Robotics and Animatronics in Disney

Lecture 6: Humanoid Modeling and Control

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Goals

- Introduce a method for automatically simplifying dynamics models for humanoid robots
- Introduce model identification methods for humanoid robots
- Discuss the right level of details for robot modeling

Automatic Model Reduction for Humanoid Robots

[Yamane 2012]

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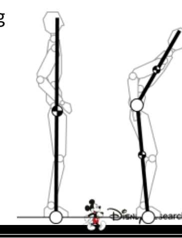
Motivation

Building simplified models for humanoid control

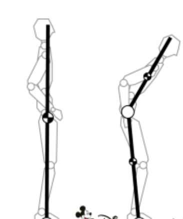
1. Choose a simple mechanical system
2. Derive and linearize the equation of motion
3. Define state and input mapping



Motivation

Issues

- Accuracy
- Model parameters
- State/input mapping
- Other models/configuration



Contributions

Automatic derivation of simplified dynamics models

- Given: nominal pose, contact constraints, reduced DOF

Unified state and input mapping

- Use the same code for any simplified model

Related Work

- Humanoid robots: inverted pendulum [Kajita 1995], cart-table [Kajita 2003], IP with reaction wheel [Lee 2007] …
  - Based on intuition
  - Comparison to the original dynamics [Goswami 2008]
- Model reduction in structural mechanics and fluid dynamics [Hyland 1983; Lall 2003], graphics [Treuille 2006; James 2003]
  - Thousands of degrees of freedom but only a few inputs
  - Often assume stable system

Simplification Process

Full equation of motion (n joints) → Full constrained dynamics model

Contact constraints (m independent constraints) → Full constrained dynamics model

Full constrained dynamics model → (linearization) → Linear full constrained dynamics model

Linear full constrained dynamics model → (dimensionality reduction) → Linear reduced dynamics model (k DOF ($k \ll n$))

Linear reduced dynamics model → State-space model ($2k$ states)

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Full Model with Contacts

Full equation of motion

$$M(\theta)\ddot{\theta} + c(\theta,\dot{\theta}) + g(\theta) = S^T\tau + J_C^T(\theta)f_C$$

($M > 0$, symmetric) $\theta \in \mathbb{R}^n$

Contact constraints

$$J_C\ddot{\theta} + \dot{J}_C\dot{\theta} = 0$$

Full constrained dynamics model

$$\ddot{\theta} = \Phi(\theta)S^T\tau + \phi(\theta,\dot{\theta})$$

($\Phi \geq 0$, symmetric)

$$\begin{cases} \Phi = M^{-1} - M^{-1}J_C^T\left(J_C M^{-1} J_C^T\right)^{-1} J_C M^{-1} \\ \phi = -M^{-1}J_C^T\left(J_C M^{-1} J_C^T\right)^{-1} \dot{J}_C\dot{\theta} - \Phi(c+g) \end{cases}$$

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Linearization

Full constrained dynamics model

$$\ddot{\theta} = \Phi(\theta)S^T\tau + \phi(\theta,\dot{\theta})$$

$\theta = \theta_0 + \delta\theta, \dot{\theta} = 0 + \delta\dot{\theta}, \ddot{\theta} = 0 + \delta\ddot{\theta}$

Linear full constrained dynamics model

$$\delta\ddot{\theta} = \Phi_0 S^T\delta\tau + \Gamma\delta\theta + \Lambda\delta\dot{\theta}$$

$\Phi_0 = \Phi(\theta_0)$

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Simplification Process

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Dimensionality Reduction

Linear full constrained dynamics model

? $\delta\ddot{\theta} = \Phi_0 S^T \delta\tau + \Gamma\delta\theta + \Lambda\delta\dot{\theta}$

Linear reduced dynamics model k DOF ($k \ll n$)

$\hat{M}\ddot{q} + \hat{C}\dot{q} + \hat{G}q = u$

$q \in \mathbb{R}^k$: generalized coordinates of the simplified model

What to maintain after reduction?

