.

[*McGeer 1990*]

Models of Human Locomotion: Passive dynamics

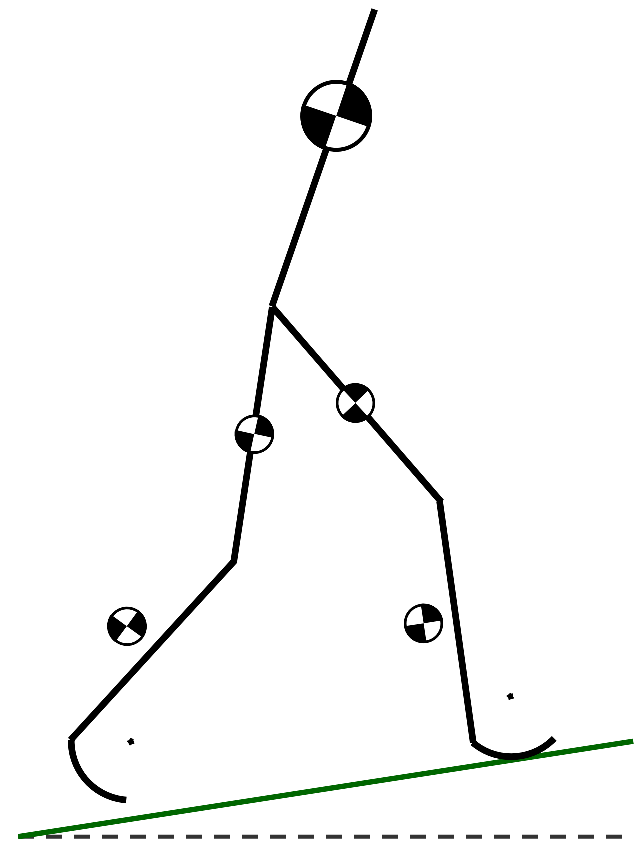
Principles of passive dynamics have been used in robotics

[*Collins & Ruina 2005*]

The *Kneed Walker*

Goal: 3D people tracking based on the Kneed Walker

- a 5 DOF planar model of human locomotion
- powered by joint torques and an impulsive toe-off
- capable of walking on hills or level ground, running, …



[*Brubaker and Fleet 2008*]

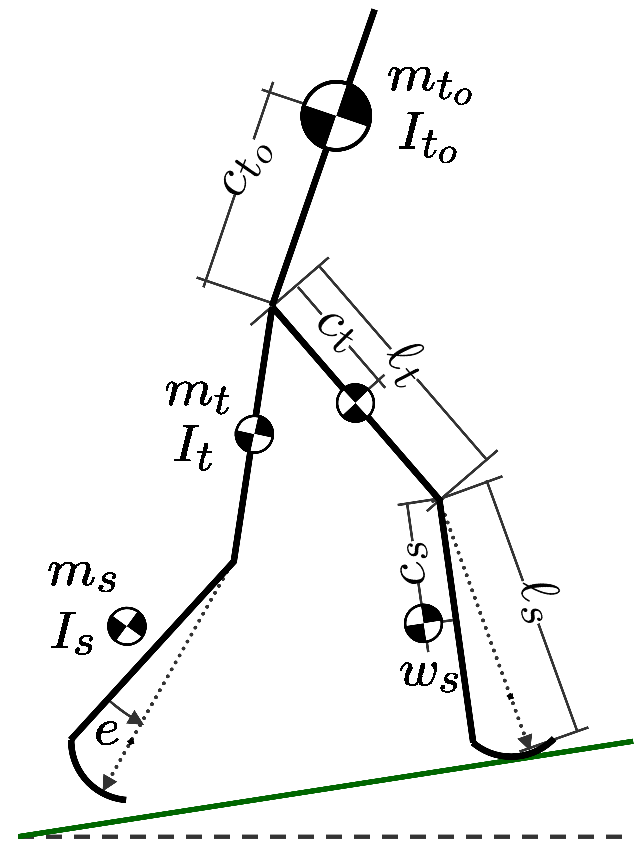
Kneed Walker: Inertial parameters

Kneed walker comprises

- a torso
- two legs (with knees)
- rounded feet

Specified by

- part lengths, masses, mass centers, and moments of inertia
- stance / swing foot



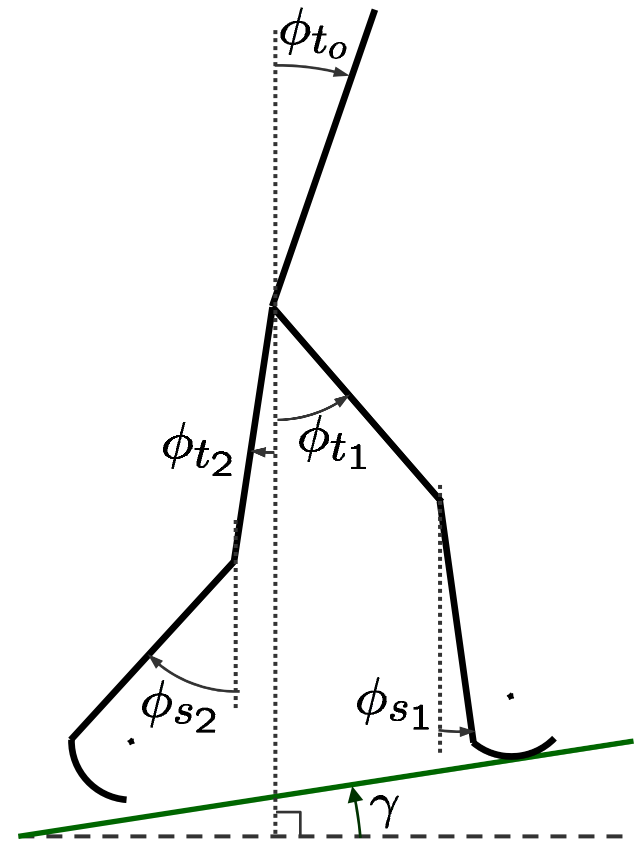
Kneed Walker: Generalized coordinates

Model state $\mathbf{x}^T = (\mathbf{q}^T, \dot{\mathbf{q}}^T)$ is given by the part orientations

$$\mathbf{q}^T = (\phi_{t_o}, \phi_{t_1}, \phi_{t_2}, \phi_{s_1}, \phi_{s_2})$$

and their angular velocities

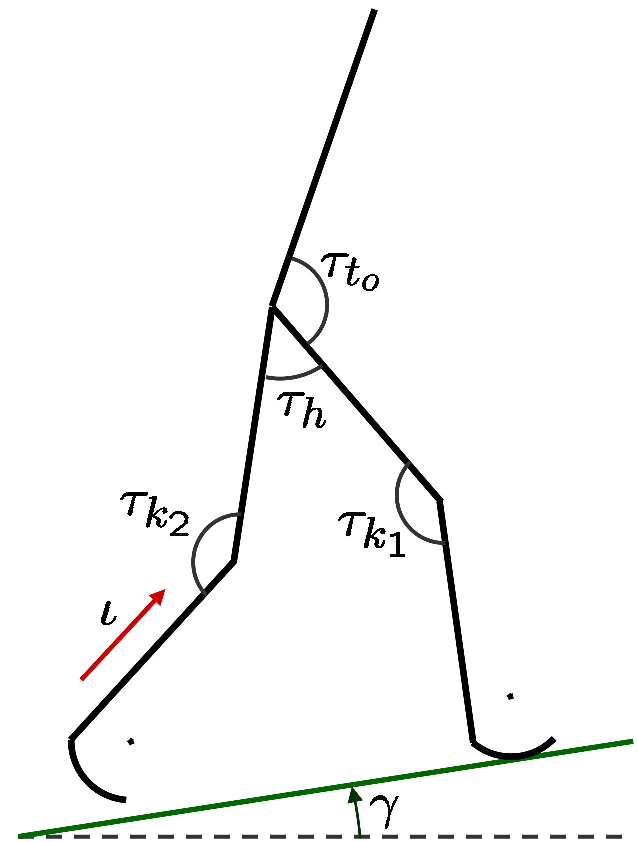
$$\dot{\mathbf{q}}^T = (\dot{\phi}_{t_o}, \dot{\phi}_{t_1}, \dot{\phi}_{t_2}, \dot{\phi}_{s_1}, \dot{\phi}_{s_2})$$



Kneed Walker: Applied forces

Dynamics due to:

- joint torques $\tau_{t_o}, \tau_h, \tau_{k_1}, \tau_{k_2}$ (for torso, hip, & knees)
- impulse applied at toe-off (with magnitude ι)
- gravitational acceleration (w.r.t. ground slope γ)



