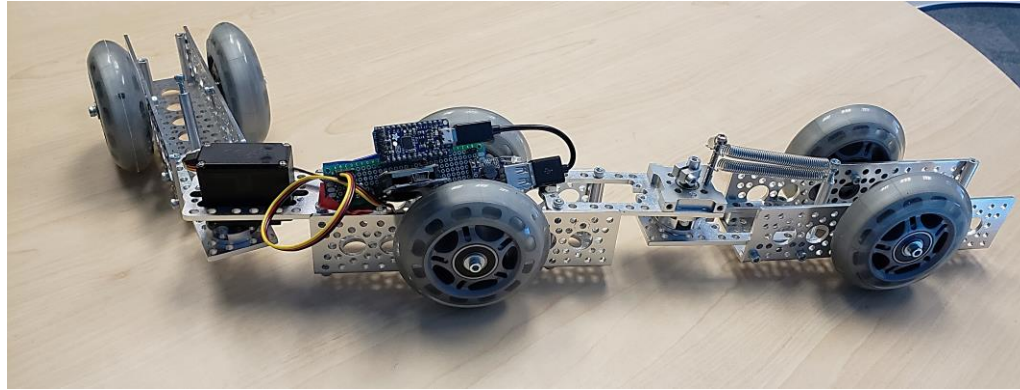


COMS W4733: Computational Aspects of Robotics

Lecture 28: Applications and State of the Art

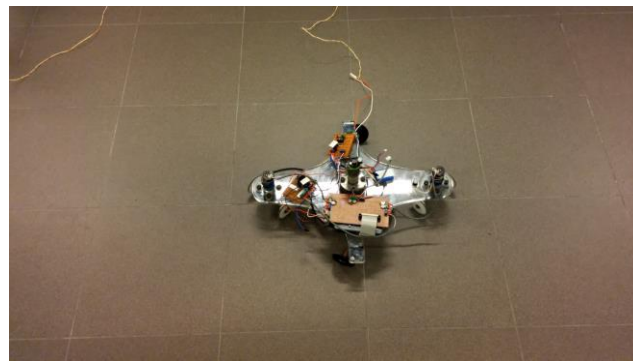


Instructor: Tony Dear

The Field of Robotics

- Robotics is a very *interdisciplinary* area that only partially encompasses CS
- This class: Covered “computational” aspects of many common tasks and goals
- In a sense, all of robotics is computational!
- We’ve only barely scratched the surface in both methods and applications
- Case study: Robot locomotion (my own research)

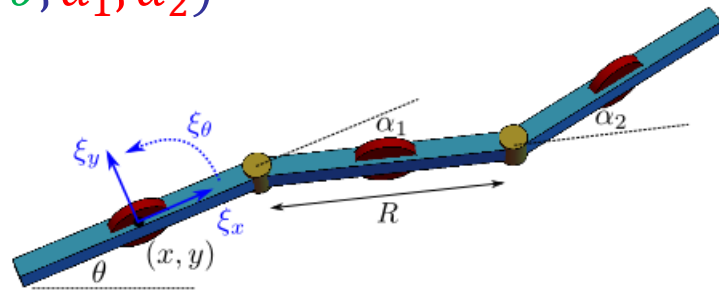
Locomotion Geometry



Kinematic Structure

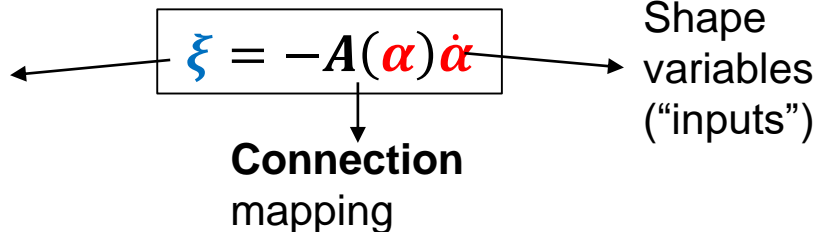
- Configuration variables: $\mathbf{q} = (\mathbf{g}, \boldsymbol{\alpha})^T = (x, y, \theta, \alpha_1, \alpha_2)^T$

- Body velocities: $\boldsymbol{\xi} = (\xi_x, \xi_y, \xi_\theta)^T = \mathbf{R}(\theta) \dot{\mathbf{g}}$



- Nonholonomic constraints: $\boldsymbol{\omega}_\xi(\boldsymbol{\alpha}) \boldsymbol{\xi} + \boldsymbol{\omega}_\alpha(\boldsymbol{\alpha}) \dot{\boldsymbol{\alpha}} = 0$

Position
variables
("outputs")



Shape
variables
("inputs")