- Somewhat task-dependent
- Here we choose kinetic energy

Kinetic Energy of the Constrained System

- Need inertia matrix, but Φ_0 is not invertible
- Singular value decomposition: $\Phi_0 = U\Sigma U^T$

Singular values

$\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_l > \sigma_{l+1} = \sigma_{l+2} = \cdots = \sigma_n = 0$

$\bar{\Sigma}$

$\bar{\Phi}_0 = \bar{U}\bar{\Sigma}\bar{U}^T$

$\bar{U} \in \mathbb{R}^{n \times l}$

$\bar{\Phi}_0 > 0$

Inertia matrix: $\bar{\Phi}_0^{-1} = \bar{U}\bar{\Sigma}^{-1}\bar{U}^T$

Kinetic energy: $T = \frac{1}{2}\delta\dot{\theta}^T\bar{\Phi}_0^{-1}\delta\dot{\theta}$

Approximating Kinetic Energy

$T = \frac{1}{2}\delta\dot{\theta}^T\bar{U}\bar{\Sigma}^{-1}\bar{U}^T\delta\dot{\theta}$

Singular values

$\frac{1}{\sigma_l} \geq \frac{1}{\sigma_{l-1}} \geq \cdots \geq \frac{1}{\sigma_{l-k+1}} \geq \cdots \geq \frac{1}{\sigma_1}$

Top k singular values

$\hat{\Phi}_0^{-1} = \hat{U}\hat{\Sigma}^{-1}\hat{U}^T$ $\quad \hat{U} \in \mathbb{R}^{n \times k}$

$\hat{T} = \frac{1}{2}\delta\dot{\theta}^T\hat{U}\hat{\Sigma}^{-1}\hat{U}^T\delta\dot{\theta}$

State mapping $\dot{q} = \hat{U}^T\delta\dot{\theta}$ or $\delta\dot{\theta} = \hat{U}\dot{q}$

$\hat{T} = \frac{1}{2}\dot{q}^T\hat{\Sigma}^{-1}\dot{q}$ → Inertia matrix $\hat{M} = \hat{\Sigma}^{-1}$

Input Mapping

Consider the power applied by the joint torques

- Full model: $\delta\dot{\theta}^T S^T\tau = \dot{q}^T\hat{U}^T S^T\delta\tau$ (State mapping)
- Simplified model: $\dot{q}^T u$

→ $u = \hat{U}^T S^T \delta\tau$

Computing $\hat{G}$ and $\hat{C}$

$\hat{M}\ddot{q} + \hat{C}\dot{q} + \hat{G}q = u$

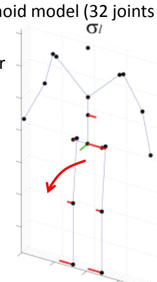
- Compute inverse dynamics at many static poses $\theta_0 + \Delta\theta_i$ and compute joint torque $\tau_i = \tau_0 + \delta\tau_i$
- $q = \hat{U}^T\Delta\theta_i, u = \hat{U}^T S^T\delta\tau_i$
  → $\hat{G}\hat{U}^T\Delta\theta_i = \hat{U}^T S^T\delta\tau_i$
- Compute the $\hat{G}$ that best fits the samples

Example

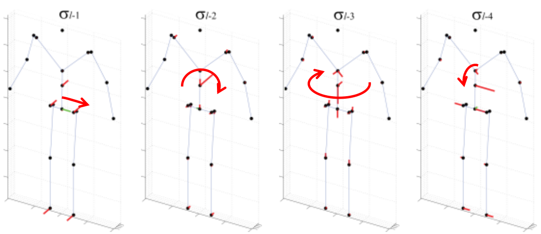
38 DOF humanoid model (32 joints + 6 DOF pelvis)

σ_l

1st singular vector



Example



2nd 3rd 4th 5th

Control

- Input (joint torque) mapping: $u = \hat{U}^T S^T \delta\tau$
  - Number of inputs: k (simplified) < $n - 6$ (original)
- Optimization
  - Cost function: input mapping error, desired joint trajectories
  - Constraints: dynamic, friction, and COP

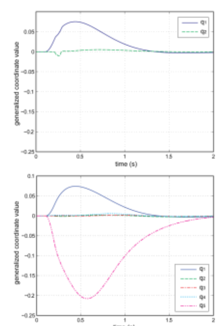
Simulation

- 2 or 5 DOF models for each task
  - 2 DOF models don't work in some tasks, possibly due to unmodeled dynamics
  - Various nominal poses
- Balance controller: linear quadratic regulator (LQR)