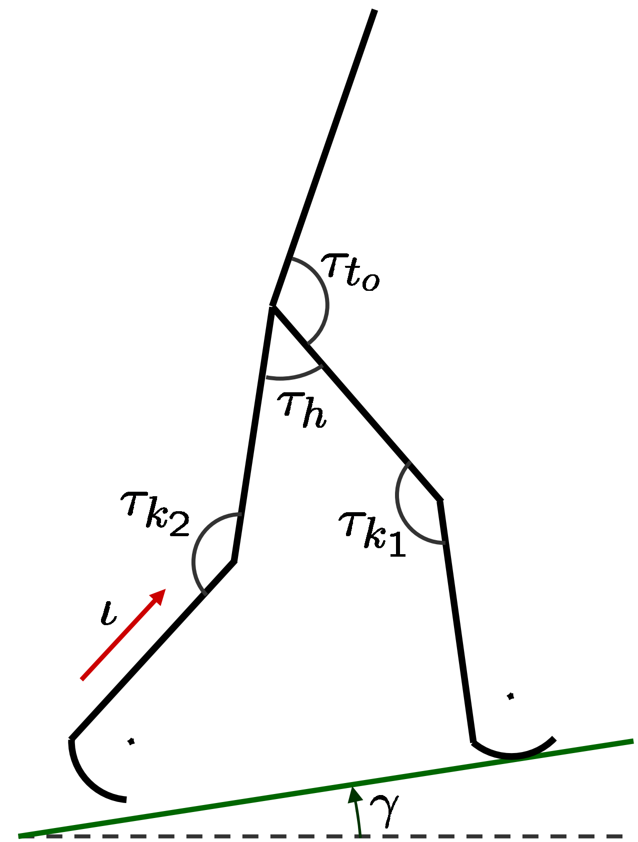
Kneed Walker: Applied forces

Joint torques are parameterized as damped linear springs.

For hip torque

$$\tau_h = \kappa_h(\phi_{t_2}+\phi_{t_1}-\phi_h) - d_h(\dot\phi_{t_2}+\dot\phi_{t_1})$$

with stiffness and damping coefficients, κ_h and d_h, and resting length ϕ_h

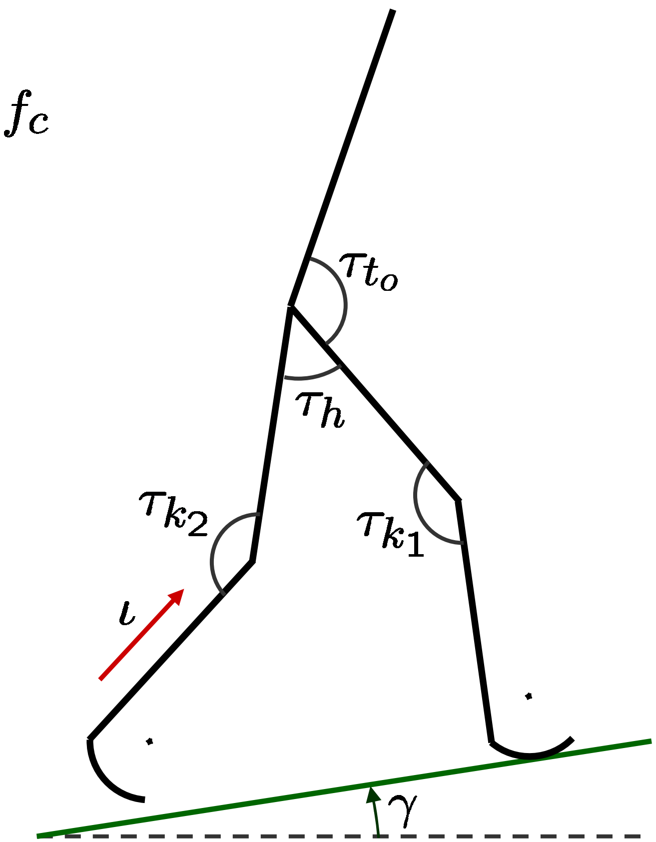


Kneed Walker: Equations of motion

Equations of motion

$$\mathcal{M}\ddot{\mathbf{q}} \;=\; f_s(\vec{\kappa}, \vec{d}, \vec{\phi}) + f_g + f_c$$

generalized
mass matrix

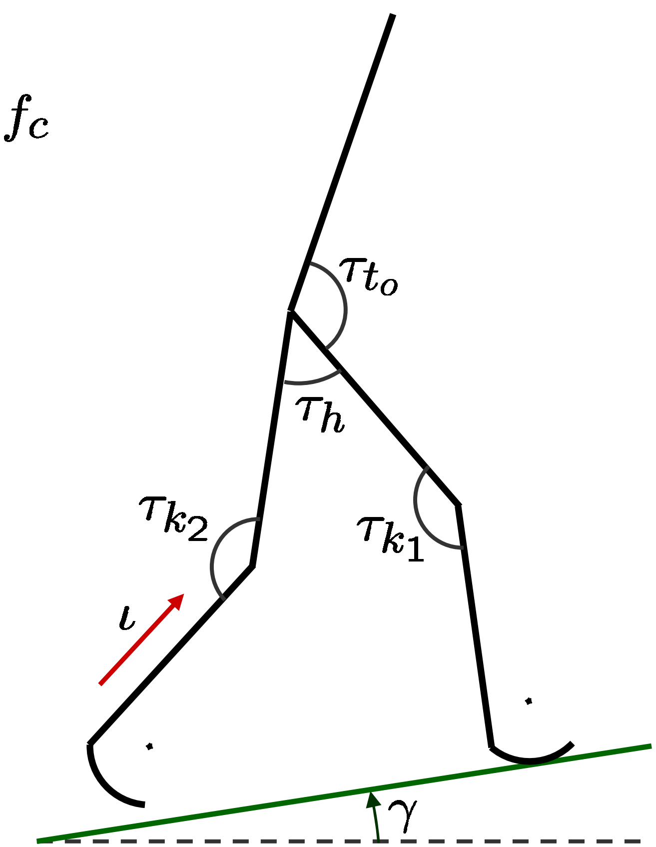


Kneed Walker: Equations of motion

Equations of motion

$$\mathcal{M}\ddot{\mathbf{q}} = f_s(\vec{\kappa}, \vec{d}, \vec{\phi}) + f_g + f_c$$

acceleration

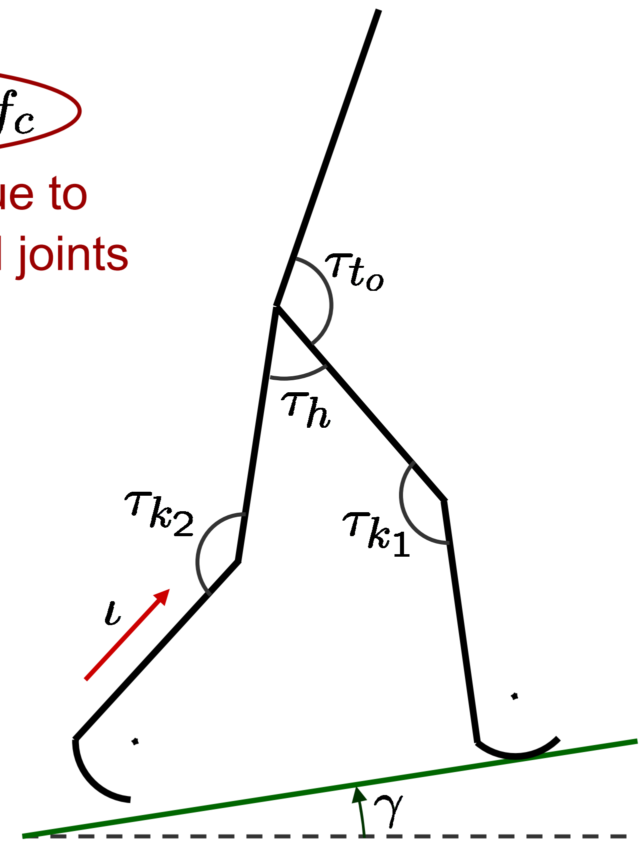


Kneed Walker: Equations of motion

Equations of motion

$$\mathcal{M}\,\ddot{\mathbf{q}} = f_s(\vec{\kappa}, \vec{d}, \vec{\phi}) + f_g + f_c$$

