Reduction and Identification for Models of Locomotion: an Emerging Systems Theory for Neuromechanics

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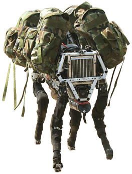
February 18, 2014

Autonomous machines will pervade our world

Össur

Raytheon

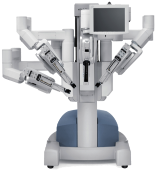
U–Pitt



BDI

Willow

Google



Intuitive

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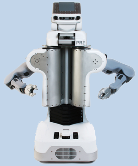

Willow

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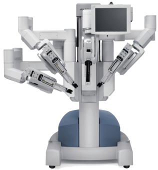

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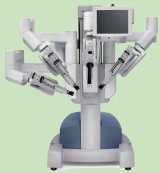

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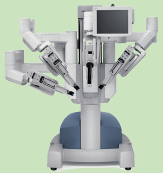

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Autonomous machines will pervade our world

Neuromechanics

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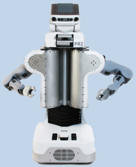
Gaits & Grasps

Cyber–Physical Systems

BDI



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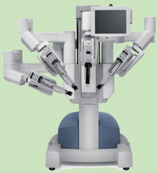


Intuitive

Dynamic Gaits & Dexterous Grasps

Dynamic Locomotion

- speeds measured in bodylengths/sec
- scales ranging from cm to m

Dexterous Manipulation

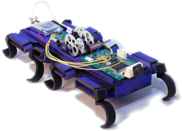
- high–precision pick–and–place, repetitive assembly
- fold towels; wash dishes

Future direction

- co–robots in factory & home

Boston Dynamics, Inc.

Koditschek *et al.*



Fearing *et al.*

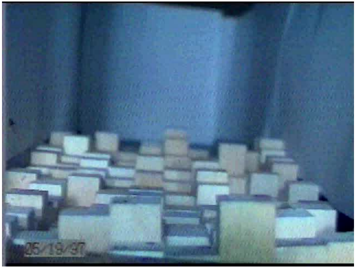
Willow

Rethink

Neuro–Mechanical Systems

Fundamentals of sensorimotor control

- mechanosensory feedback
- passive self–stabilization



Sponberg & Full

Design of Assistive Devices

- prosthesis, exoskeleton
- Brain–Machine Interface

Future direction

- personalized healthcare

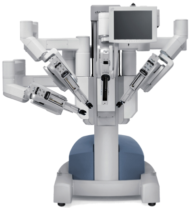
Össur

U–Pitt

Cyber–Physical Systems (CPS)

Automated Healthcare

- teleoperated surgery
- remote diagnosis



Intuitive

Brewer *et al.*

Human-in-the-Loop

- (semi–)autonomous vehicles
- energy demand response
- social cyber–physical systems

Google

PG&E

Future direction

- co–design *cyber*–and–*physical* systems

Fundamental engineering challenges

Neuromechanics

Future direction:

- automated & personalized healthcare

Gaits & Grasps

Future direction:

- co–robots in factory & home

Cyber–Physical Systems

Future direction:

- co–design *cyber* & *physical*

Fundamental engineering challenges

Neuromechanics

Future direction:

- automated & personalized healthcare

Gaits & Grasps

Future direction:

- co–robots in factory & home

Challenges:

- sensitive to environment
- relies on careful calibration

Cyber–Physical Systems

Future direction:

- co–design *cyber* & *physical*

Fundamental engineering challenges

Neuromechanics

Future direction:

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Cyber–Physical Systems

Future direction:

- co–design *cyber* & *physical*

Challenges:

- distributed, multi–agent
- large scale, multi–physical

Fundamental engineering challenges

Neuromechanics

Future direction:

- automated & personalized healthcare

Challenges:

- generalization across task/environment
- translation across scale, material, & morphology

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Cyber–Physical Systems

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Common engineering challenge

Dynamic interaction between computational & mechanical components

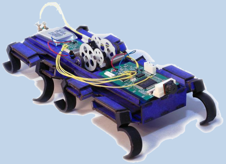
Dynamic interaction between computation & mechanics

Gaits & Grasps

Controller

sensors, computers

↓



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Objects & Obstacles

terrain, agents

Dynamic interaction between computation & mechanics

Gaits & Grasps

Controller

sensors, computers

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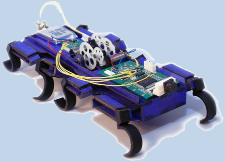

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Objects & Obstacles

terrain, agents

Neuromechanics

Nervous system

sensorimotor elements

↑

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Environment

predator/prey/partner

Dynamic interaction between computation & mechanics

Gaits & Grasps

Controller

sensors, computers

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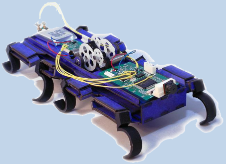

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Objects & Obstacles

terrain, agents

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Environment

predator/prey/partner

Cyber–Physical Sys

Social planner

distributed sensor web

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Society

infrastructure, economy

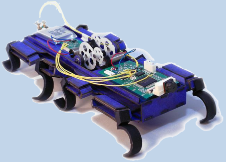
Dynamic interaction between computation & mechanics

Gaits & Grasps

Controller

sensors, computers

↓



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sensorimotor elements

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Environment

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Cyber–Physical Sys

Social planner

distributed sensor web

↕

↕

Society

infrastructure, economy

Interaction dynamics are piecewise–defined, distributed

Need new framework for modeling and control

Analytical, computational, & experimental framework

Neuromechanics

nervous system $\leftrightarrow$ environment

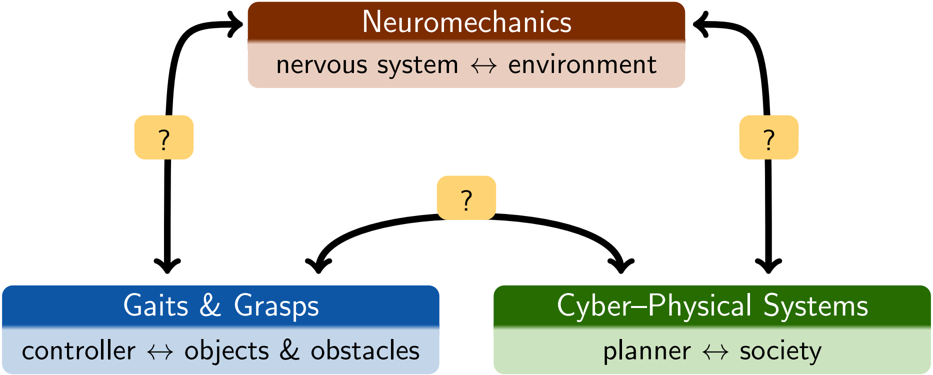
Gaits & Grasps

controller $\leftrightarrow$ objects & obstacles

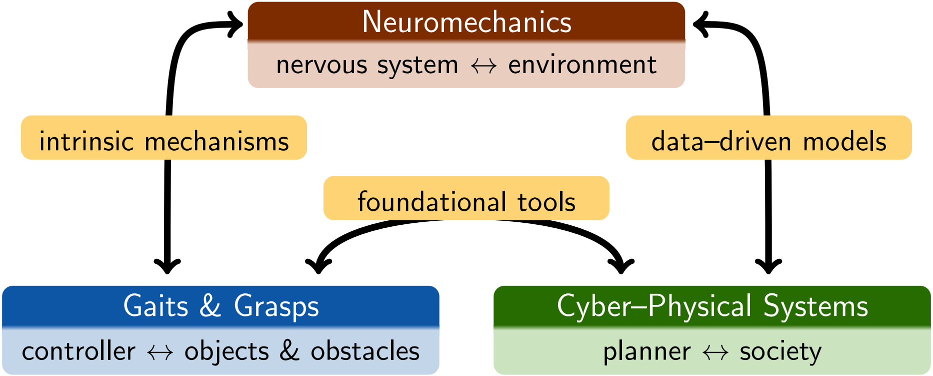
Cyber–Physical Systems

planner $\leftrightarrow$ society

Analytical, computational, & experimental framework



Analytical, computational, & experimental framework



Analytical, computational, & experimental framework

Neuromechanics
nervous system $\leftrightarrow$ environment

intrinsic mechanisms

data–driven models

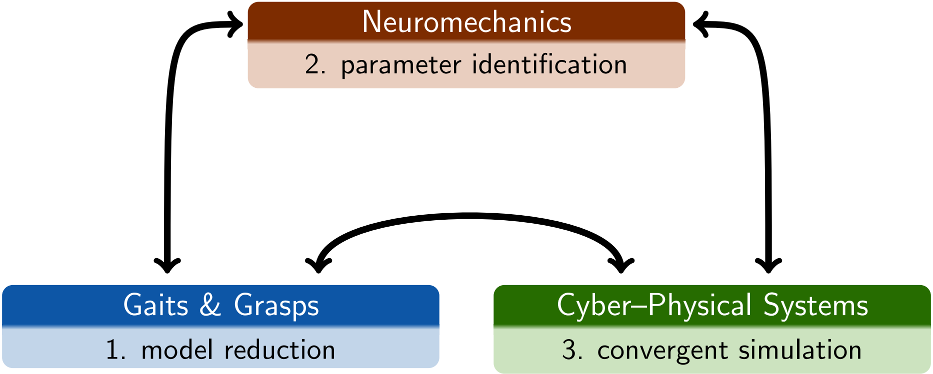
foundational tools

Gaits & Grasps
controller $\leftrightarrow$ objects & obstacles

Cyber–Physical Systems
planner $\leftrightarrow$ society

Seek a unified framework
Engineer dynamic interactions between computation & mechanics

