

# Modeling & Control of a Longboard-Riding Robot

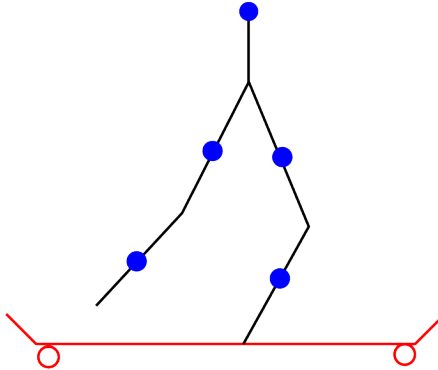
Matt Keeter  
mkeeter@mit.edu

6.832 Final Project  
Spring 2012

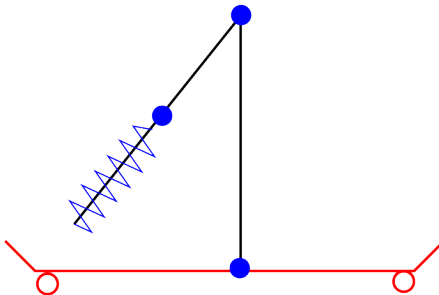
# Inspiration



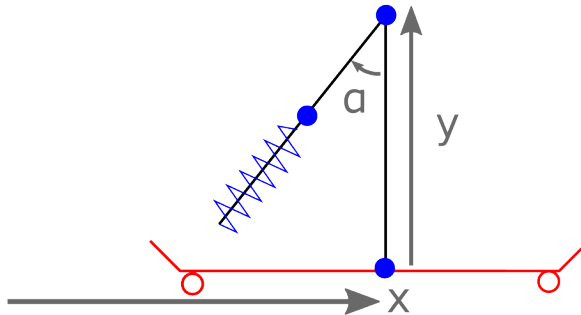
# System Model



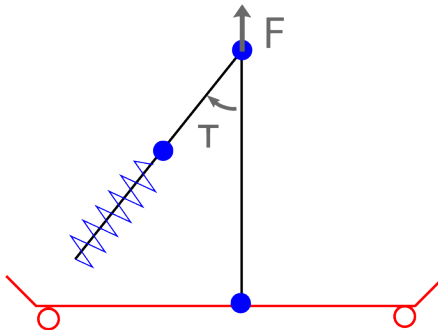
# Simplified Model



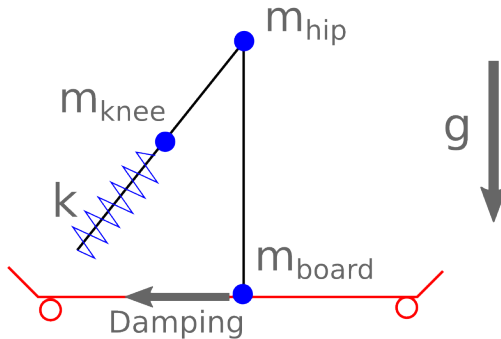
# State Variables



# Control Inputs



# System Parameters



- $\mathbf{q} = [x, y, \alpha]'$



# System Summary

- $\mathbf{q} = [x, y, \alpha]'$
- $\mathbf{u} = [F, \tau]'$

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- $\mathbf{u} = [F, \tau]'$
- Gliding and pushing modes
  - $y_{\text{toe}} \leq 0 \rightarrow$  pushing
  - $y_{\text{toe}} > 0 \rightarrow$  gliding

- Wrote tools to automatically solve dynamics

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- Exports as MATLAB scripts

# Feedback Linearization

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(as well as constants)