spring torques — forces due to gravity and joints



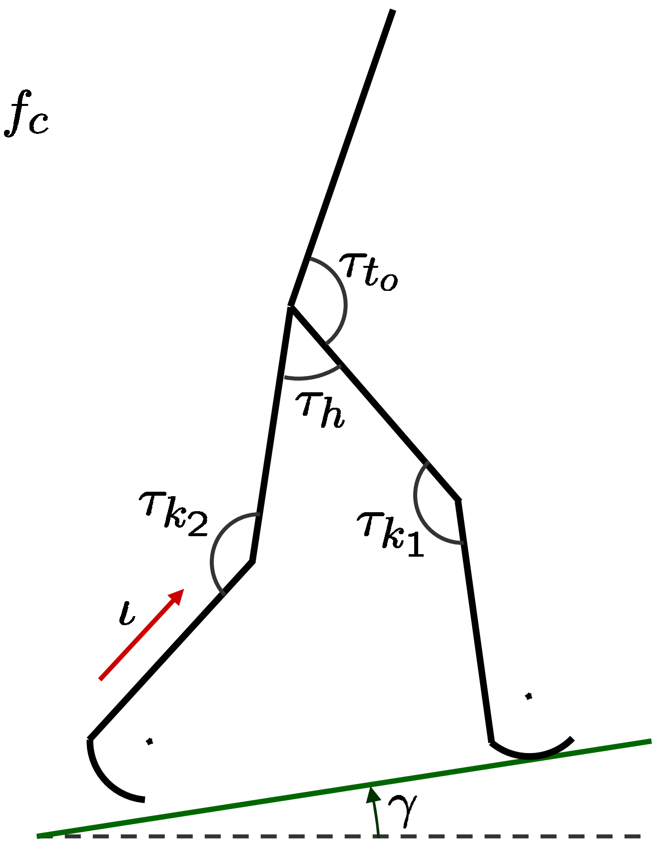
Kneed Walker: Equations of motion

Equations of motion

$$\mathcal{M}\,\ddot{\mathbf{q}} \;=\; f_s(\vec{\kappa}, \vec{d}, \vec{\phi}) + f_g + f_c$$

… plus ground collisions

and joint limits (esp. knee)



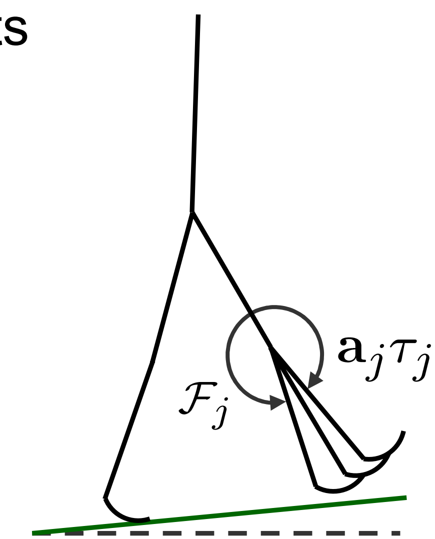
Kneed Walker: Joint limits

Joint limits easily expressed as constraints $\mathbf{a}^T\mathbf{q} \geq b$

When a joint limit violation is detected in simulation

- first localize constraint boundary (i.e., the time at which joint limit is reached) and treat as an impulsive collision
- then, as long as constraint is “active”, include a virtual reactive force to ensure joint limits
- augmented equations of motion

$$\begin{bmatrix} \mathcal{M} & -\mathbf{a} \\ \mathbf{a}^T & \mathbf{0} \end{bmatrix} \begin{pmatrix} \ddot{\mathbf{q}} \\ \tau \end{pmatrix} = \begin{pmatrix} \mathcal{F} \\ \mathbf{0} \end{pmatrix}$$



Prior for the Kneed Walker

How do we design a prior distribution over the dynamics parameters to encourage plausible human-like walking motions?

Assumption: Human walking motions are characterized by efficient, stable, cyclic gaits.

Approach:

- Find control parameters that produce optimal cyclic gaits over a wide range of natural human speeds and step lengths, for a range of surface slopes.
- Assume additive process noise in the control parameters to capture variations in style.

Efficient, cyclic gaits

Search for dynamics parameters $\vec{\theta} = (\vec{\kappa},\ \vec{d},\ \vec{\phi},\ \iota)$ and initial state $\mathbf{x} = (\mathbf{q},\ \dot{\mathbf{q}})$ that produce cyclic locomotion at speed s, step length ℓ, and slope γ with minimal "energy".

Solve

$$\min_{\vec{\theta},\mathbf{x}} E(\vec{\theta},\ \mathbf{x};\ s,\ \ell,\ \gamma) \quad \text{s.t.} \quad C(\vec{\theta},\ \mathbf{x};\ s,\ \ell,\ \gamma) < \epsilon$$

where

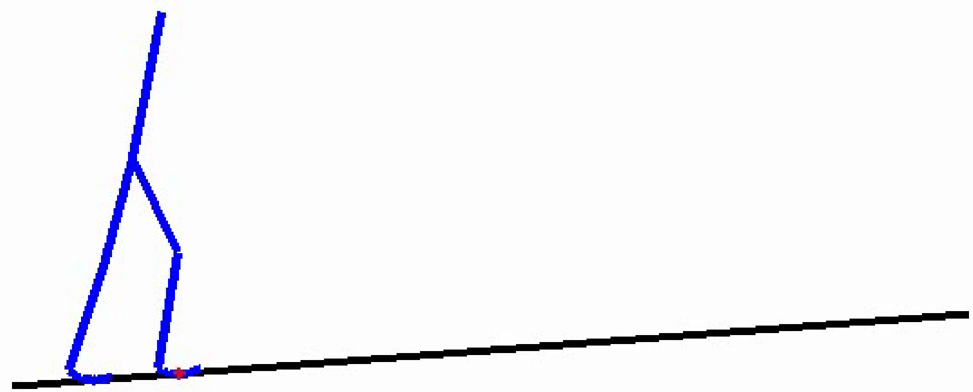
$$E(\vec{\theta}, \mathbf{x}; s, \ell, \gamma) \ = \ \alpha_\iota \iota^{1.5} + \sum_{j \in joints} \frac{\alpha_j}{T} \int_0^T \tau_j(t; \mathbf{x}_0, \vec{\theta}, \gamma)^2 \, dt$$

and $C(\vec{\theta}, \mathbf{x}; s, \ell, \gamma)$ measures the deviation from periodic motion with target speed and step-length

Efficient, cyclic gaits

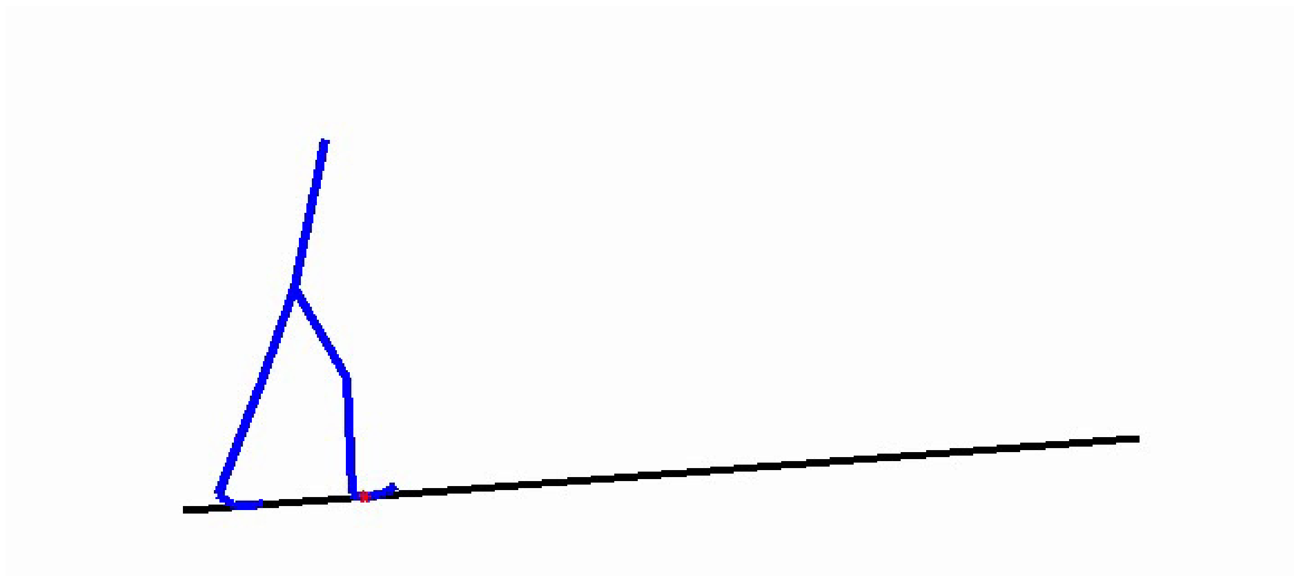
Speed: 5.8 km/hr; Step length: 0.6 m; Slope: 0°