Today's theme: framework for studying locomotion



Overview of today's talk

Locomotion

animals are adept at dynamic locomotion

1. Reduction

models for periodic gaits generically reduce dimensionality

2. Identification

reduction enables scalable algorithm for parameter estimation

3. Simulation

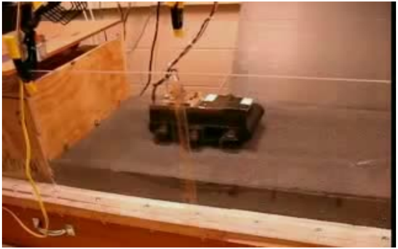
convergent numerical simulation for piecewise–defined dynamics

Future Directions

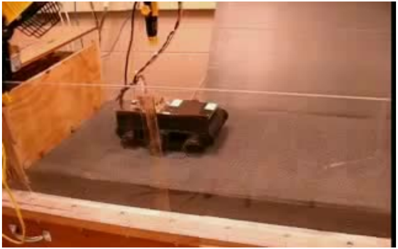
robust gaits, maneuver synthesis, and inverse modeling

Animals are extremely adept at dynamic locomotion

flat–terrain gait



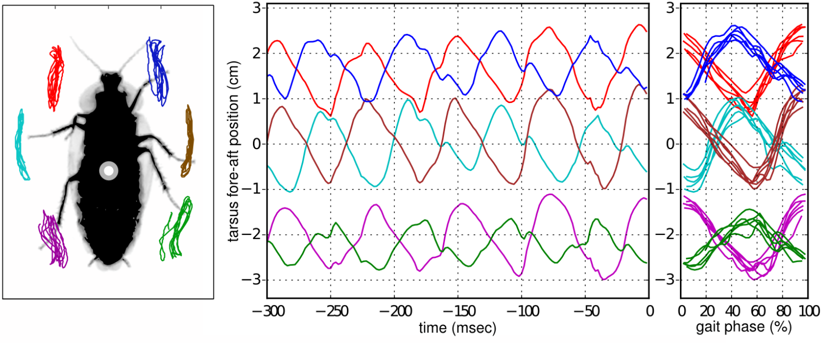
optimized gait



Sandbot RHex robot; Li *et al.* PNAS 2009

zebra–tailed lizard; Li *et al.* JEB 2012

Empirically, animals use few degrees-of-freedom



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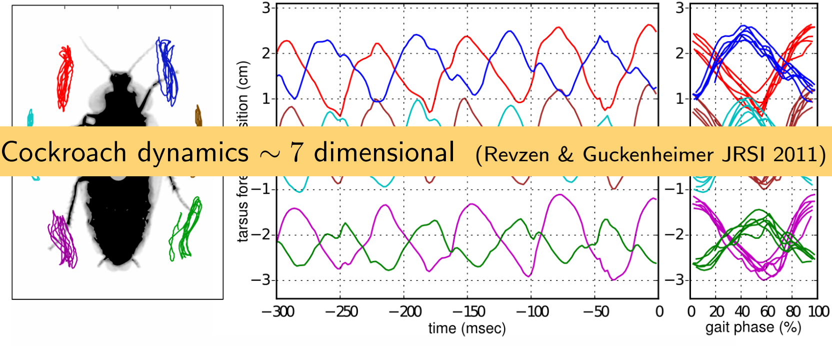

Cockroach dynamics ∼ 7 dimensional (Revzen & Guckenheimer JRSI 2011)

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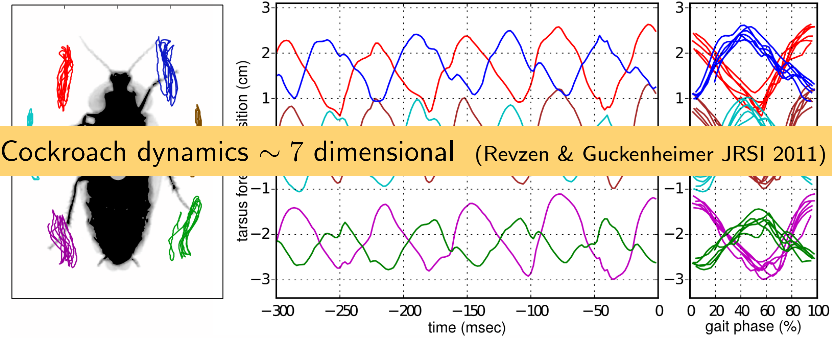

Cockroach dynamics $\sim$ 7 dimensional (Revzen & Guckenheimer JRSI 2011)

Mechanisms for reduction in neural or environmental models

Neural synchronization
Cohen et al. J. Math. Bio 1982

Physiological symmetry
Golubitsky et al. Nature 1999

Muscle activation synergy
Ting & Macpherson J. Neurosci. 2005

Granular media solidification
Li et al. Science 2013

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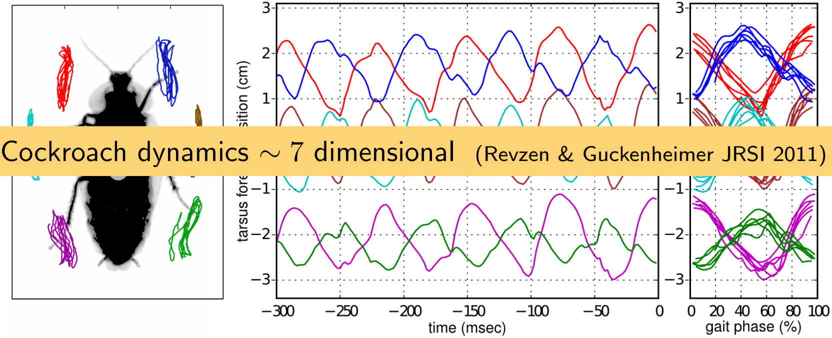

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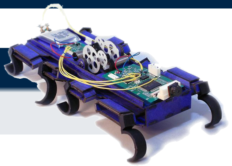
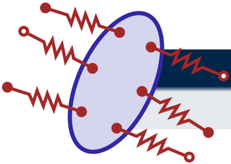
Need reduction tool for interaction between body and environment

Use simple models to study animal and robot gaits

physical system

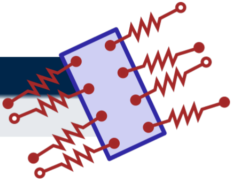
animal, robot

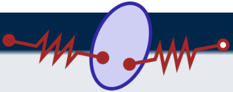




detailed model

10–100 states





reduced-order model

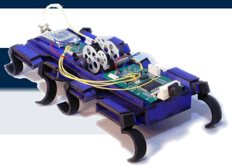
~ 10 states

Full & Koditschek JEB 1999

Use simple models to study animal and robot gaits

physical system

animal, robot



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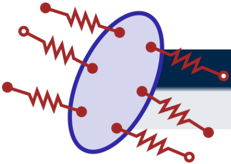

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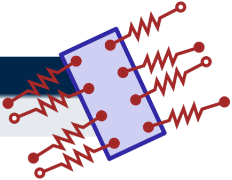

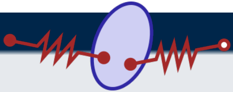

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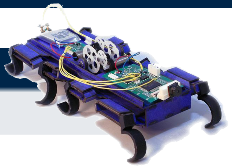
animal, robot



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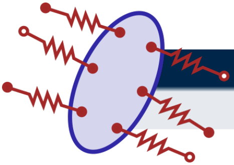

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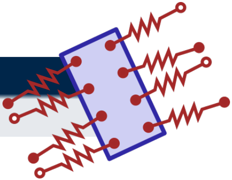

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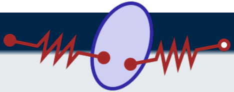

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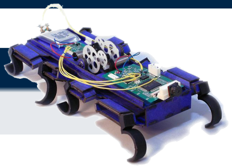
physical system

animal, robot



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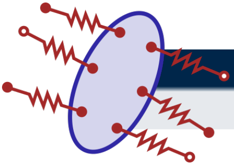

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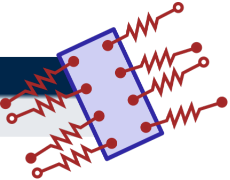
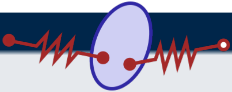


1. reduction

reduced-order model

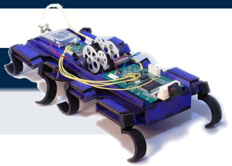


~ 10 states

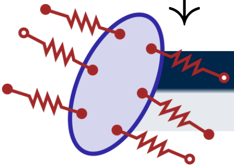
Use simple models to study animal and robot gaits

physical system

animal, robot



2. identification



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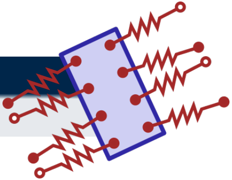

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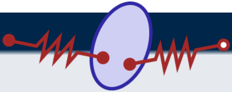


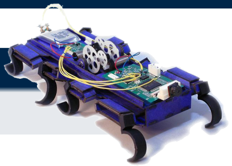
reduced-order model

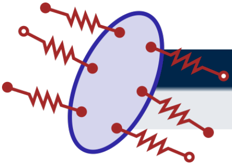
~ 10 states

Model Reduction

physical system

animal, robot





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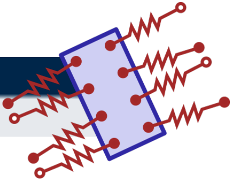