# Feedback Linearization

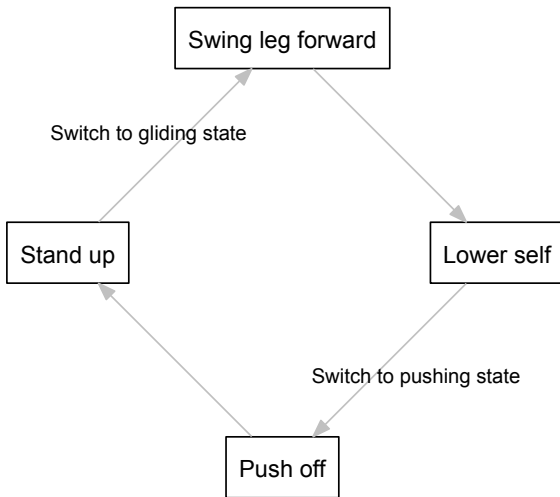
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- Plug in  $\ddot{y}$ ,  $\ddot{\alpha}$  for feedback linearization
  - $\ddot{y} = \ddot{y}_{\text{desired}}$
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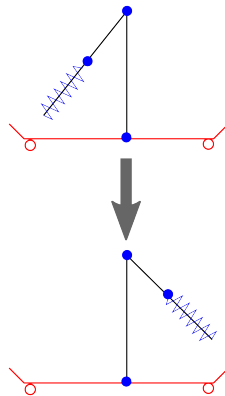
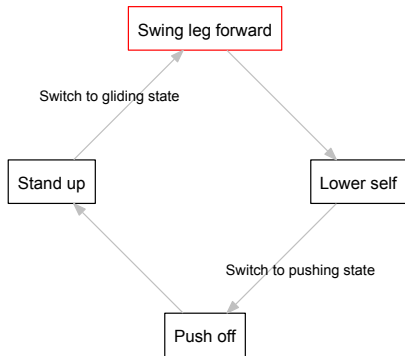
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- Double integrator control

# Controller Strategy

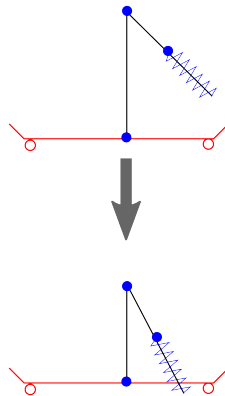
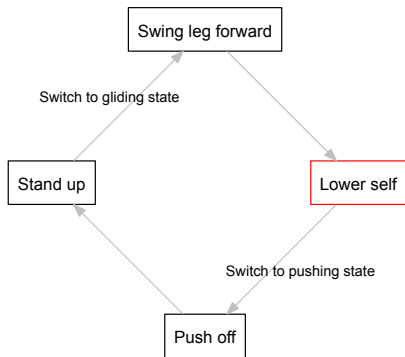
High-level strategy breaks motion into stages



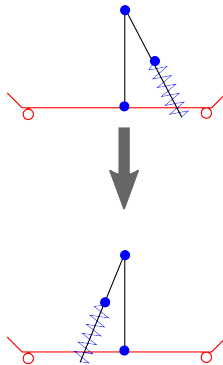
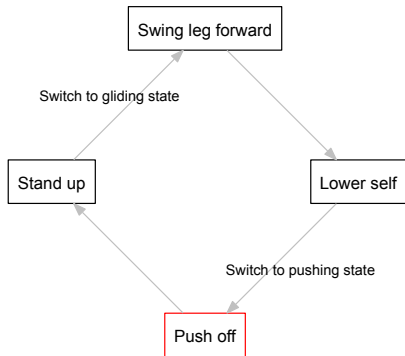
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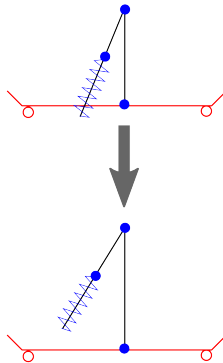
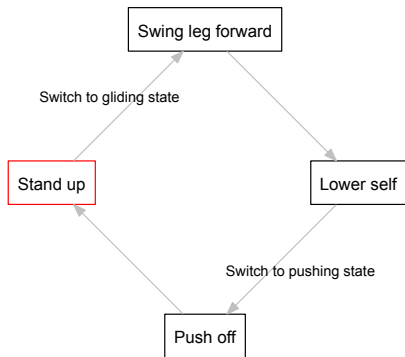
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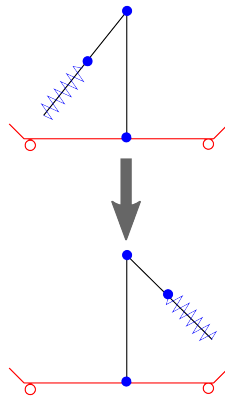
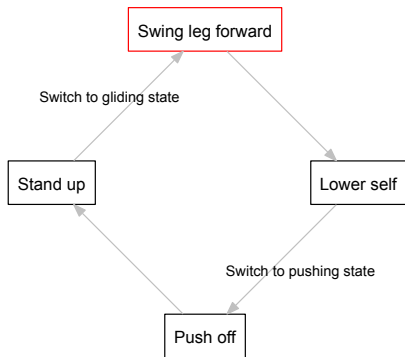
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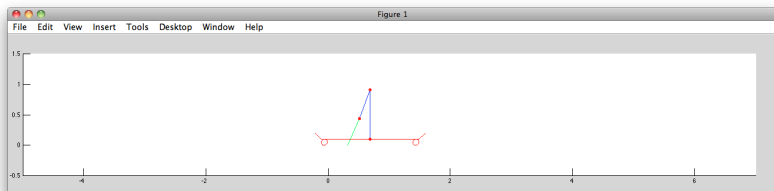
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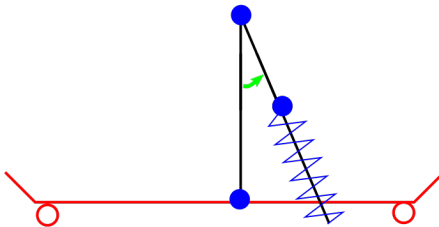
# Controller Parameters