Efficient, cyclic gaits



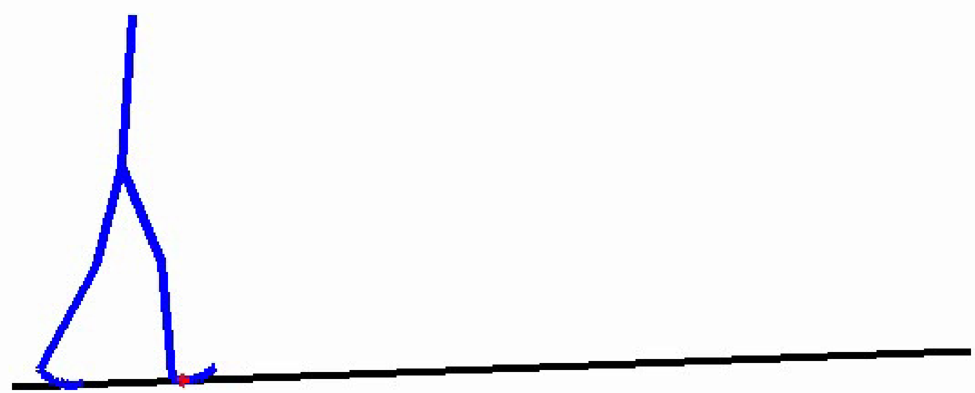
Speed: 3.6 km/hr; Step length: 0.4 m; Slope: 4.3°

Efficient, cyclic gaits



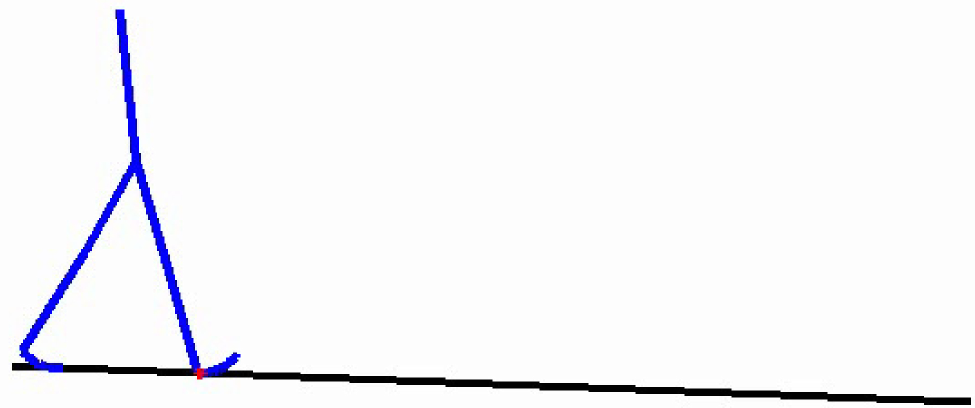
Speed: 6.5 km/hr; Step length: 0.6 m; Slope: 4.3°

Efficient, cyclic gaits



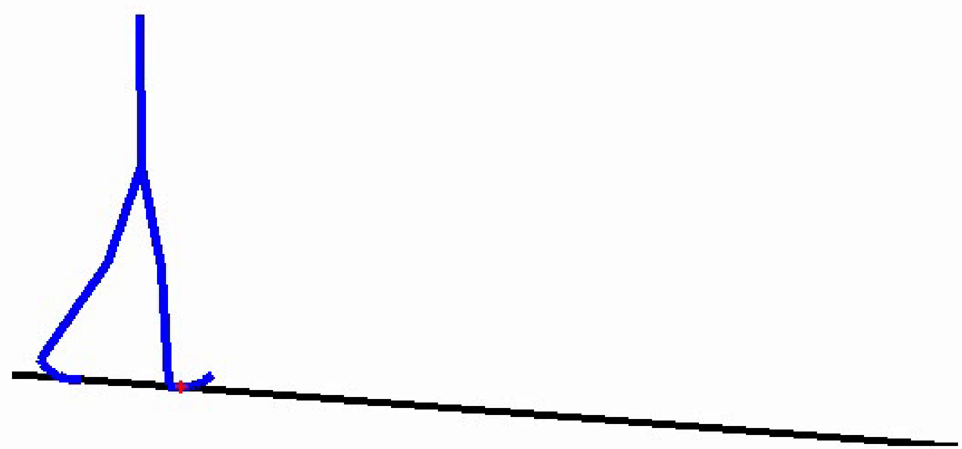
Speed: 5.0 km/hr; Step length: 0.6 m; Slope: 2.1°

Efficient, cyclic gaits



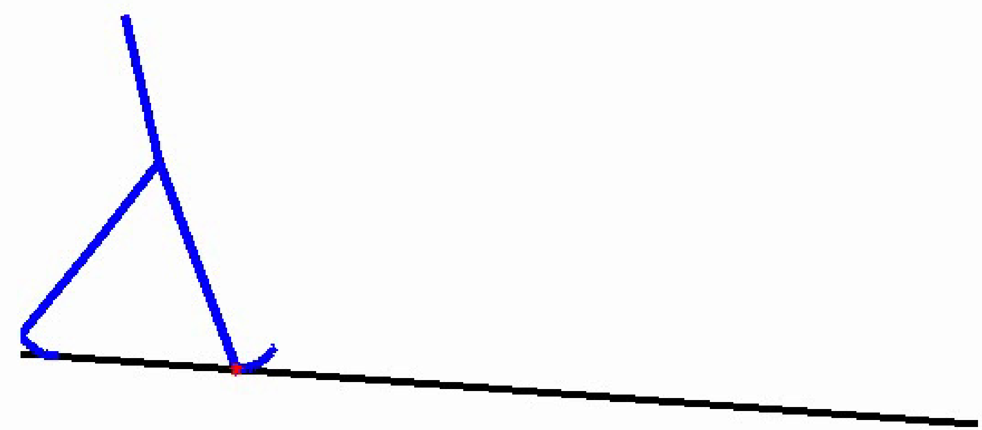
Speed: 4.3 km/hr; Step length: 0.8 m; Slope: -2.1°

Efficient, cyclic gaits



Speed: 3.6 km/hr; Step length: 0.6 m; Slope: -4.3°

Efficient, cyclic gaits



Speed: 5.8 km/hr; Step length: 1.0 m; Slope: -4.3°

Stochastic dynamics

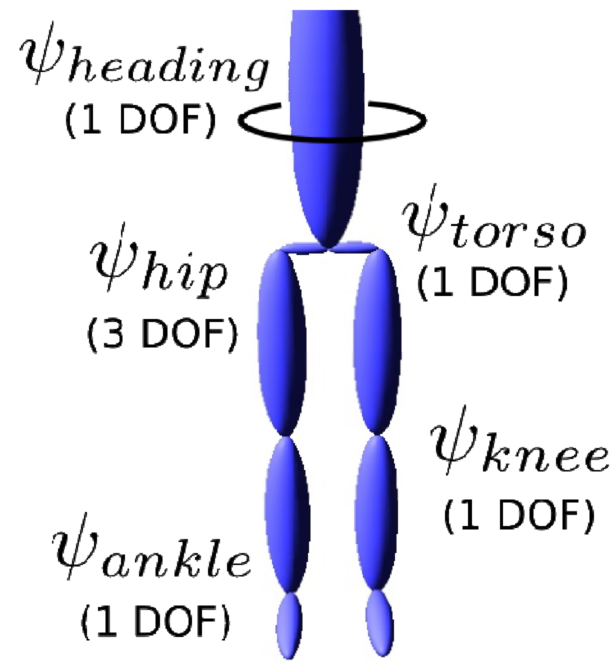
Our prior over human walking motions is derived from the manifold of optimal cyclic gaits:

- We assume additive noise on the control parameters (spring stiffness, resting lengths, and impulse magnitude).
- We also assume additive noise on the resulting torques.

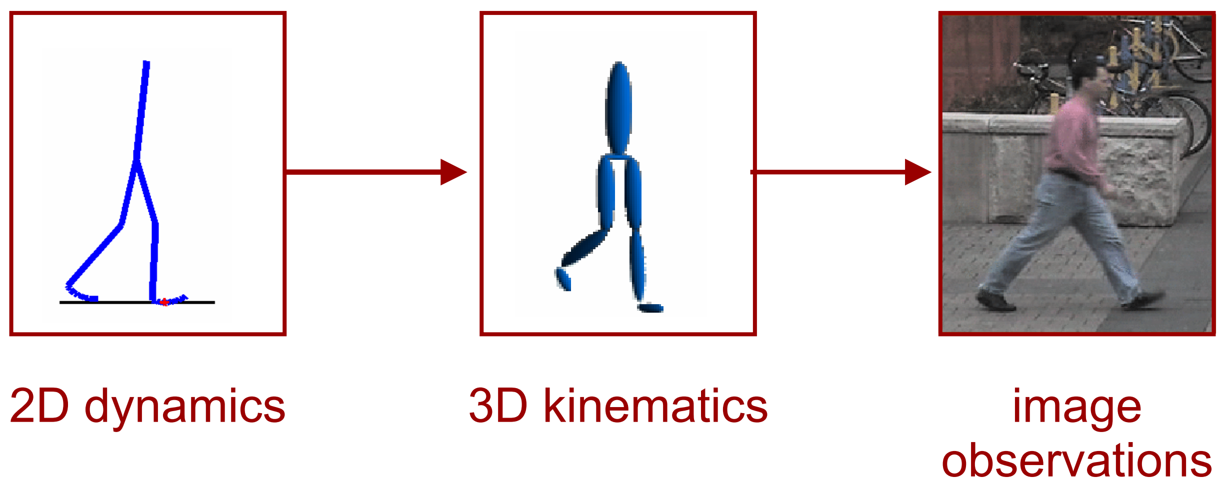
3D kinematic model

Kinematic parameters (15D) include global torso position and orientation, plus hips, knees and ankles.