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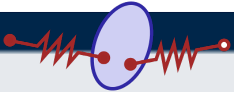
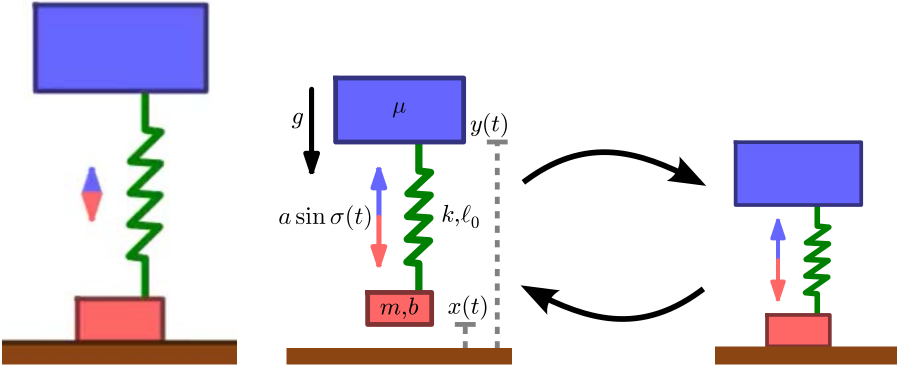


reduced-order model

< 10 states

Dimension loss in vertical hopper



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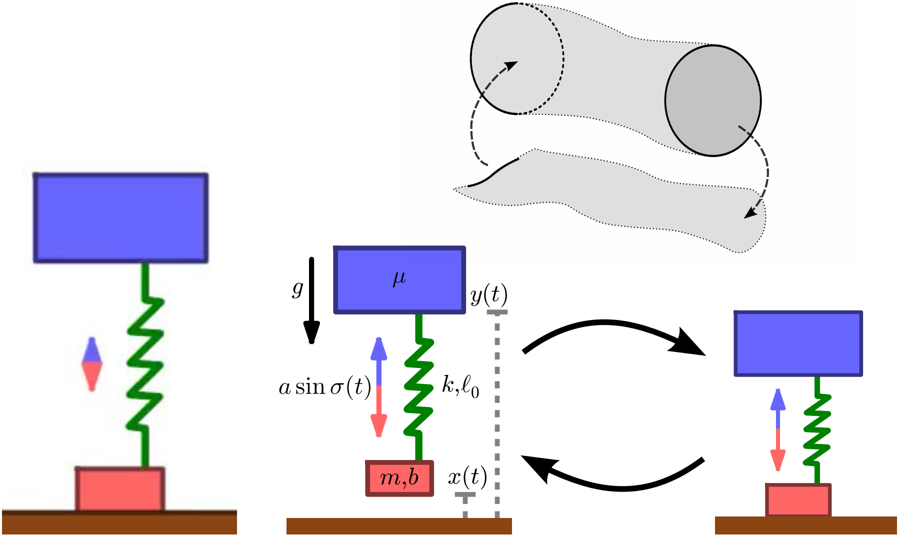
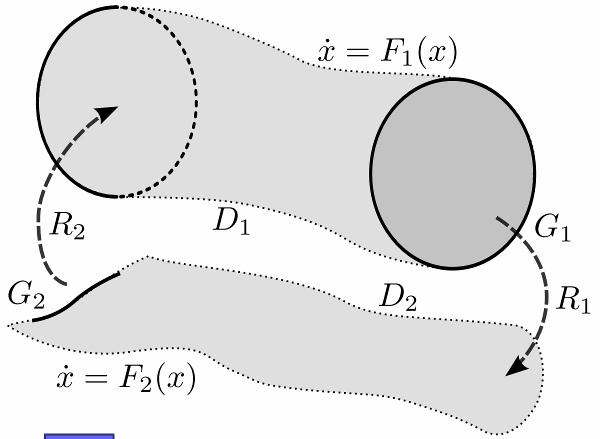
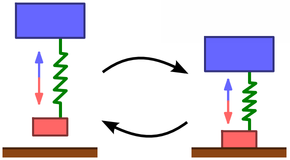
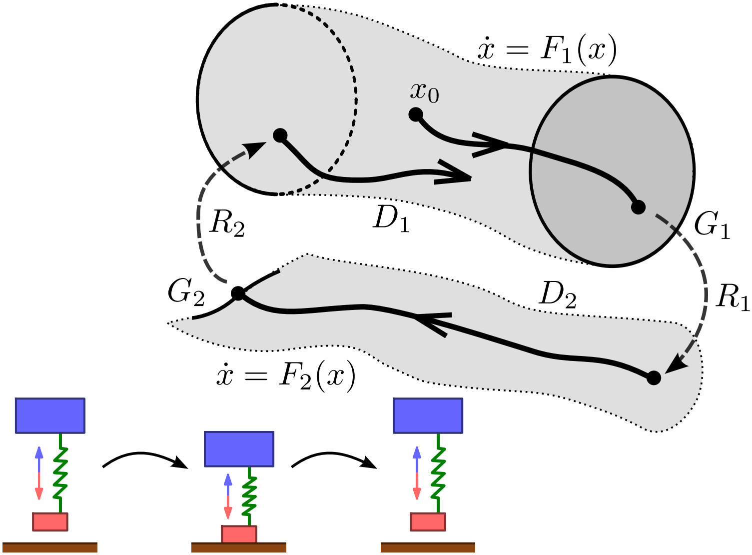


Hybrid dynamical system





Trajectory for a hybrid dynamical system



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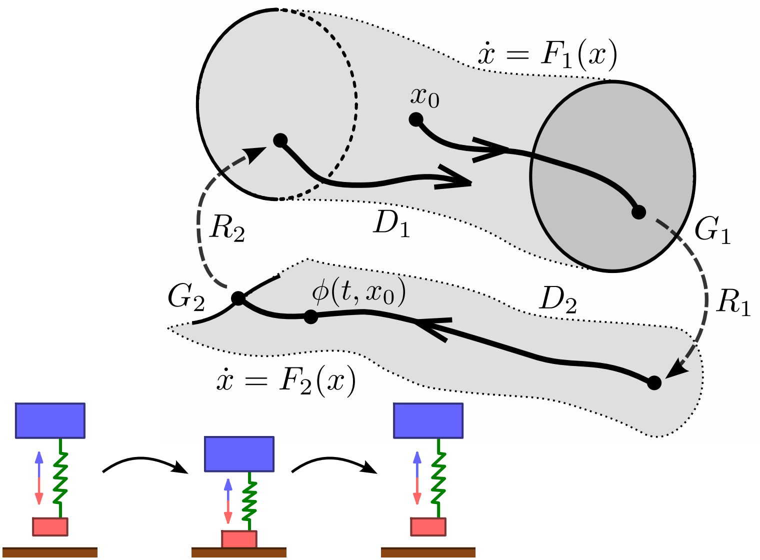
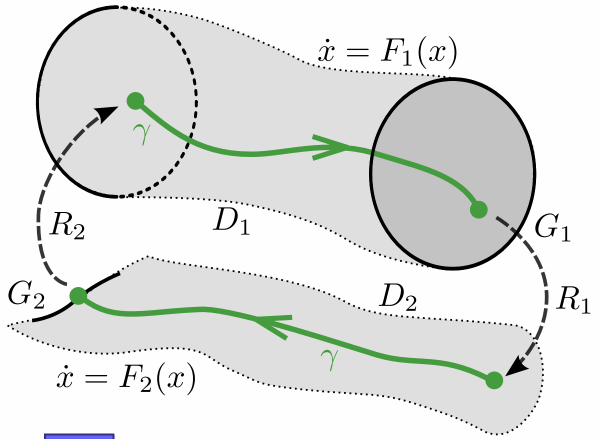
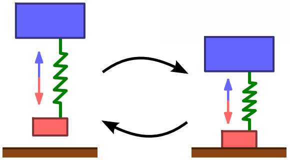
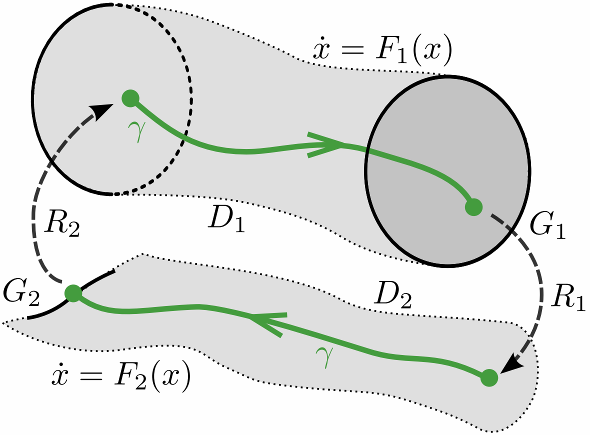