Controller is parameterized by three terms:

$\alpha_{\text{hit}}$		Angle of collision
$\alpha_{\text{stand}}$		Angle ending push
$\ddot{\alpha}_{\text{swing}}$		Swinging acceleration

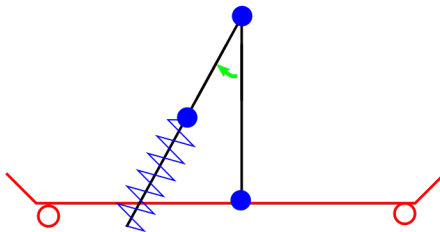
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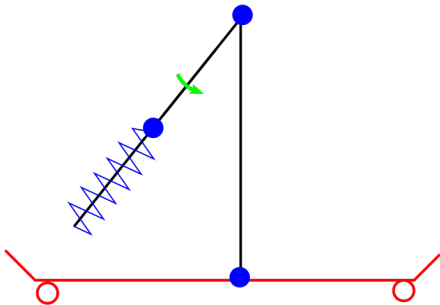
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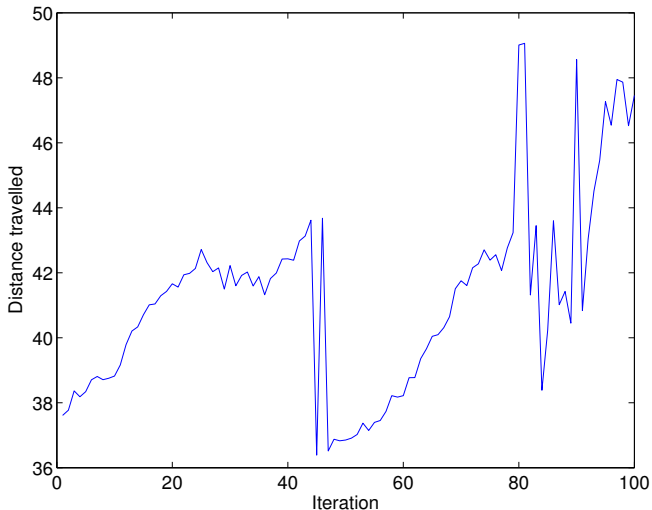


# Stochastic Gradient Descent

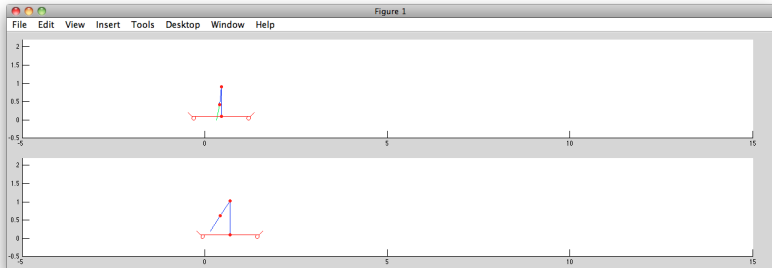
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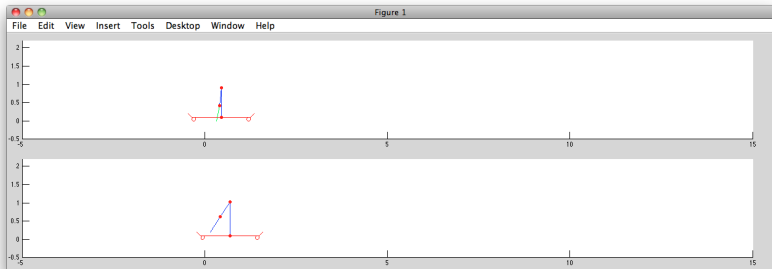


# Optimized Demo





# Optimized Demo



20% improvement!

- Developed simplified system model
- Wrote dynamics-solving tools
- Designed high-level controller behavior
- Used gradient descent to optimize parameters

# Questions?