- dynamics constrain contact of stance foot, two hip angles (in sagittal plane), and knee and ankle angles
- other parameters modeled as smooth, second-order Markov processes
- limb lengths assumed to be static



Graphical model



Bayesian people tracking

Image observations: $\mathbf{z}_{1:t} \equiv (\mathbf{z}_1, ..., \mathbf{z}_t)$

State: $\mathbf{s}_t = [d_t, k_t]$

dynamics pose

Bayesian people tracking

Image observations: $\mathbf{z}_{1:t} \equiv (\mathbf{z}_1, \ldots, \mathbf{z}_t)$

State: $\mathbf{s}_t = [d_t, k_t]$

Posterior distribution:

$$p(\mathbf{s}_{1:t} \,|\, \mathbf{z}_{1:t}) \;\propto\; \underbrace{p(\mathbf{z}_t \,|\, \mathbf{s}_t)}_{\text{likelihood}} \; \underbrace{p(\mathbf{s}_t \,|\, \mathbf{s}_{1:t-1})}_{\text{transition}} \; \underbrace{p(\mathbf{s}_{1:t-1} \,|\, \mathbf{z}_{1:t-1})}_{\text{posterior}}$$

Bayesian people tracking

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Sequential Monte Carlo inference:

- particle set $\mathcal{S}_t = \{\, \mathbf{s}_{1:t}^{(j)} \,,\, w_t^{(j)} \}_{j=1}^{N}$ approximates $p(\mathbf{s}_{1:t} \,|\, \mathbf{z}_{1:t})$

Bayesian people tracking

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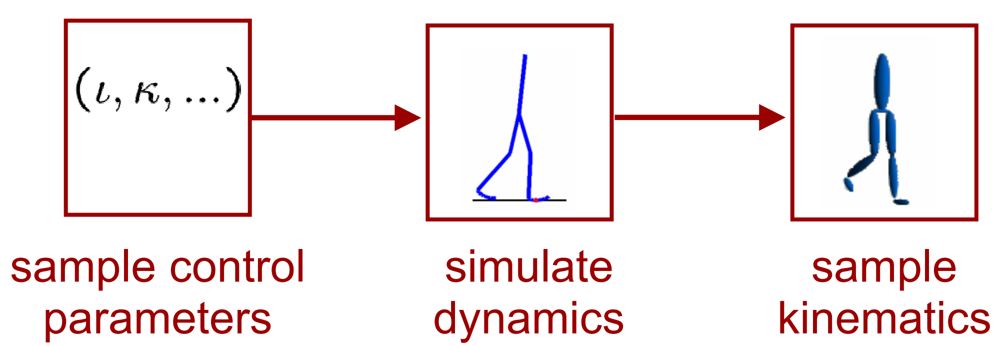
- step 1. sample next state: $\mathbf{s}_t^{(j)} \sim p(\mathbf{s}_t \,|\, \mathbf{s}_{t-1}^{(j)})$



Bayesian people tracking

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$$p(\mathbf{s}_{1:t} \,|\, \mathbf{z}_{1:t}) \;\propto\; p(\mathbf{z}_t \,|\, \mathbf{s}_t)\; p(\mathbf{s}_t \,|\, \mathbf{s}_{1:t-1})\; p(\mathbf{s}_{1:t-1} \,|\, \mathbf{z}_{1:t-1})$$

Sequential Monte Carlo inference:

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- step 1. sample next state: $\mathbf{s}_t^{(j)} \sim p(\mathbf{s}_t \,|\, \mathbf{s}_{t-1}^{(j)})$
- step 2. update weight: $w_t^{(j)} = c\, w_{t-1}^{(j)}\, p(\mathbf{z}_t \,|\, \mathbf{s}_t^{(j)})$
- resample when the effective number of samples becomes small

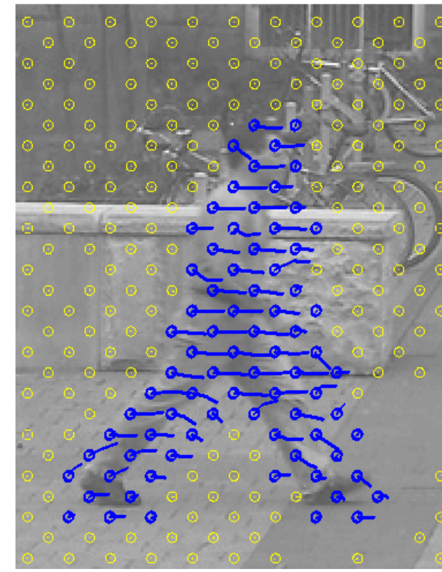
Image observations

Foreground model

Gaussian mixture for
$p(\vec{I}(x,y), \nabla L(x,y))$

Background model

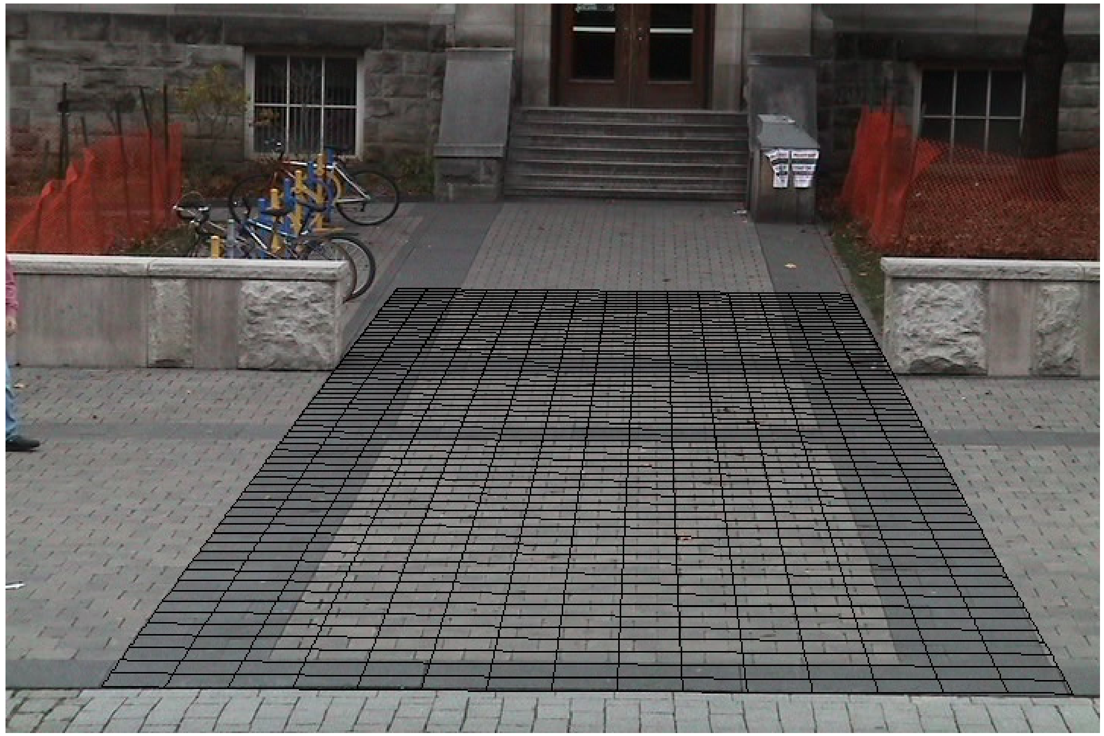
mean color (RGB) and
luminance gradient
$E[\vec{I}(x,y),\ \nabla L(x,y)]$
with covariance matrix



Optical flow

robust regression for
translation in local
neighborhoods

Calibration and initialization



Camera calibrated with respect to ground plane.

Gravity assumed to be known relative to the ground.