Geometric Motion Planning

$$\xi = -A(\alpha)\dot{\alpha}$$

Input trajectory: $\psi: [0, t] \rightarrow \alpha$

Integrate velocity \rightarrow odometry:

$$-\int A_i(\alpha(t))\dot{\alpha}(t) dt = -\int_{\psi} A_i(\alpha) d\alpha$$

Stokes'
theorem

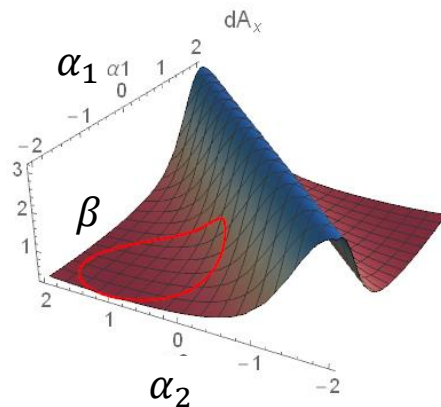
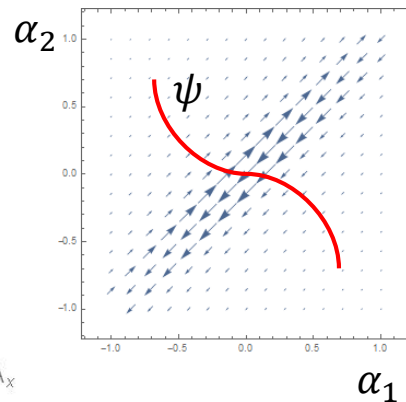


ψ is periodic \rightarrow closed
curve in shape space

$$-\int_{\beta} dA_i(\alpha)$$

Measure of
displacement

exterior derivative



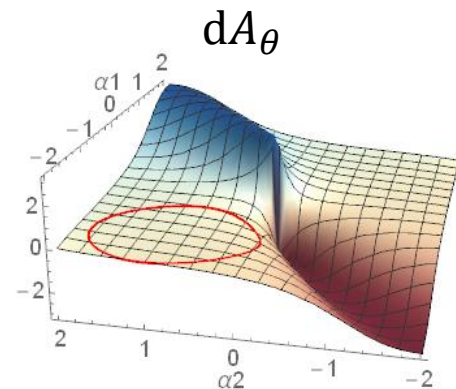
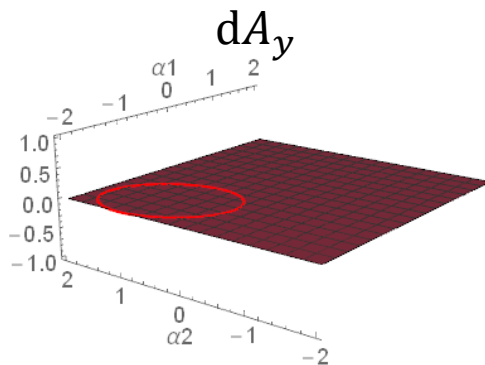
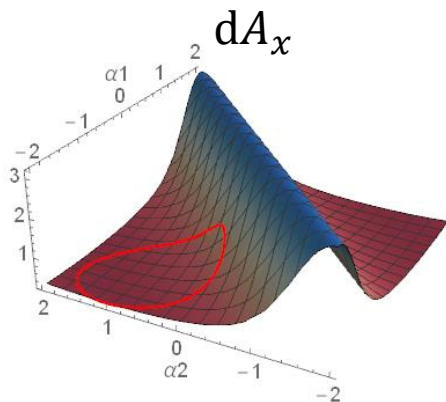
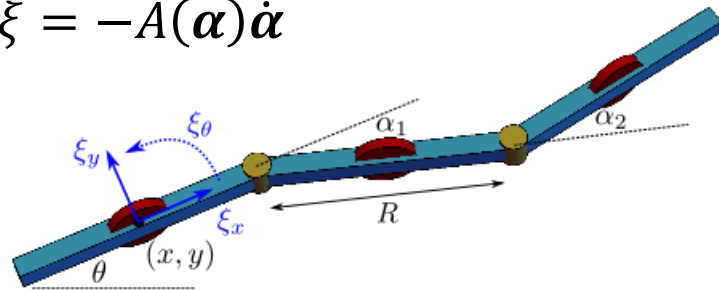
Snake Robot Connection

$$A(\alpha) = \frac{1}{D} \begin{pmatrix} \frac{R}{2}(\cos \alpha_1 + \cos(\alpha_1 - \alpha_2)) & \frac{R}{2}(1 + \cos \alpha_1) \\ 0 & 0 \\ \sin \alpha_1 + \sin(\alpha_1 - \alpha_2) & \sin \alpha_1 \end{pmatrix}$$