Periodic orbit γ for a hybrid dynamical system

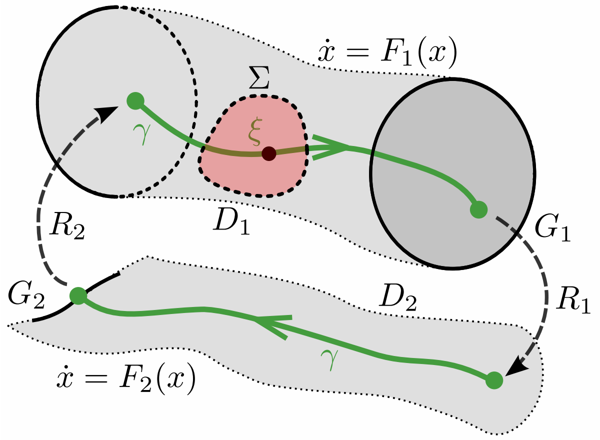




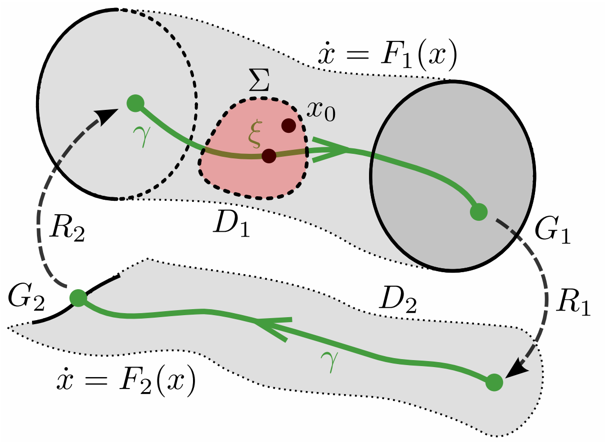
Poincaré map for periodic orbit γ



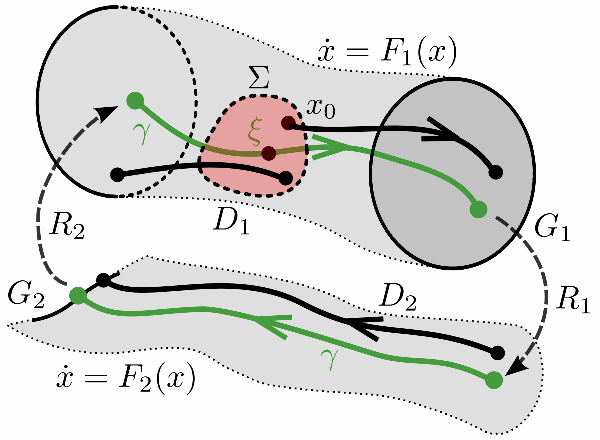
Poincaré map for periodic orbit γ



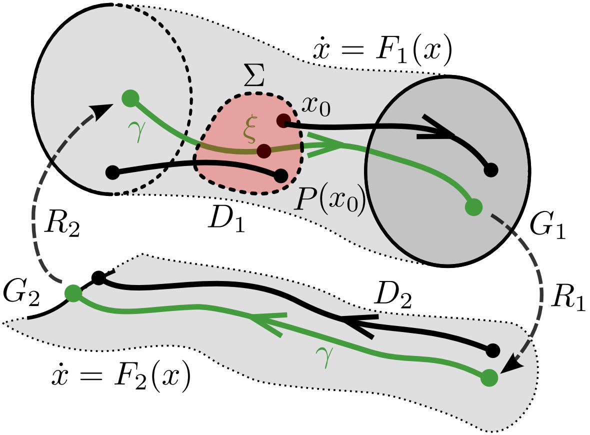
Poincaré map for periodic orbit γ



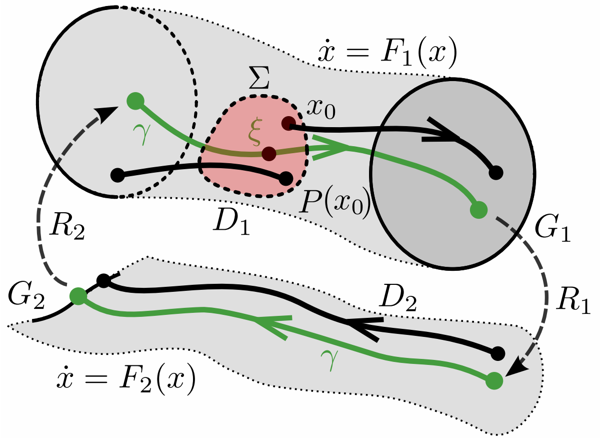
Poincaré map for periodic orbit γ



Poincaré map for periodic orbit γ



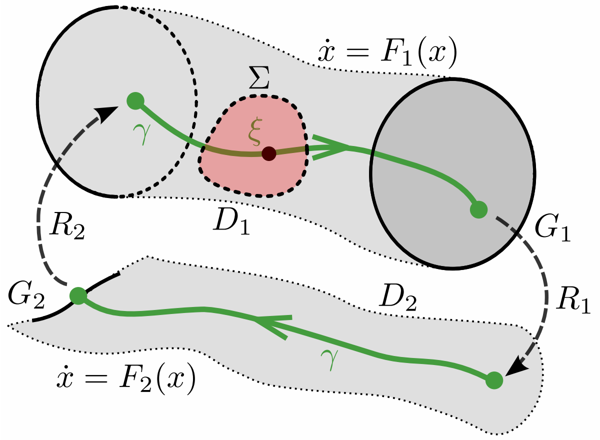
Poincaré map for periodic orbit γ



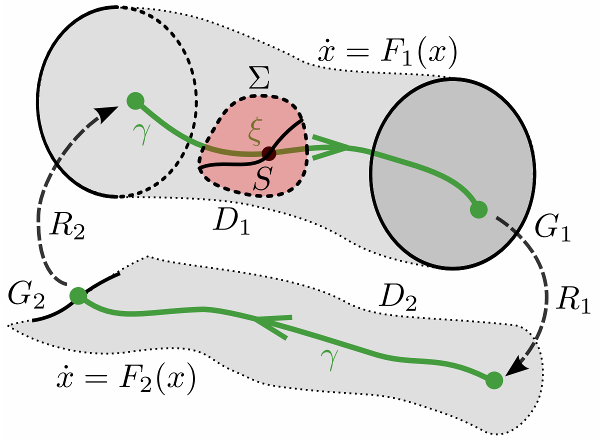
Theorem (Aizerman & Gantmacher JMAM 1958)

The Poincaré map P is smooth in a neighborhood of ξ.

Model reduction near hybrid periodic orbit γ



Model reduction near hybrid periodic orbit γ



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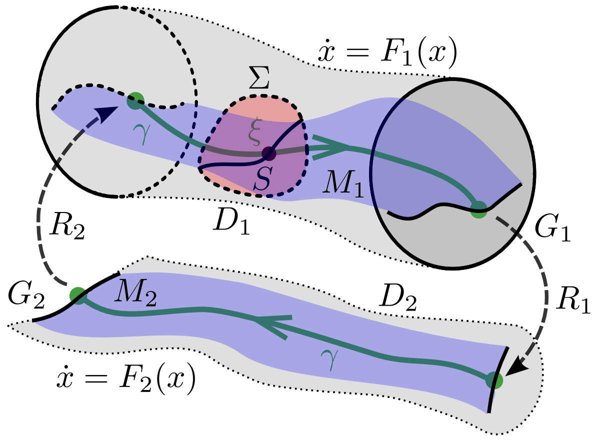

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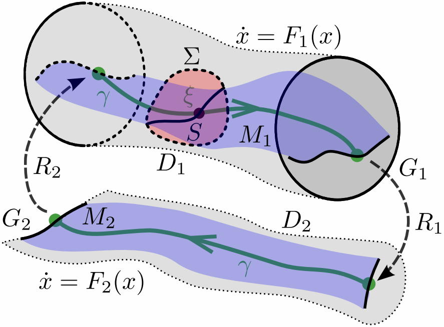
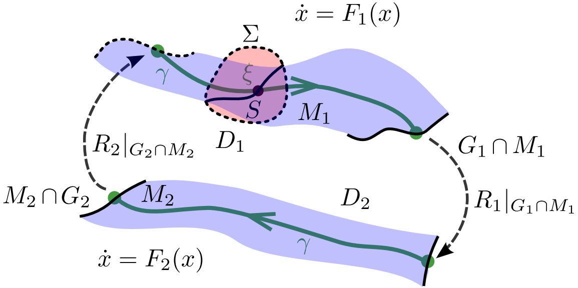


Theorem (Burden, Revzen, Sastry (arXiv:1308.4158))

Let $n = \min_j \dim D_j - 1$. *If* $\operatorname{rank} DP^n = r$ *near* ξ, *then trajectories starting near* γ *contract to a collection of hybrid-invariant* $(r+1)-$*dimensional submanifolds* $M_j \subset D_j$ *in finite time.*

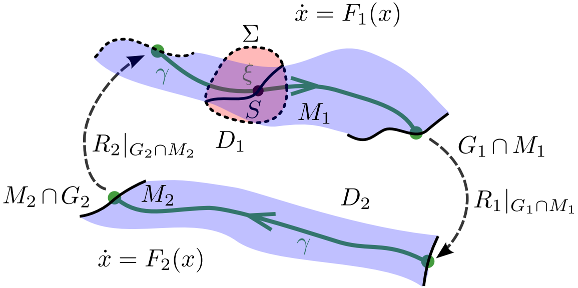
Model reduction near hybrid periodic orbit γ



Corollary (Burden, Revzen, Sastry (arXiv:1308.4158))

The submanifolds M_j determine a hybrid system with periodic orbit γ.

Model reduction near hybrid periodic orbit γ



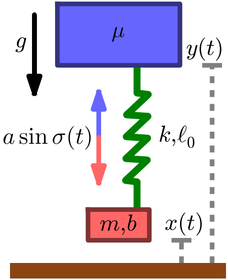
Corollary (Burden, Revzen, Sastry (arXiv:1308.4158))

The submanifolds M_j determine a hybrid system with periodic orbit γ.

γ *is asymptotically stable in the original hybrid system*

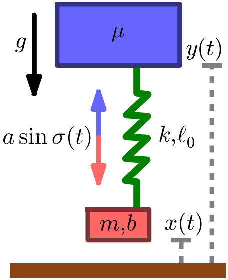
$\iff$ γ *is asymptotically stable in the reduced hybrid system.*

Spontaneous reduction in vertical hopper



Numerically linearizing Poincaré map P on ground,
we find $DP(\xi)$ has eigenvalue $\simeq 0.57$,
therefore DP^2 is constant rank near ξ.

Spontaneous reduction in vertical hopper



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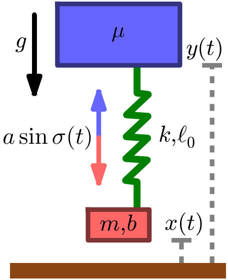
hopper reduces one degree–of–freedom after a single “hop”.