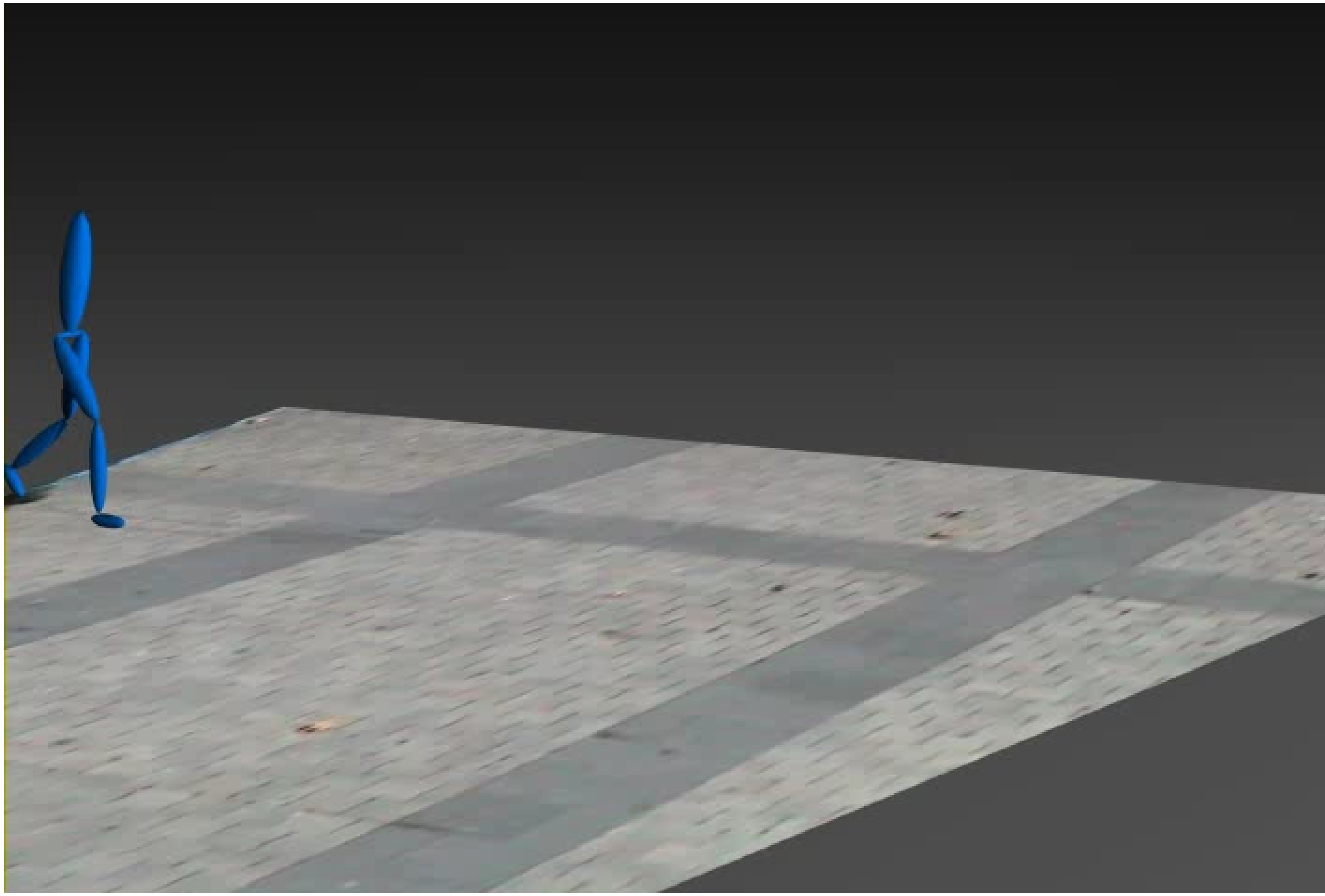
Body position, pose and dynamics coarsely hand-initialized.

Expt 1: Walking sequence

Expt 1: Walking sequence

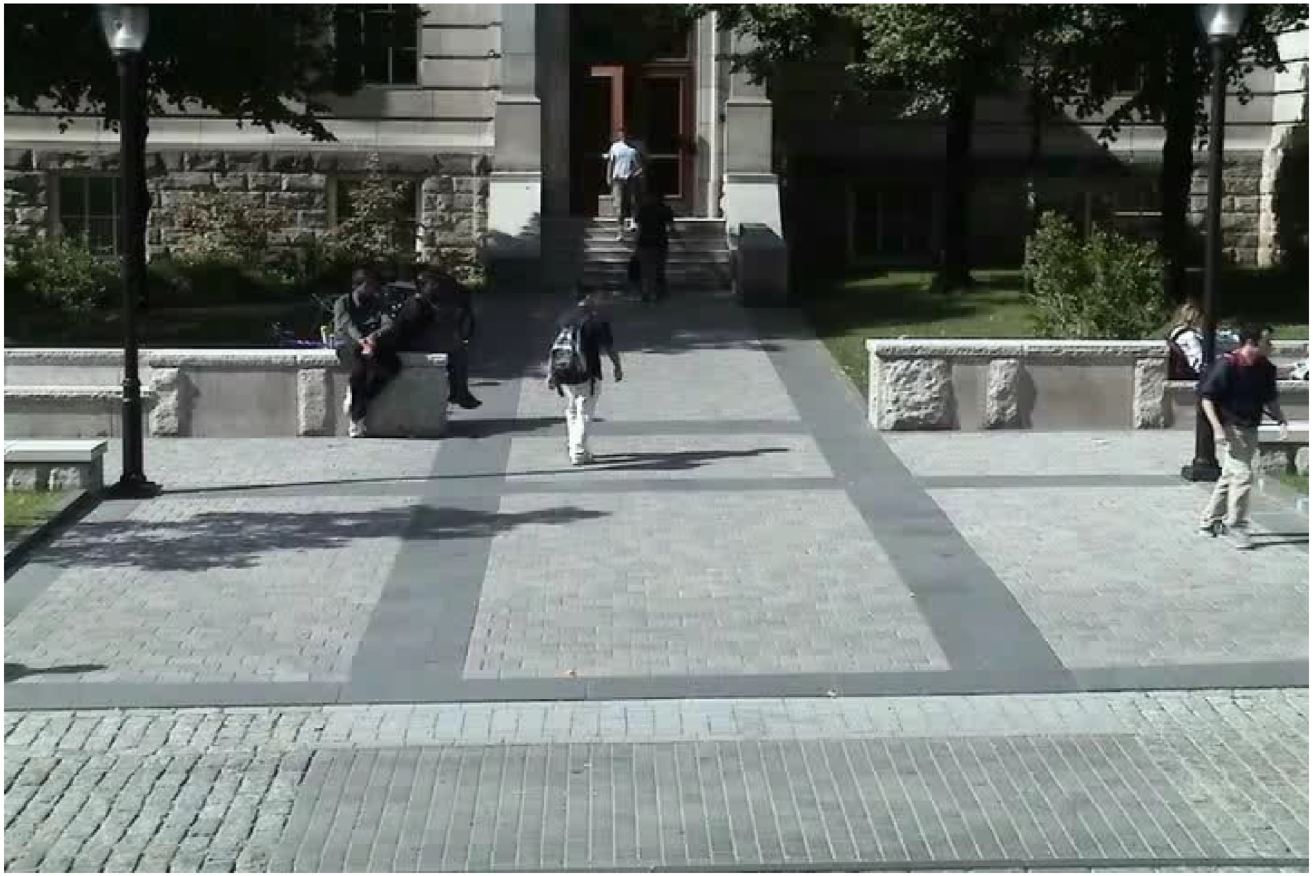
MAP trajectory (half speed)

Expt 1: Synthetic rendering



MAP trajectory (half speed)