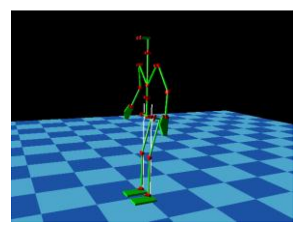
$$J = \int_0^\infty \left(\begin{pmatrix} q^T & \dot{q}^T \end{pmatrix} \begin{pmatrix} Q_1 & 0 \\ 0 & Q_2 \end{pmatrix} \begin{pmatrix} q \\ \dot{q} \end{pmatrix} + u^T R u \right) dt$$

$$Q_1 = 100, Q_2 = 1 \times 10^{-3}, R = 1 \times 10^{-2}$$

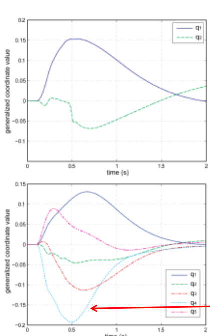
Simulation: Pushed from Back



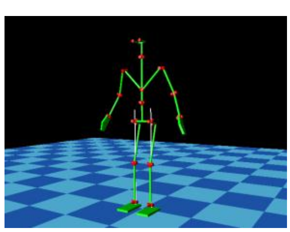
200N for 0.1s



Pushed at Right Shoulder

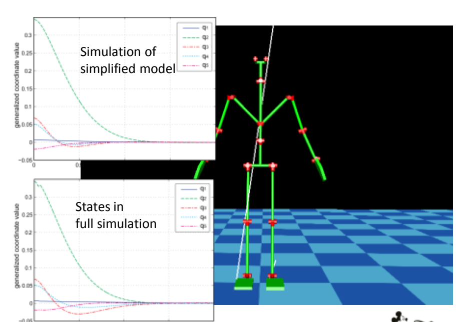


2DOF model cannot maintain balance



Twist not modeled in the 2DOF model

Changing to a New Pose



Changing to a New Pose

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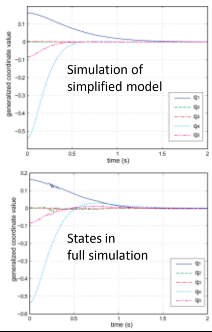

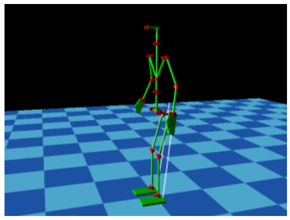

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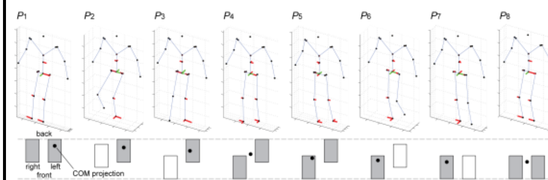
Combine Multiple Controllers



Manually designed nominal poses and contact constraints

No contact

Contact

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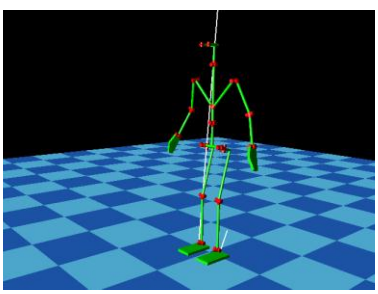
Combine Multiple Controllers



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Summary

- Automatically generate simplified models of humanoid robots with contacts given:
  - Nominal configuration
  - Contact constraints
  - Reduced DOF
- State/input mapping
  - State mapping uses the same code for any model
  - Input mapping is redundant and allows other control objectives

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Model Identification

[Yamane 2011]

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Target Parameters

- Kinematic model: joint angle sensor offsets
  - Potentiometer's zero angle drift
- Inertial model: link mass and center of mass
  - Total weight from CAD model ~60kg
  - Actual weight ~90kg
  - Larger discrepancy than electric robots due to hose and oil
  - Omit moments of inertia

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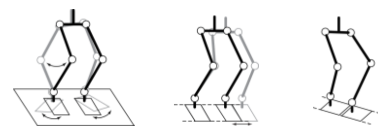
Kinematic Parameters

- Existing solutions
  - External measurements (e.g., motion capture): cumbersome to set up, not always available
  - Calibration jig: not enough samples for complex robots

Kinematic Parameters

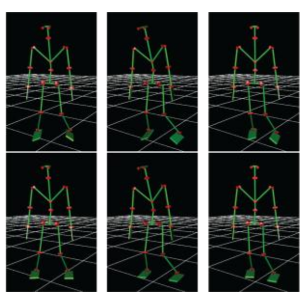
- Our solution
  - IMU for global information
  - Easily enforced kinematic constraints (e.g., flat on floor, parallel feet)