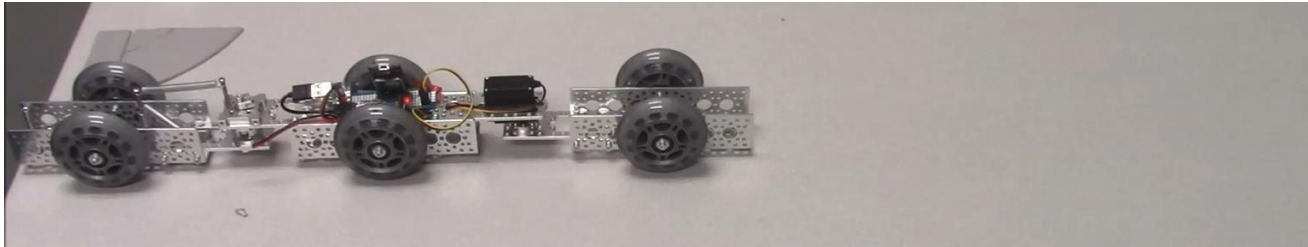
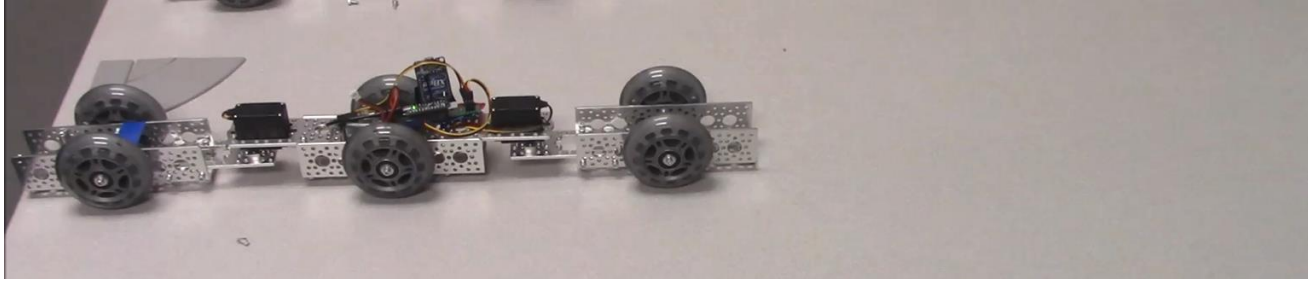
$$D = \sin \alpha_1 + \sin(\alpha_1 - \alpha_2) - \sin \alpha_2$$

Gaits are closed loops
in shape space

$$\xi = -A(\alpha)\dot{\alpha}$$

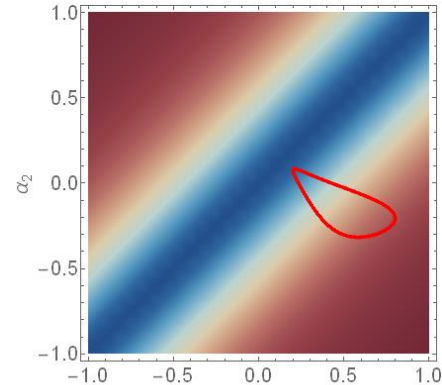
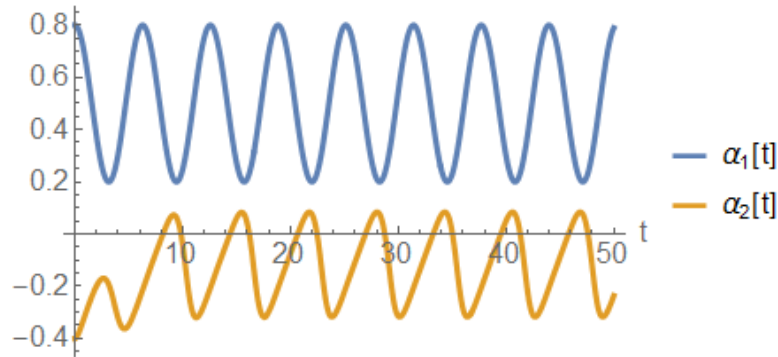


A “Small” Modification: Motor to Spring

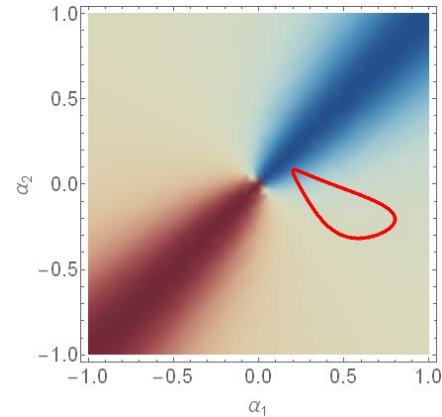


Non-Singular Gaits

- Both joints start far away from each other
- Damping slows the compliant joint more than spring pushing it