Spontaneous reduction in vertical hopper



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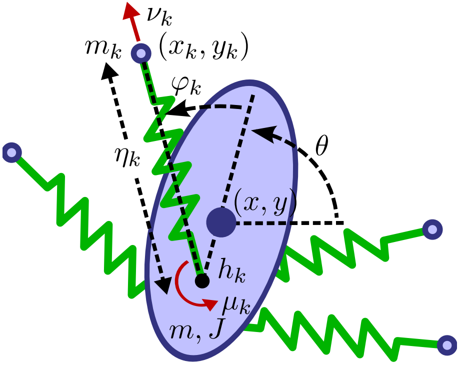
Corollary (Burden, Revzen, Sastry (arXiv:1308.4158))

hopper reduces one degree–of–freedom after a single "hop".

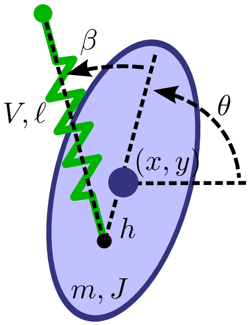
Interpretation

Holonomic ground contact constraint persists after liftoff.

Model with n legs reduces to Lateral Leg–Spring

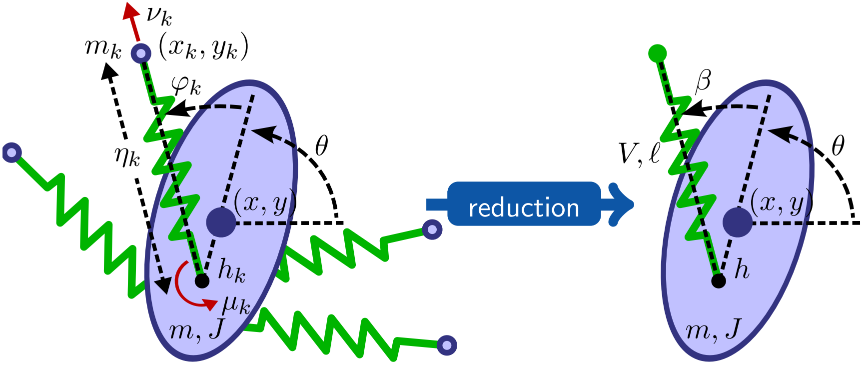


$(3 + 2n)$ degrees–of–freedom



3 degrees–of–freedom
Schmit & Holmes 2001

Model with n legs reduces to Lateral Leg–Spring



$(3 + 2n)$ degrees–of–freedom

3 degrees–of–freedom
Schmit & Holmes 2001

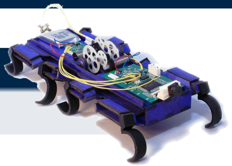
Controller (Burden, Revzen, Sastry (arXiv:1308.4158))

Smooth feedback law reduces $2n$ degrees–of–freedom after one stride.

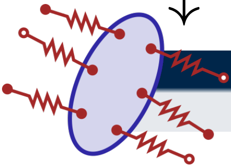
Parameter Identification

physical system

animal, robot

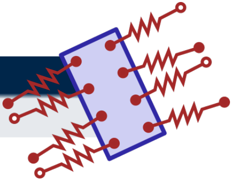


2. identification ↓

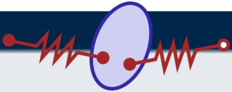


detailed model

10–100 DOF



1. reduction ↓



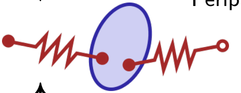
reduced-order model

< 10 DOF

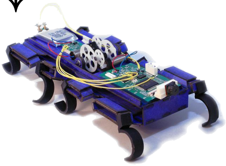
Parametric identification for models of rhythmic behavior

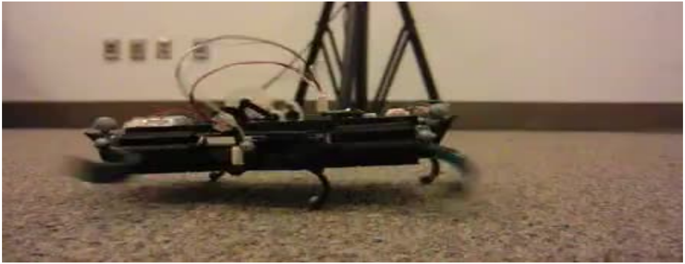
identification

Periplaneta americana (Poly-PEDAL Lab, http://polypedal.berkeley.edu/)



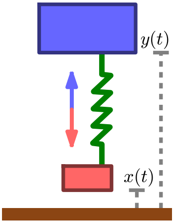
identification





DynaROACH robot (Olin Robotics Lab, http://orb.olin.edu)

Identification of initial conditions



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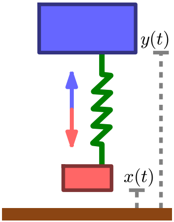
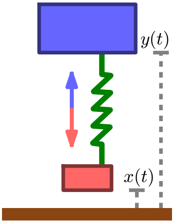


$$Y(\phi(t, z)) = y(t)$$

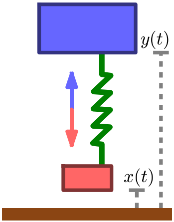
Identification of initial conditions



$$Y(\phi(t, z)) = y(t)$$

$\eta_i = Y(\phi(iT, z^*)) + w_i$,
w_i iid random variables

Identification of initial conditions



$Y(\phi(t,z)) = y(t)$

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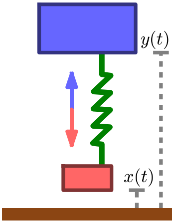
w_i iid random variables

Identification problem

Solve $\arg\min_{z\in D_j} \varepsilon\left(z, \{\eta_i\}\right)$, where $\varepsilon\left(z, \{\eta_i\}\right) := \sum_i \|Y(\phi(iT, z)) - \eta_i\|^2$.

Identification of initial conditions



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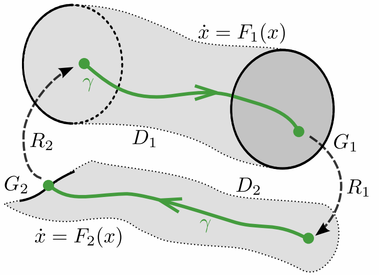
Assumption (smooth observations)

Y is smooth along trajectories, i.e. $Y(\phi(t, z))$ is a smooth function of t.

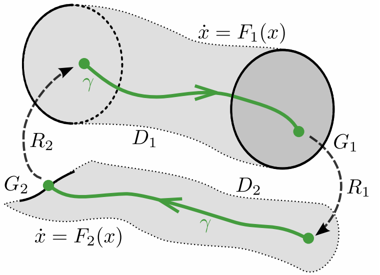
Identification on original hybrid model vs. reduced model



Identification on $\bigcup_j D_j$

$$\arg\min_{z \in D_j} \varepsilon\left(z, \{\eta_i\}\right)$$

Identification on original hybrid model vs. reduced model



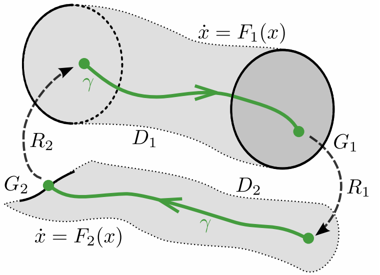
Identification on $\bigcup_j D_j$

$$\arg\min_{z \in D_j} \varepsilon\left(z, \{\eta_i\}\right)$$

$\nabla\varepsilon$ undefined on $G_j \subset D_j$

R_j not generally invertible

Identification on original hybrid model vs. reduced model



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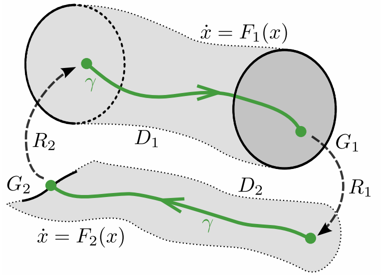

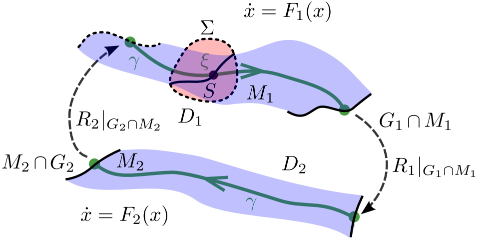

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Identification on $\bigcup_j M_j$

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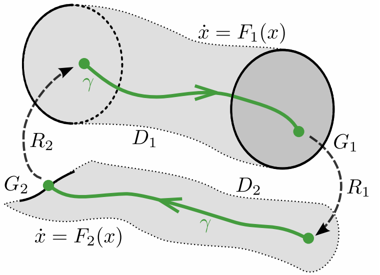
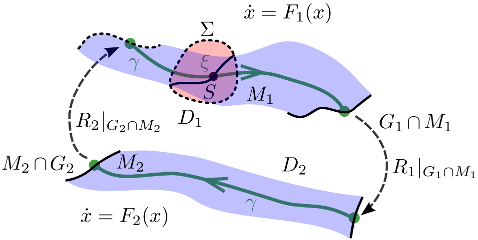
R_j not generally invertible

global optimization needed

Burden, Ohlsson, Sastry SysID 2012

Identification on original hybrid model vs. reduced model





Identification on $\bigcup_j D_j$

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Identification on $\bigcup_j M_j$

$$\arg\min_{z \in M_j} \varepsilon\left(z, \{\eta_i\}\right)$$

$\nabla\varepsilon$ undefined on $G_j \subset D_j$

R_j not generally invertible

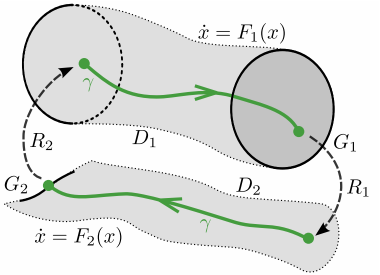
$\nabla\varepsilon$ well-defined on $G_j \cap M_j$