Kinematic Parameters

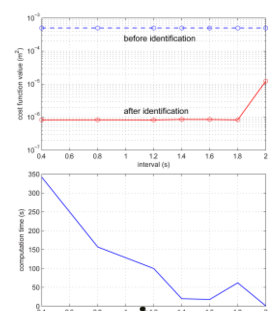
Before

After



Kinematic Parameters

- Cost function error vs. sample interval



Inertial Parameters

- Equation of motion with inertial parameters ϕ:

$$M(\theta,\phi)\ddot{\theta} + c(\theta,\dot{\theta},\phi) + g(\theta,\phi) = S^T\tau + J_c^T(\theta)f_c$$

$$F(\theta,\dot{\theta},\ddot{\theta},\phi) = S^T\tau + J_c^T(\theta)f_c$$

- F is a linear function of ϕ [Mayeda et al. 1984]

$$F(\theta,\dot{\theta},\ddot{\theta},\phi) = A(\theta,\dot{\theta},\ddot{\theta})\phi$$

Regressor

Identification

- Existing solutions
  - Collect samples of $\theta_k, \dot{\theta}_k, \ddot{\theta}_k, \tau_k, f_{ck}$
  - Concatenate all samples: $\bar{A}\phi = \bar{F} = \bar{S}^T\bar{\tau} + \bar{J}_c^T\bar{f}_c$

  $\rightarrow \phi = \bar{A}^{\#}F$

- Issues with humanoid robots
  - All τ and f_c may not be available
  - Difficult to derive a symbolic representation
  - Difficult to obtain enough excitation

Partial Force Measurement

[Mistry et al. 2009]

- Generalization of [Ayusawa et al. 2009]: identification only from contact force measurement
- Divide into available and unavailable measurements

$$\bar{F} = \bar{H}_a^T \begin{pmatrix} \bar{\tau}_a \\ \bar{f}_{ca} \end{pmatrix} + \bar{H}_u^T \begin{pmatrix} \bar{\tau}_u \\ \bar{f}_{cu} \end{pmatrix}$$

- $\bar{N}_u$: null space basis of $\bar{H}_u^T$

$$\bar{F}_N = \bar{N}_u \bar{F} = \bar{N}_u \bar{H}_a^T \begin{pmatrix} \bar{\tau}_a \\ \bar{f}_{ca} \end{pmatrix}$$

- $\bar{N}_u \bar{A} \phi = \bar{F}_N$: only includes measurable forces

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Computing the Regressor

- Strictly identifiable ϕ is a linear combination of actual inertial parameters (mass, local center of mass)
- Difficult to obtain ϕ for humanoid robots due to complexity
- We use standard inertial parameters instead and compute the regressor by numerical inverse dynamics and finite difference of inertial parameters

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Estimation

- Difficult to obtain enough excitation
  - Robot needs to balance
  - Results in invalid parameters (negative mass etc.)
- Ideas
  - Ignore unreliable parameter space: omit small singular values of A and use pseudo inverse ("least square")
  - Prevent inconsistent results: gradient-based optimization with lower and upper bounds ("gradient")

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Results

- Test data: 3 trials for "teapot" tracking; 1 for identification, 2 for cross-validation
- Torque information is not available for position-controlled joints (upper body)
- Parameters: with (LS) and without (L) symmetry constraint

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Results

Force estimation errors

	parameter set	L			LS		
	number of parameters	92			56		
	condition number of regressor	1.38×10^5			3.81×10^4		
	maximum condition number	1×10^6	1×10^3	1×10^2	1×10^6	1×10^3	1×10^2
least square	direct validation	n/a	n/a	1.56×10^5	n/a	n/a	1.97×10^5
	cross validation (1)	n/a	n/a	7.13×10^5	n/a	n/a	5.77×10^5
	cross validation (2)	n/a	n/a	7.93×10^5	n/a	n/a	9.47×10^5
gradient	direct validation	1.52×10^5	1.52×10^5	1.52×10^5	1.99×10^5	1.99×10^5	1.99×10^5
	cross validation (1)	5.28×10^5	5.28×10^5	5.29×10^5	4.51×10^5	4.51×10^5	4.50×10^5
	cross validation (2)	7.29×10^5	7.29×10^5	7.30×10^5	5.81×10^5	5.81×10^5	5.84×10^5

n/a: Resulted in negative mass

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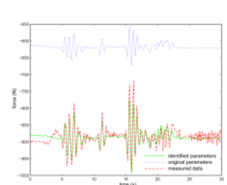
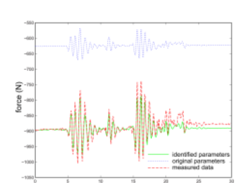
Results



Direct validation



Cross validation

Vertical force of base

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Humanoid Robot Control in Dynamic Environments

[Zheng and Yamane Humanoids 2011]