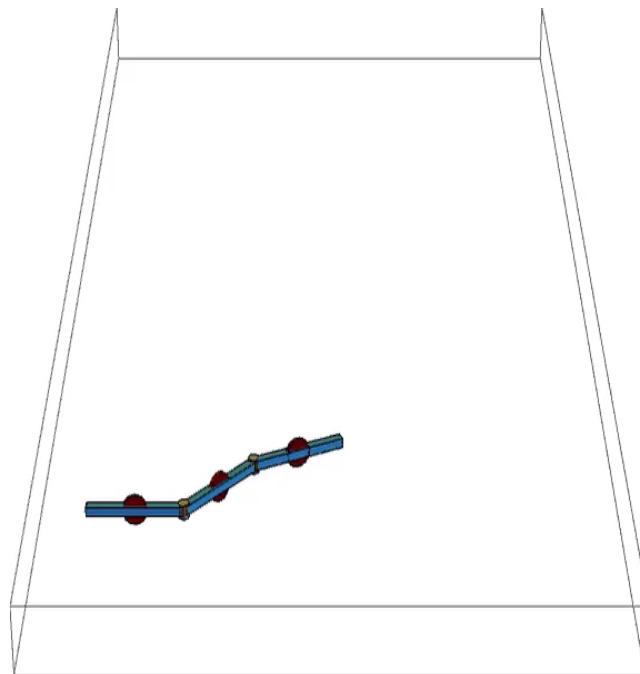
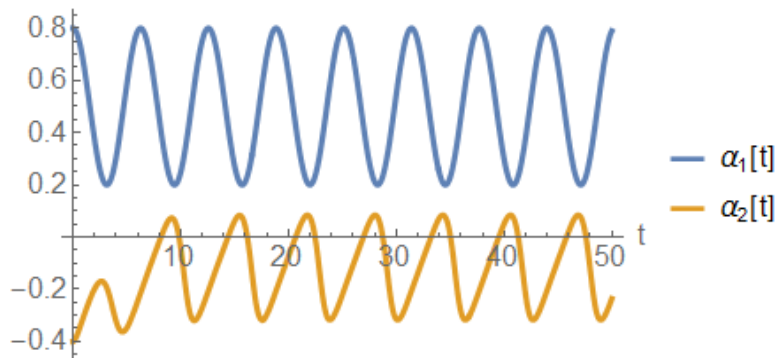
dA_x



dA_θ

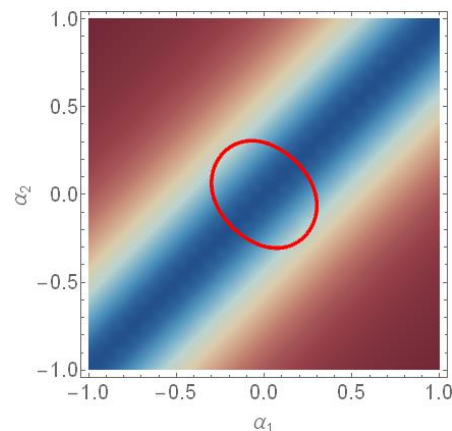
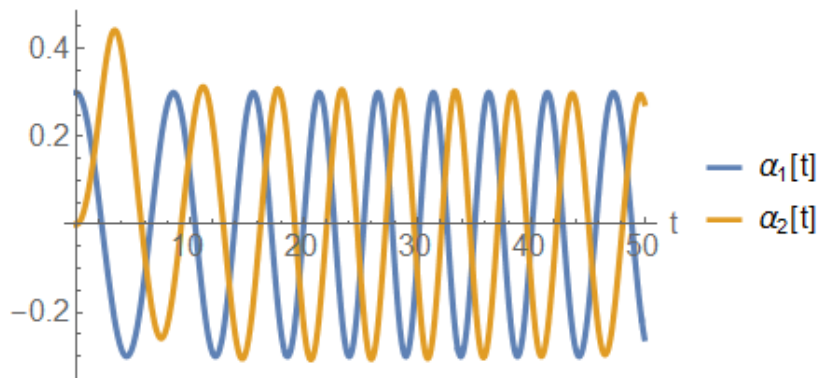
Non-Singular Gaits

- Both joints start far away from each other
- Damping slows the compliant joint more than spring pushing it

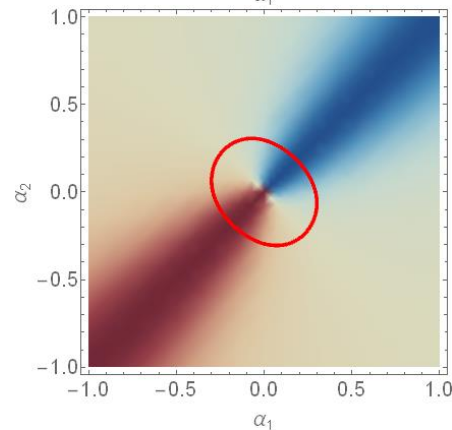


Singular Gaits

- Joints start near one another
- Insufficient damping to stop compliant joint crossing α_1