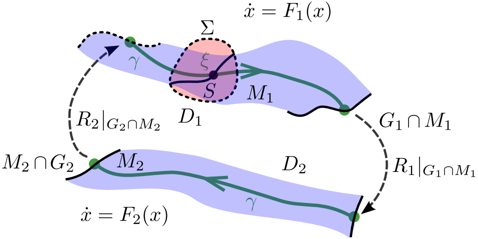
$R_j|_{M_j}$ invertible

global optimization needed

Burden, Ohlsson, Sastry SysID 2012

Identification on original hybrid model vs. reduced model





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$R_j|_{M_j}$ invertible

first–order algorithms applicable

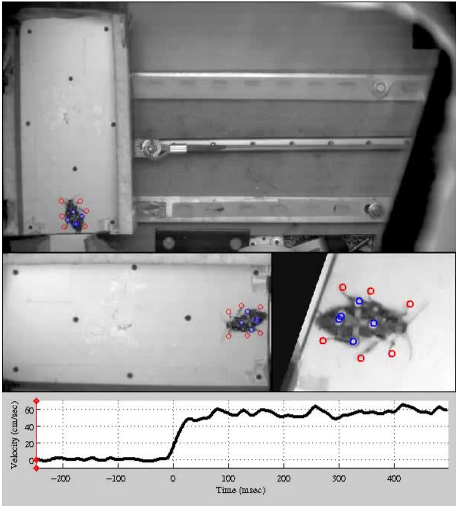
Burden, Ohlsson, Sastry SysID 2012

Novel quantitative predictions for biomechanics

observation

neural feedback appears at a delay

Revzen, Burden et al. BC 2013



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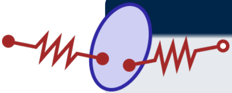
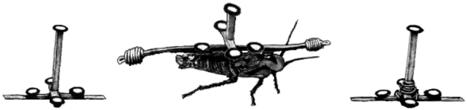


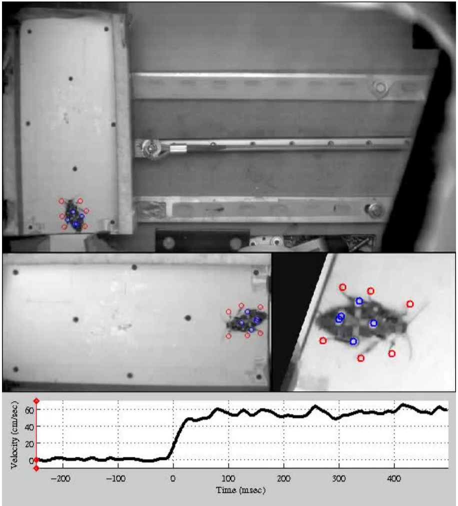
prediction

passive mechanics sensitive to inertia

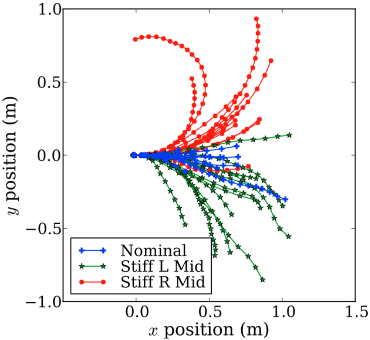
Full et al. 2002



Burden, Revzen, Moore, Sastry, Full SICB 2013



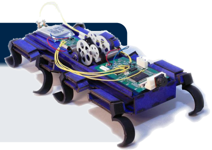
Model–based design and control of dynamic robots



design

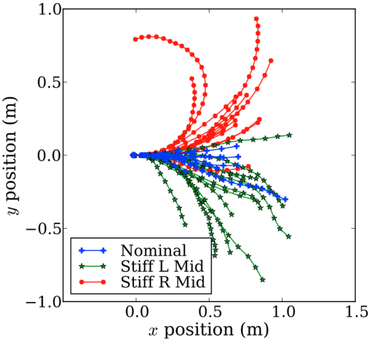
minimal use of actuators

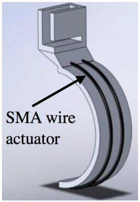
Hoover et al. 2010



Hoover, Burden, Fu, Sastry, Fearing BIOROB 2010

Model–based design and control of dynamic robots





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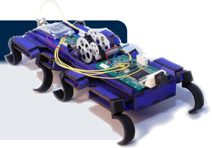
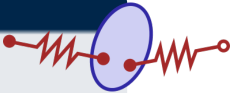


identification

control

asymmetric leg stiffness change

Proctor & Holmes 2008

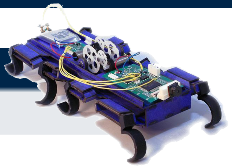


Hoover, Burden, Fu, Sastry, Fearing BIOROB 2010

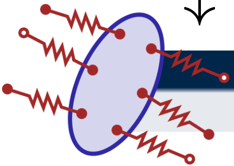
Convergent Simulation

physical system

animal, robot

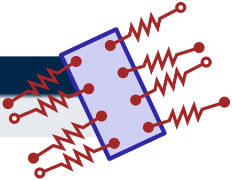


identification ↓



detailed model

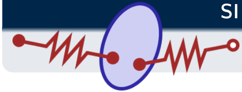
10–100 DOF



reduction ↓

simulation

simple model

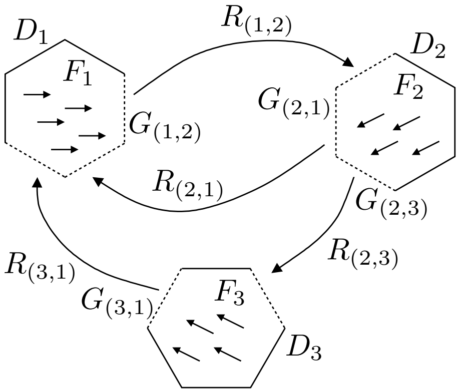


< 10 DOF

State space metric

Hybrid control systems comprised of distinct operating "modes"

- Digital controller state ("on" or "off")
- Physical/dynamical regime ("reach" or "grasp")



Burden, Gonzalez, Vasudevan, Bajcsy, Sastry (arXiv:1302.4402)

State space metric

Hybrid control systems comprised of distinct operating "modes"

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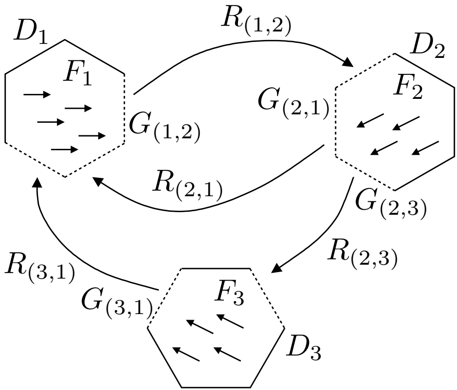

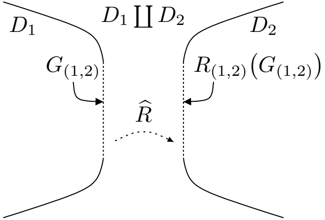

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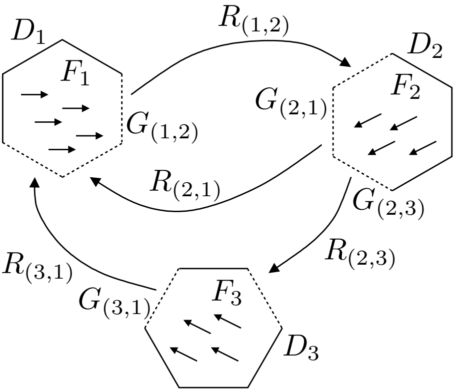
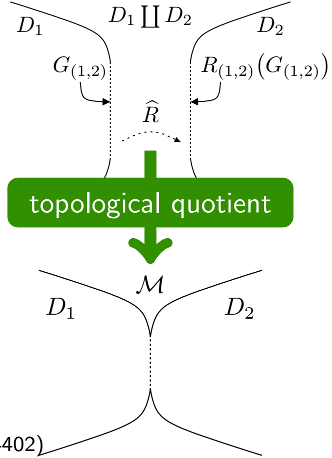


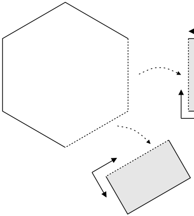


Burden, Gonzalez, Vasudevan, Bajcsy, Sastry (arXiv:1302.4402)

Convergent numerical simulation

Transition between discrete modes occurs autonomously

- simulation algorithm must control error introduced by “event detection”



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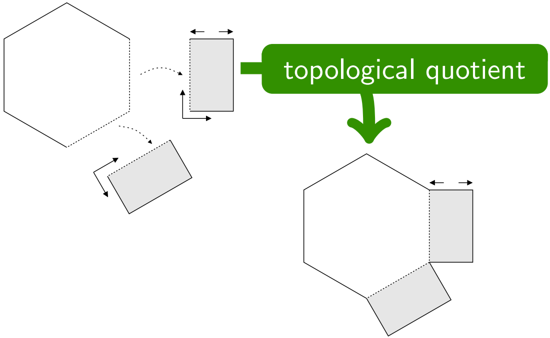