Expt 2: Occlusion and day light conditions



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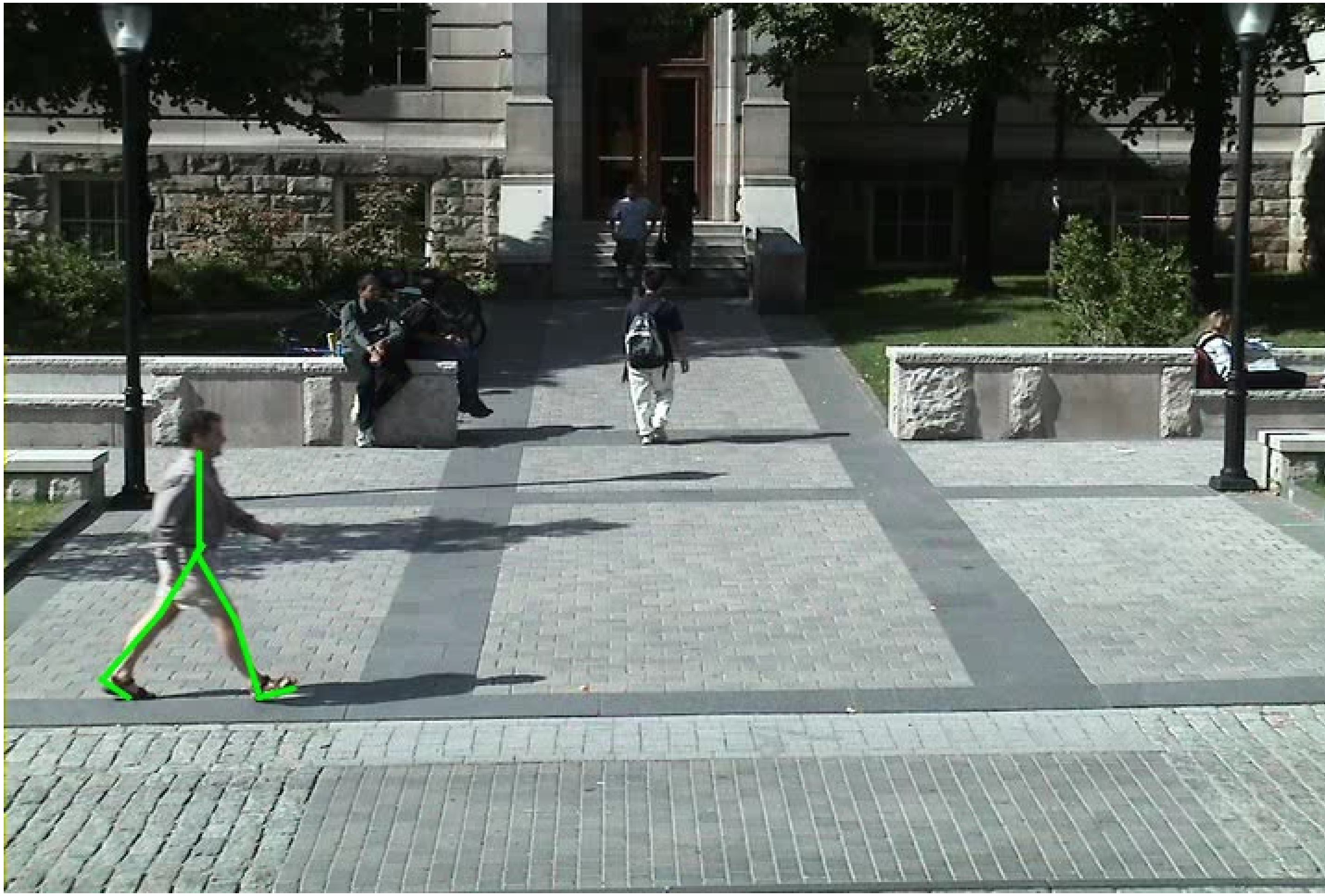
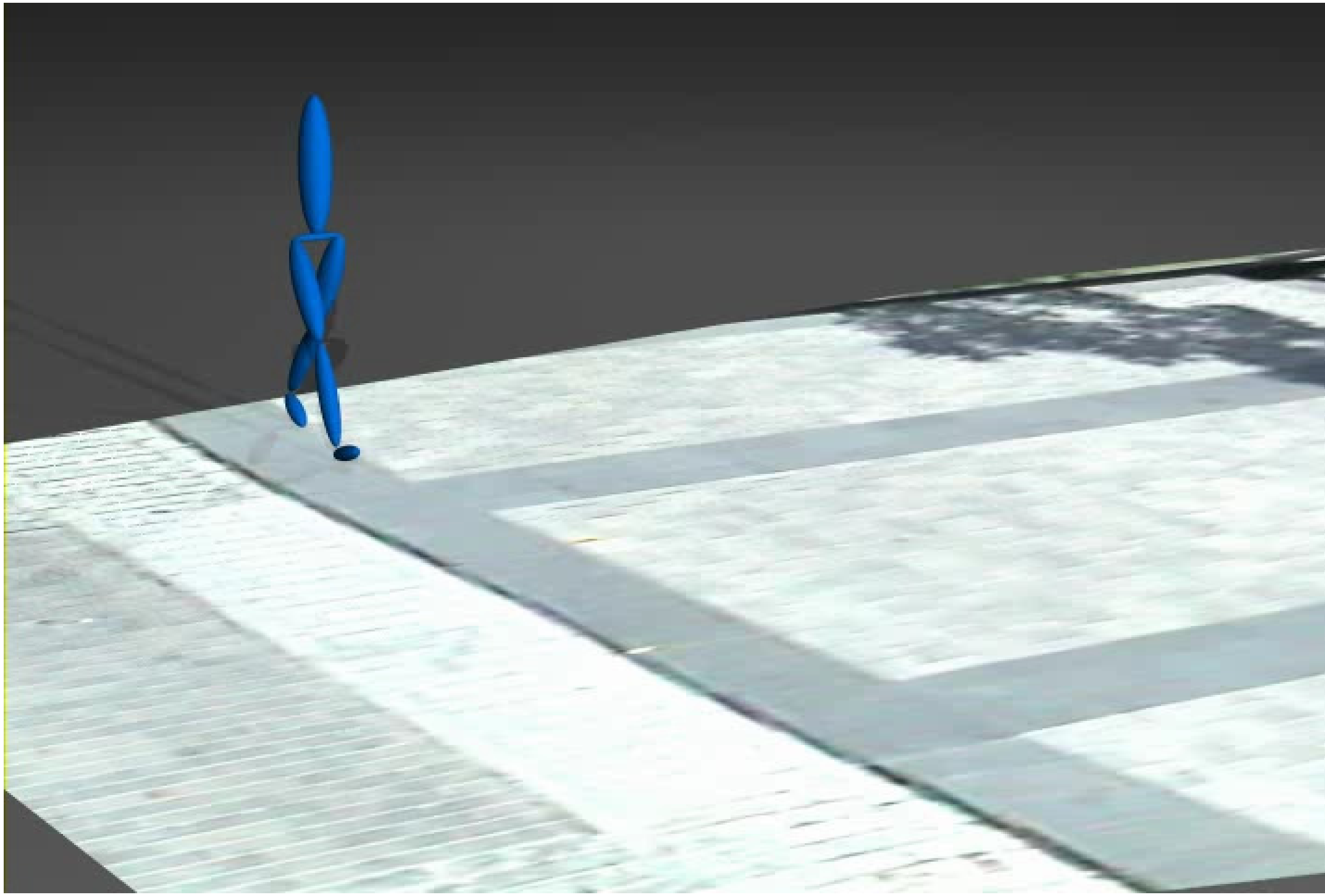


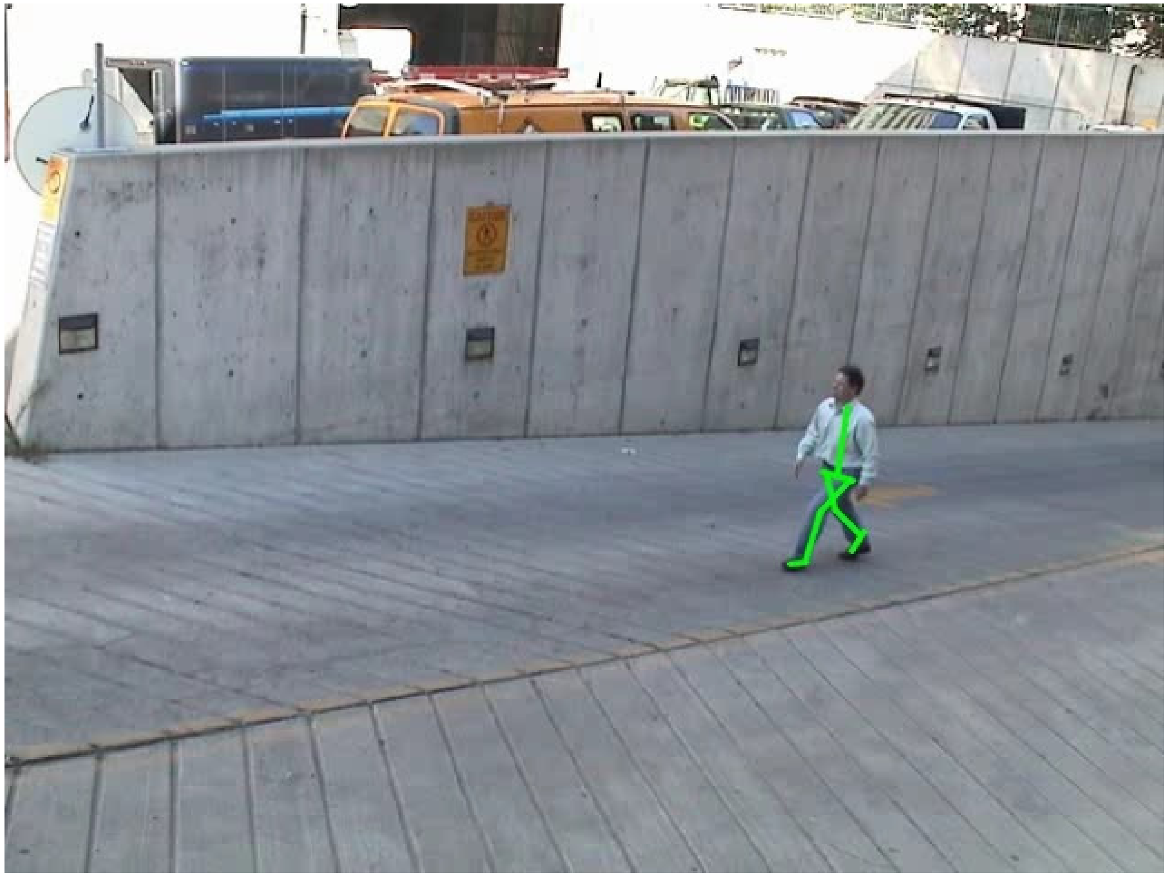
MAP trajectory (half speed)