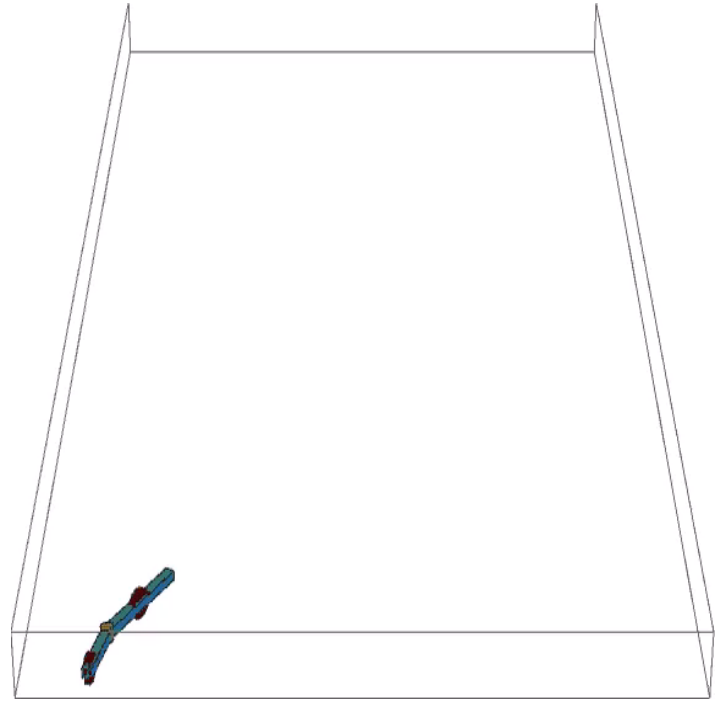
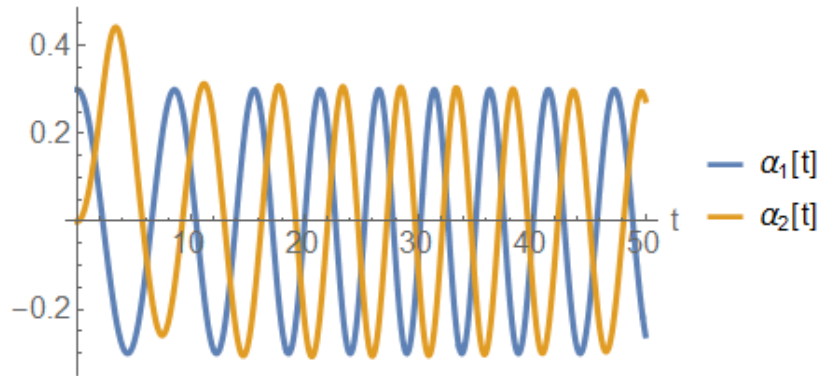
dA_x



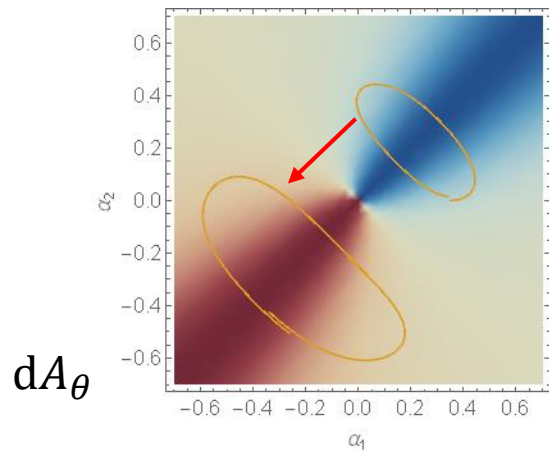
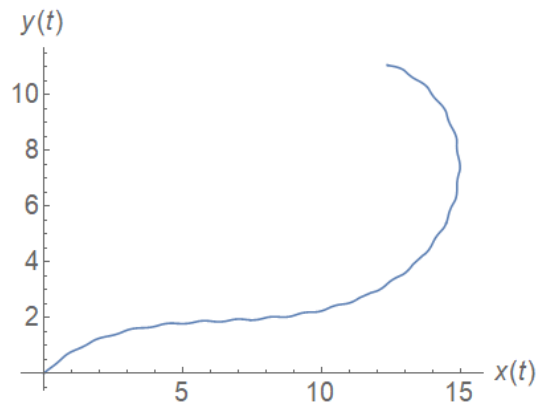
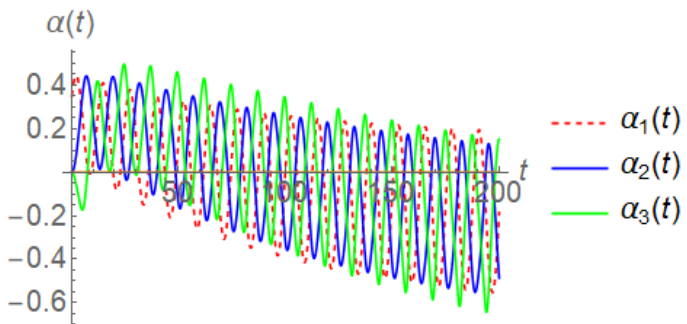
dA_θ