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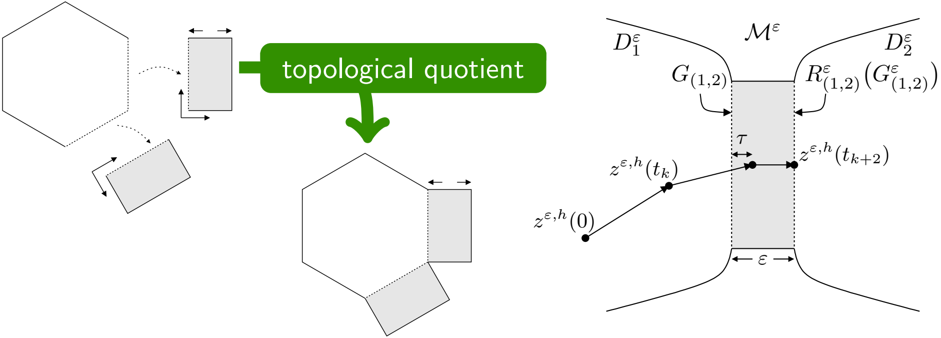
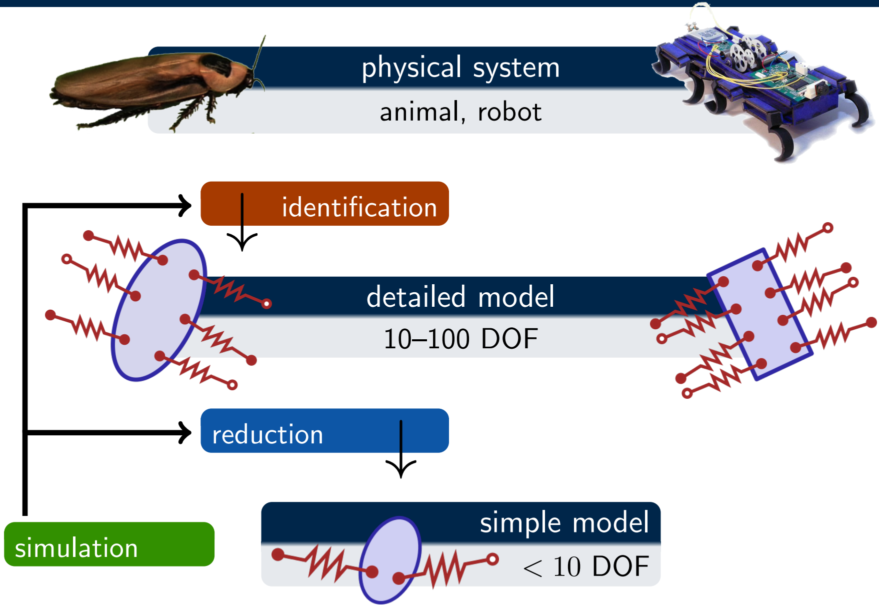


State space metric enables proof of convergence for “Forward Euler”

- Linear convergence rate for any orbitally stable execution

Burden, Gonzalez, Vasudevan, Bajcsy, Sastry (arXiv:1302.4402)

Models enable translation across scale and morphology



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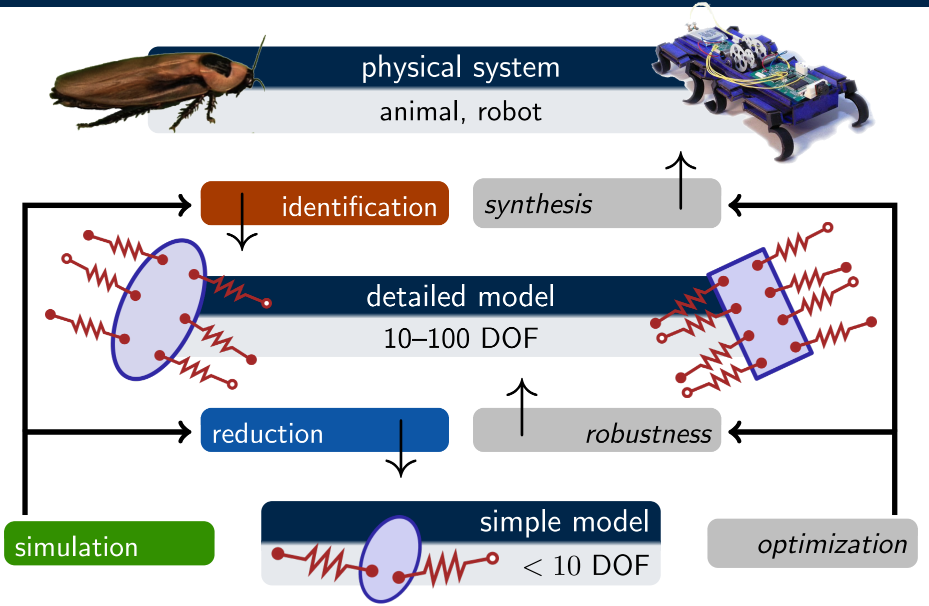

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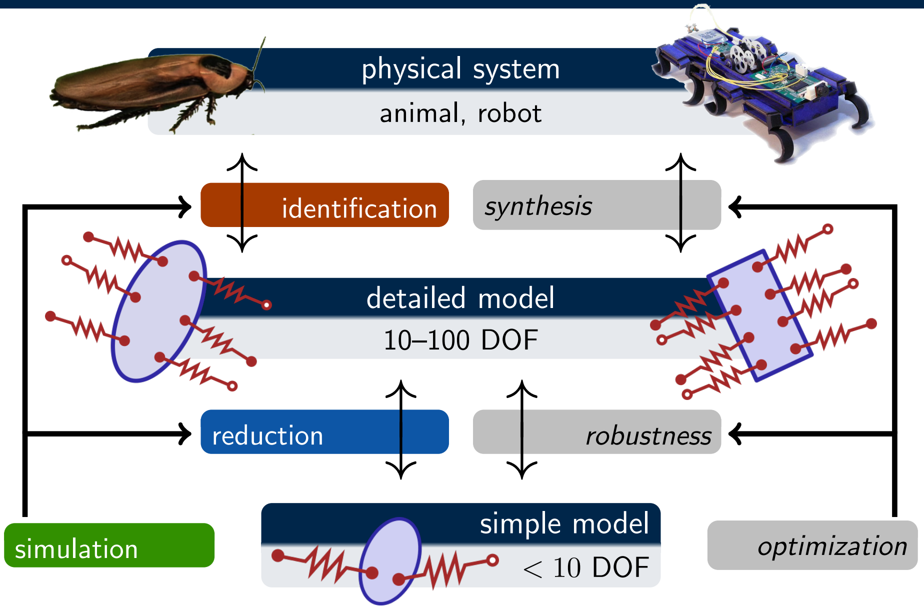
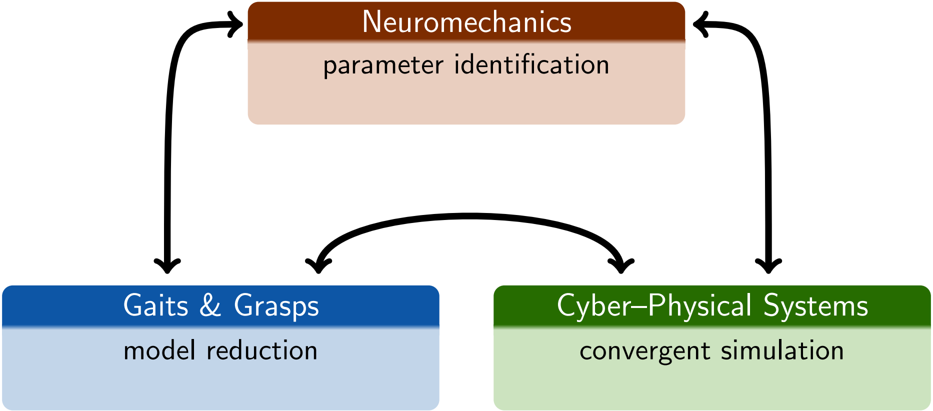


Summary of framework for studying locomotion



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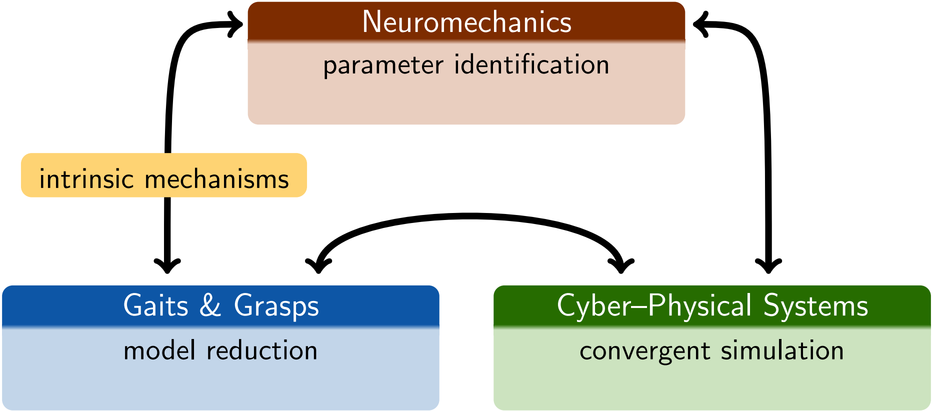

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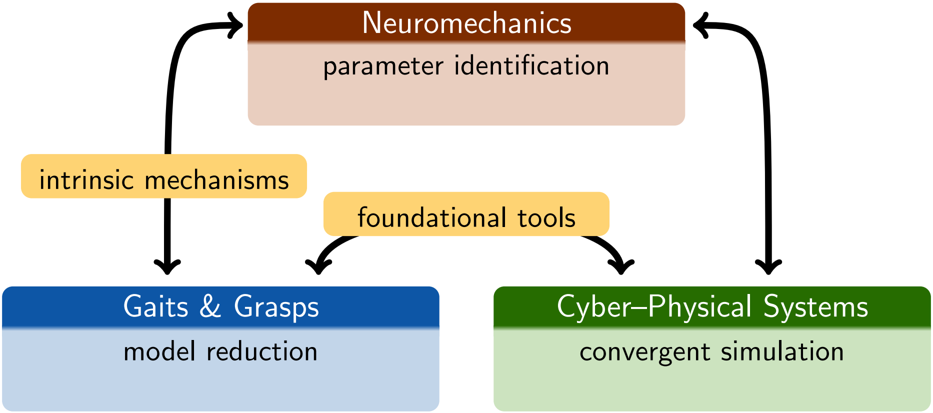