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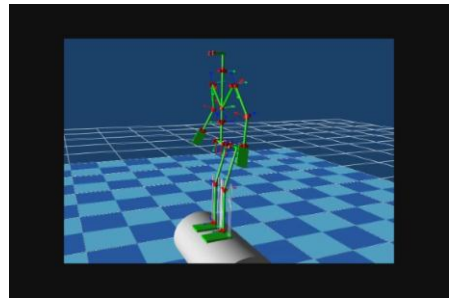
Balancing Control on a Cylinder



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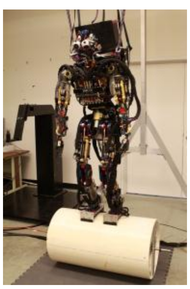
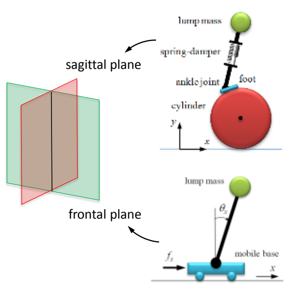
Motion Decomposition





3-D motion → two 2-D motions

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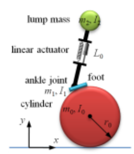
Simplified Model in Sagittal Plane

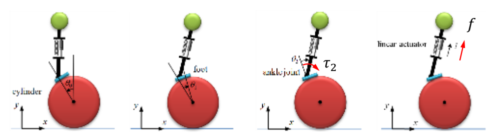


Configuration $\theta = (\theta_0 \quad \theta_1 \quad \theta_2 \quad l)^T$

Inputs $\tau = (0 \quad 0 \quad \tau_2 \quad f)^T$

ankle torque τ_2

actuator force f



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Equation of Motion in Sagittal Plane

Linearized equation of motion around $\theta = 0$

$$M\ddot{\theta} + G\theta = \tau$$

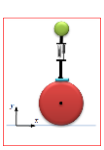
State-space equation

$$\dot{x} = Ax + Bu$$
$$y = Cx$$

where $x = (\theta^T \quad \dot{\theta}^T)^T$

$u = (\tau_2 \quad f)^T$

$y = \theta$



$x = 0$ is only equilibrium state since A has full rank

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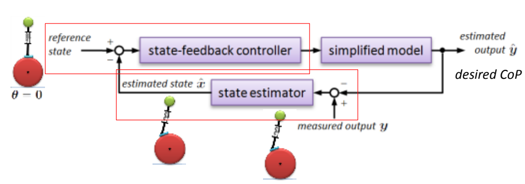
Balance Controller



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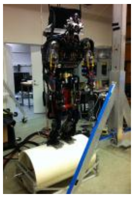
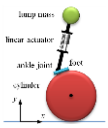
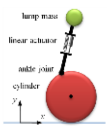
Flat Feet vs. Geta Feet

Sarcos robot with flat feet





Sarcos robot with geta feet



geta shoes

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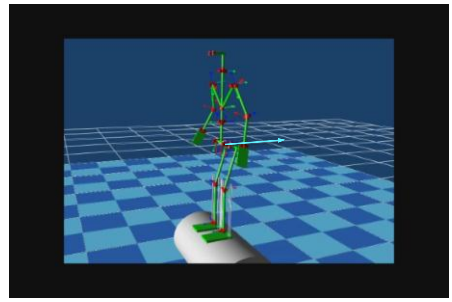
Simulation Result with Flat Feet



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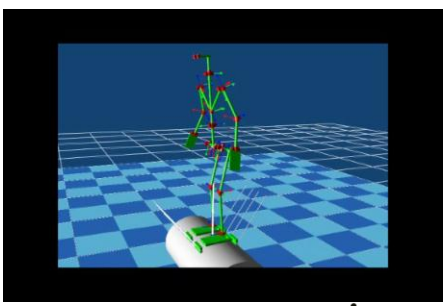
Simulation Result with Geta Feet



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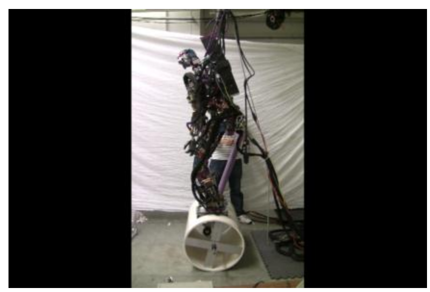
First Hardware Trial



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Discussion

- Accurately estimating model parameters is difficult
- Articulated rigid body models don't capture many aspects of humanoid robot dynamics
  - Joint friction, backlash
  - Link deformation
- What is the right level of detail for
  - Control
  - Simulation

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