Singular Gaits

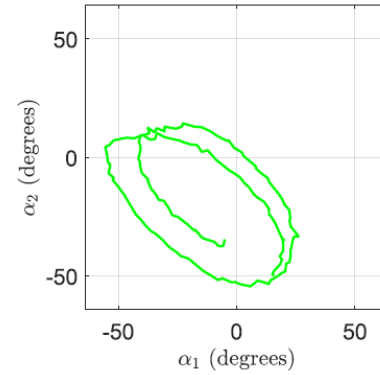
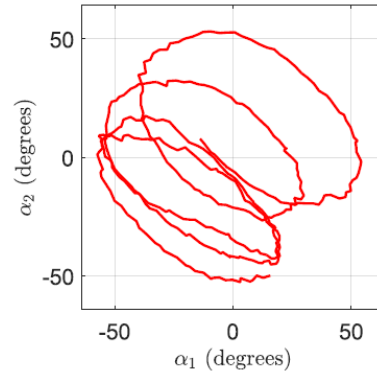
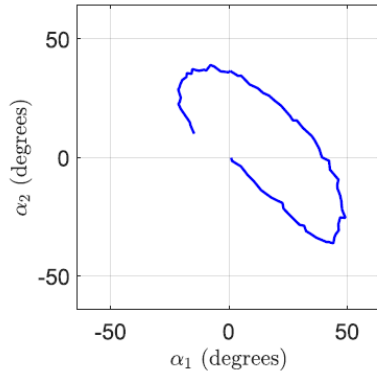
- Joints start near one another
- Insufficient damping to stop compliant joint crossing α_1



Stitching Gaits Together

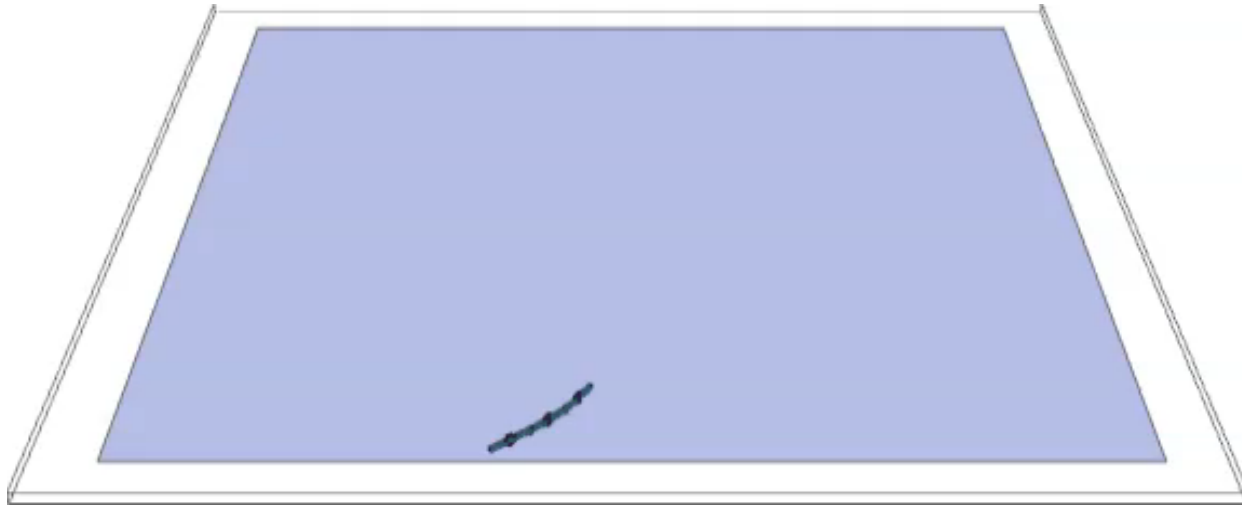


Navigation and Obstacle Avoidance



Adding External Actuation

- The robot system can be arbitrarily complex as long as we can model (or approximate the model) as kinematic—visual tools still apply!
- Ex: Passive snake on a moving plane