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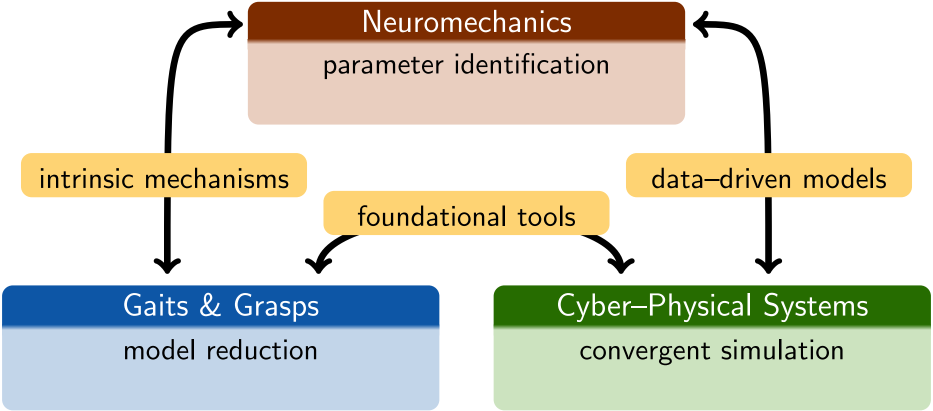

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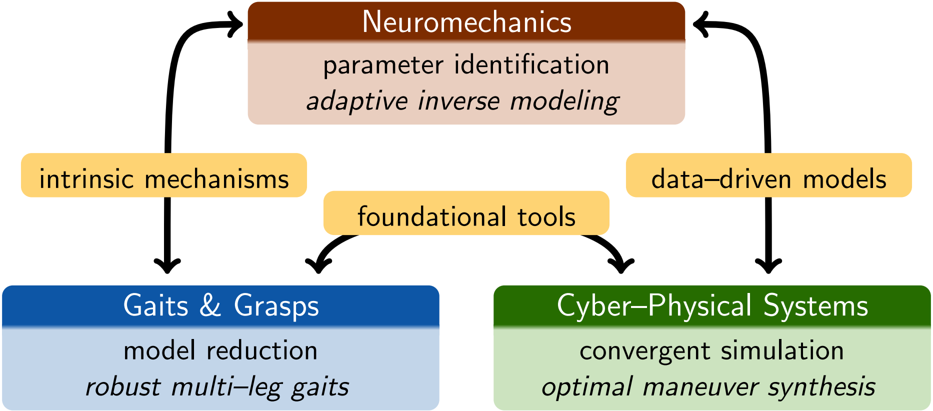
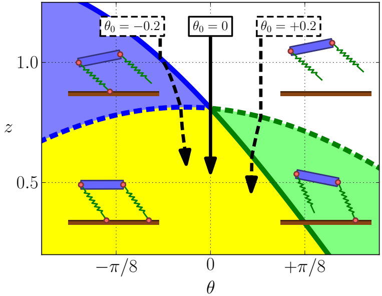


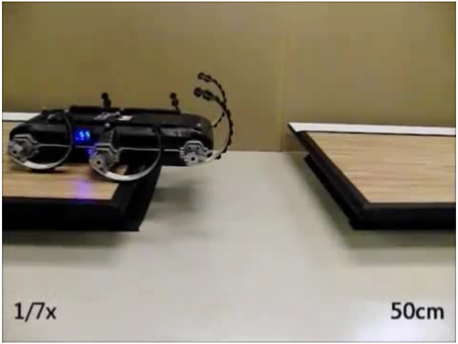
Robust multi–legged gaits

U. Minnesota Equine Center

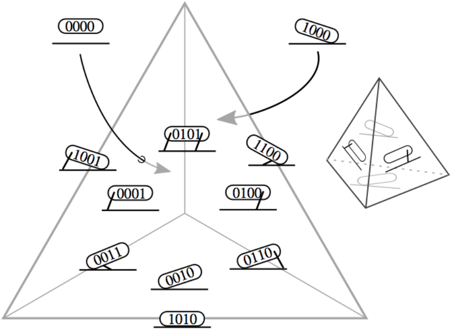
www.naturhov.dk



Optimal maneuver synthesis



X-RHex Lite (`http://kodlab.seas.upenn.edu`)

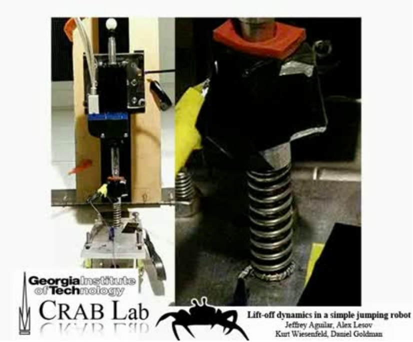


Johnson & Koditschek ICRA 2013

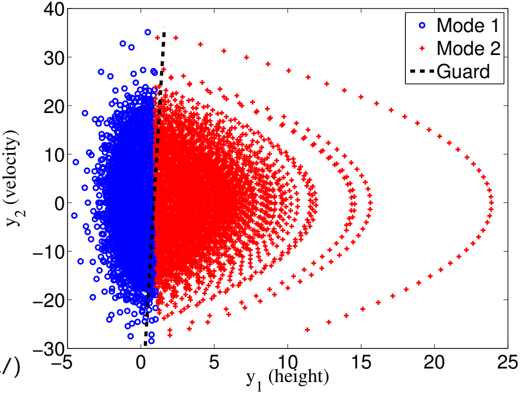
Reformulate combinatorial problem

Control yields footfall sequence; can search over continuous inputs.

Adaptive inverse modeling



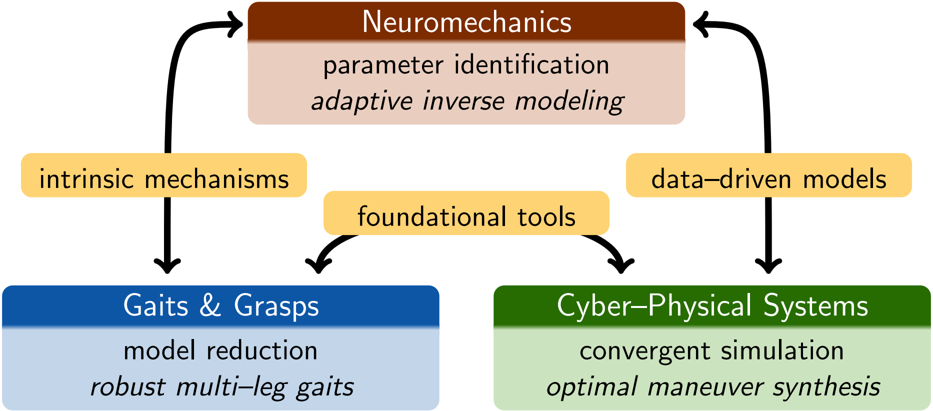
Aguilar *et al.* (`http://crablab.gatech.edu/`)

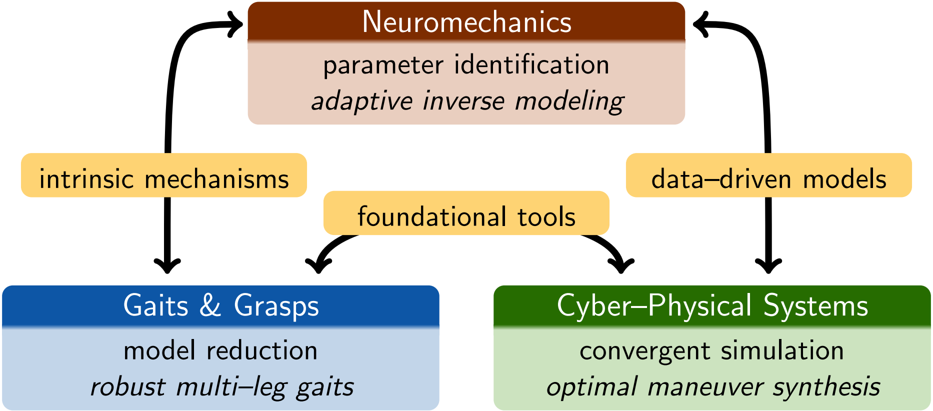


Estimate piecewise–affine model from empirical data

Use predictive model for controller synthesis

Elhamifar, Burden, Sastry (submitted)


Neuromechanics
parameter identification
adaptive inverse modeling
intrinsic mechanisms
data–driven models
foundational tools
Gaits & Grasps
model reduction
robust multi–leg gaits
Cyber–Physical Systems
convergent simulation
optimal maneuver synthesis



An emerging Systems Theory for Neuromechanics

Engineer dynamic interactions between computation & mechanics

Discussion & Questions — Thanks for your time!

Reduction

Reduced–order model emerges from intermittent contact.

Simulation

Convergent numerical simulation for hybrid control systems.

Identification

Scalable parameter identification for models of locomotion.

Collaborators

- Shankar Sastry (UCB)
- Robert Full (UCB)
- Dan Koditschek (UPenn)
- Shai Revzen (UMich)
- Aaron Hoover (Olin)
- Henrik Ohlsson (Linköping)

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