Expt 2: Synthetic rendering



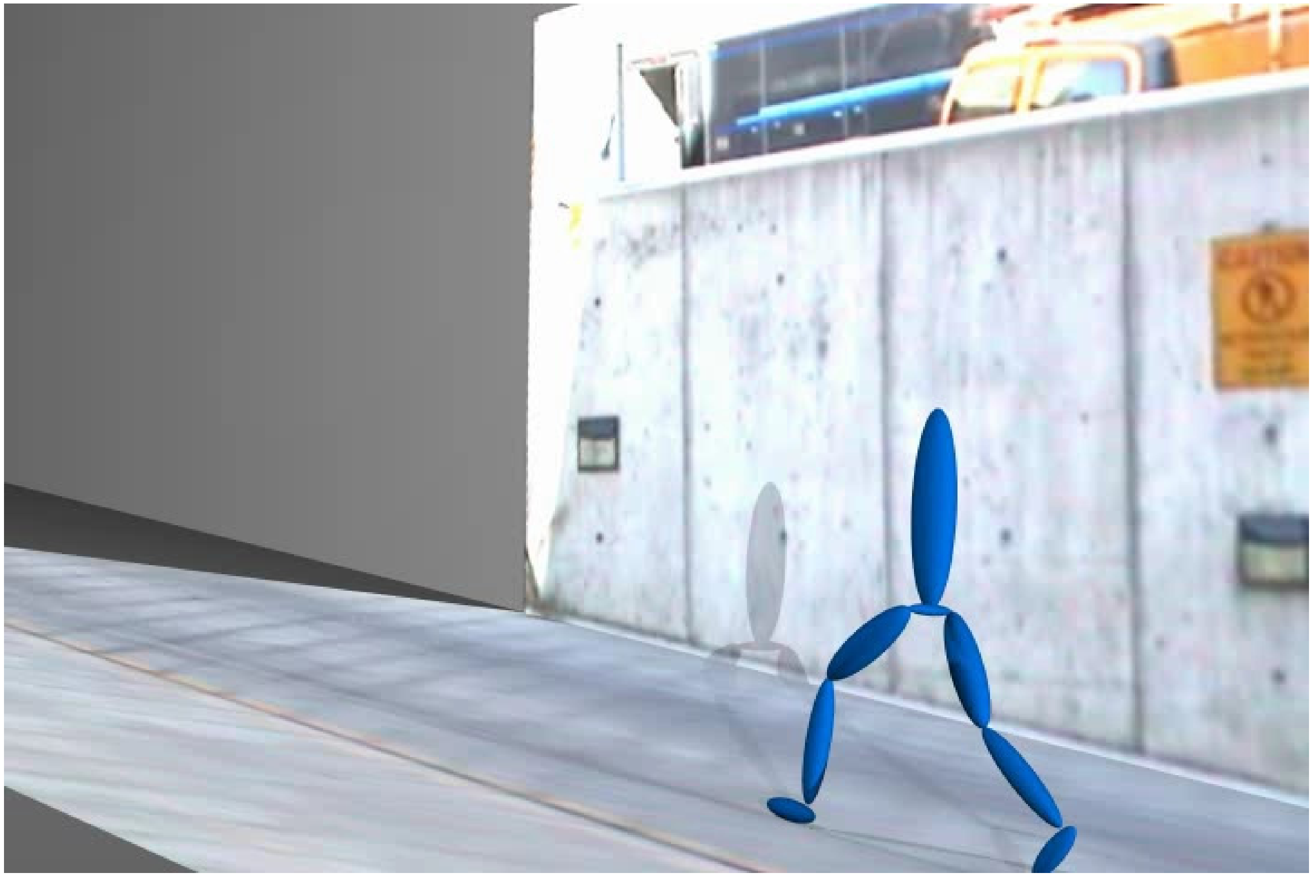
MAP trajectory (half speed)

Expt 3: Sloped surface (10^o)



MAP trajectory (half speed)

Expt 3: Sloped surface (10^o)



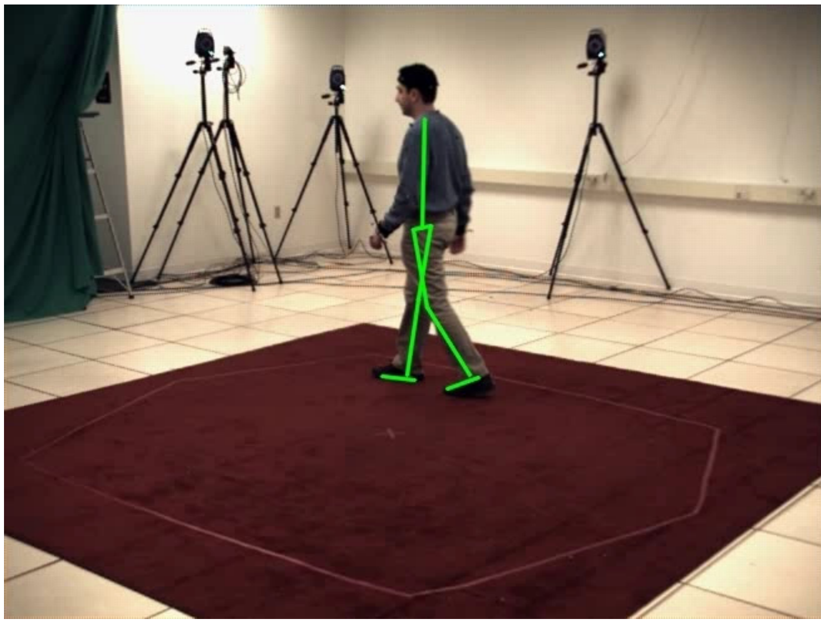
Expt 3: Sloped surface (10°)

Expt 4: HumanEva Data

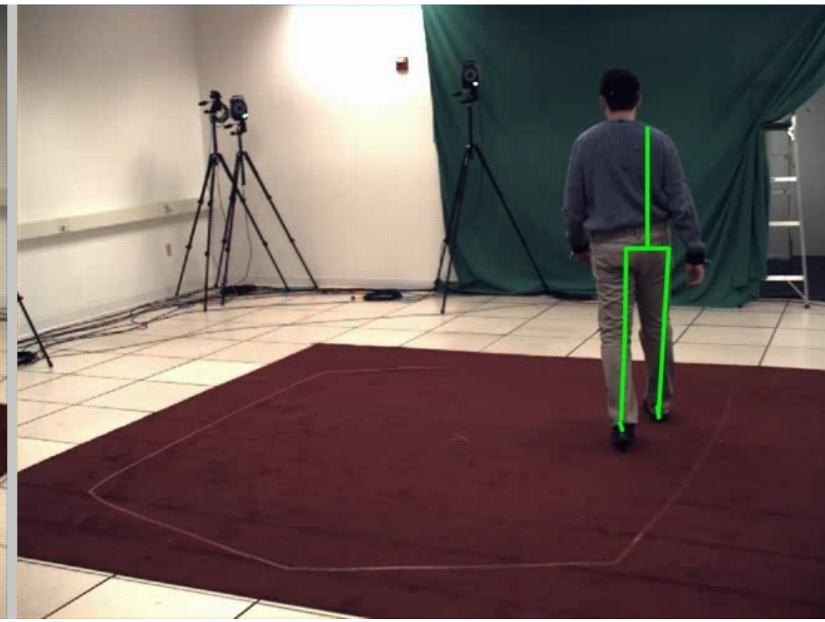
Synchronized motion capture and video

- mocap provides ground truth and data for learned models
- four cameras (for monocular and multiview tracking)
- diverse range of motions
- blind benchmark error reporting

HumanEva Results: Monocular



camera 2 used for tracking



camera 3 used for visualization

Error: median 70mm; mean 80mm; std dev 26mm

Conclusions

Low-dimensional dynamics capture key physical properties of motion and ground contact, with models that

- are stable and simple to control, and
- generalize to a wide range of walking motions

Combined with kinematic models they provide useful walking models for human pose tracking.

In the future,

- leveraging mocap to learn better priors of forces and conditional kinematic models will likely be important
- extensions to much wider range of human locomotion is essential