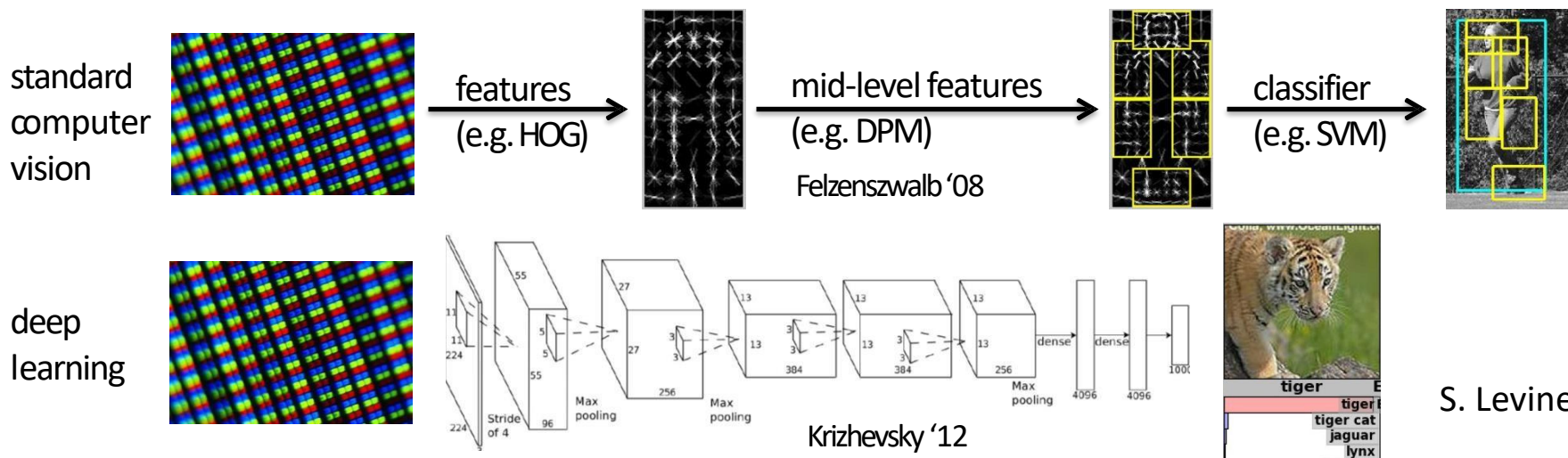


The Field of Robotics

- Robotics is a very *interdisciplinary* area that only partially encompasses CS
- This class: Covered “computational” aspects of many common tasks and goals
- In a sense, all of robotics is computational!
- We’ve only barely scratched the surface in both methods and applications
- Many other areas: Vision, learning, manipulation, planning, dynamics and control, multi-agent, human-robot interactions, ...
- Applications: industrial, medical, field, aquatic, bio-inspired, household, education, entertainment, autonomous vehicles, ...

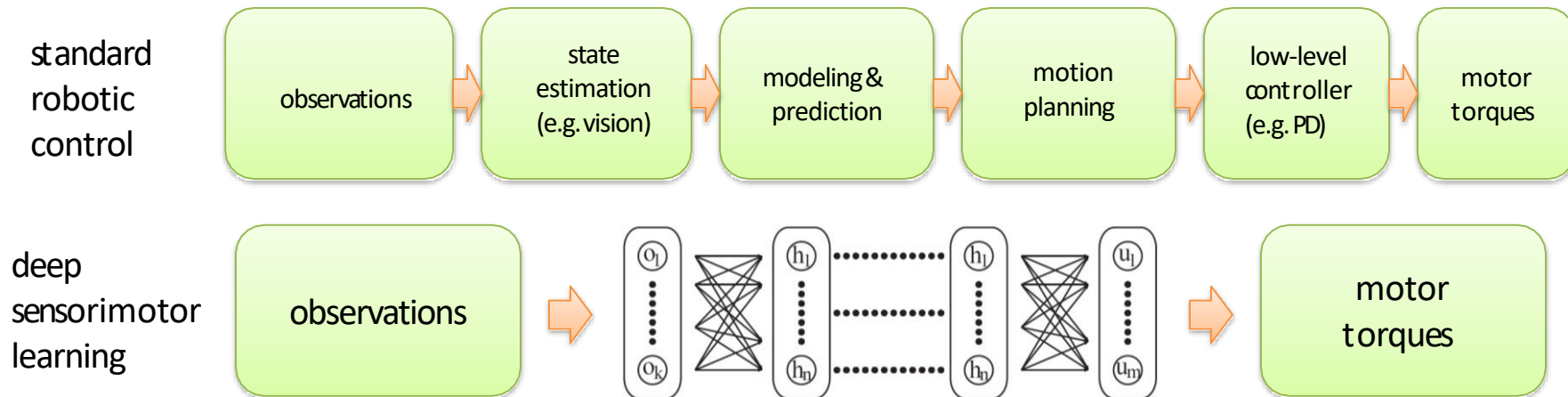
Case Study: Deep Learning and Robotics

- Many sub-areas and applications in robotics share tools and advances
- Recent successes in **deep learning** have contributed to multiple areas
- Deep learning in computer vision:

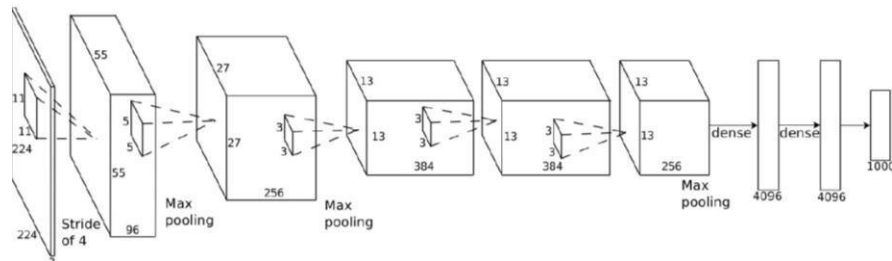


Deep Learning for Robot Control

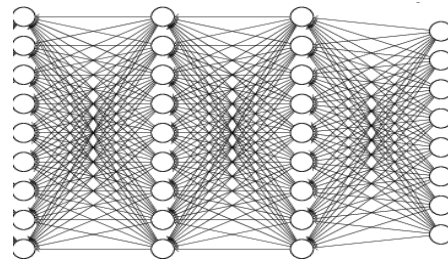
- Deep neural networks are really just fancy results of a regression
- We saw that many RL tasks can also be implemented using deep learning
- Ex: Robot control instead of vision



Deep Sensorimotor Loop

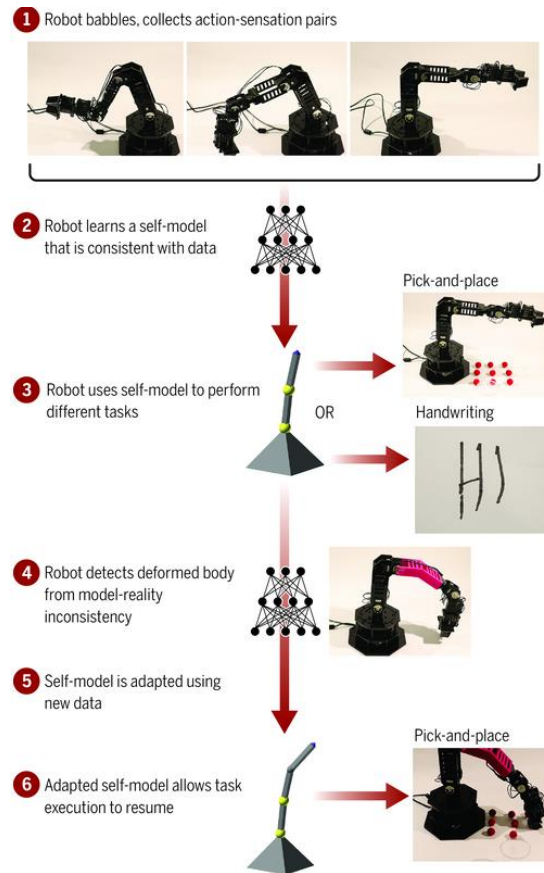


Action
(run away)



Deep Self Modeling

- R. Kwiatkowski and H. Lipson, 2019
- Instead of specifying a physical model, learn it entirely via RL and represent it with a DNN
- Model is not fixed; robot can continue learning and updating it as it gets new info
- Maybe closer to human control?



Deep Self Modeling



Deep Learning and Manipulation

- *Robot manipulation* is a highly complex task that combines (visual) perception, high- and low-level planning, and kinematic control
- Integrated sensorimotor loop is a natural candidate for a DNN representation
- Gathering data at Google Brain (S. Levine et al.):



Deep Learning for Pose Estimation

- Manipulation requires that a robot can recognize the pose of an object
- If using deep learning, large amounts of data are required
- NVIDIA: Successfully trained a DNN using synthetic (i.e., unlimited) data



Deep Learning and Assistive Robots

- Robots have huge potential to help people who need assistance in different ways, whether due to age, disability, injury, etc.
- E.g.: Fetching objects, preparing food/drink, dressing people
- Z. Erickson et al. (GA Tech): Train a DNN using forces instead of vision



Deep RL for Motion Planning

- Recall PRMs: Construct a graph by sampling and connecting points in C-space
- Determining connectivity can be expensive and/or wasteful!
- PRM-RL: Use RL to train an agent to determine point-point connectivity



Deep RL and Locomotion

- Locomotion can become a different control task for each possible robot morphology
- Traditional research specializes on particular robot classes: humanoids, quadrupeds, hexapods, snakes, fish, etc.



Bonus: Advances in Simulation

- While deep RL requires a lot of training data, another bottleneck for robotics often comes from simulation of complex physics
- NVIDIA: Use GPUs to simulate hundreds of robots to quickly learn a task
- Agents can even interact with one another



Other Deep Learning Applications

- Learning complex system dynamics in face of uncertainties, changing environments, partial state information, and high dimensionality
- Learning control policies as above
- Complex manipulation—deformable objects, tools, different geometries
- Advanced object detection, interpreting human actions and intentions
- High-level (human-level) task planning

Deep Learning Video Links

- [Deep self modeling](#) at Columbia
- [Data collection](#) at Google Brain
- [Pose estimation](#) at NVIDIA
- [Dressing robot](#) at Georgia Tech
- [PRM-RL](#) at Google Brain
- [Quadruped locomotion](#) at Google Brain
- [Robotic simulation](#) at NVIDIA

THANK YOU!

- Feel free to keep in touch if you're around next year
- Consider applying to be a TA for 4701 (AI) 😊
- Good luck on your finals and have a great summer!