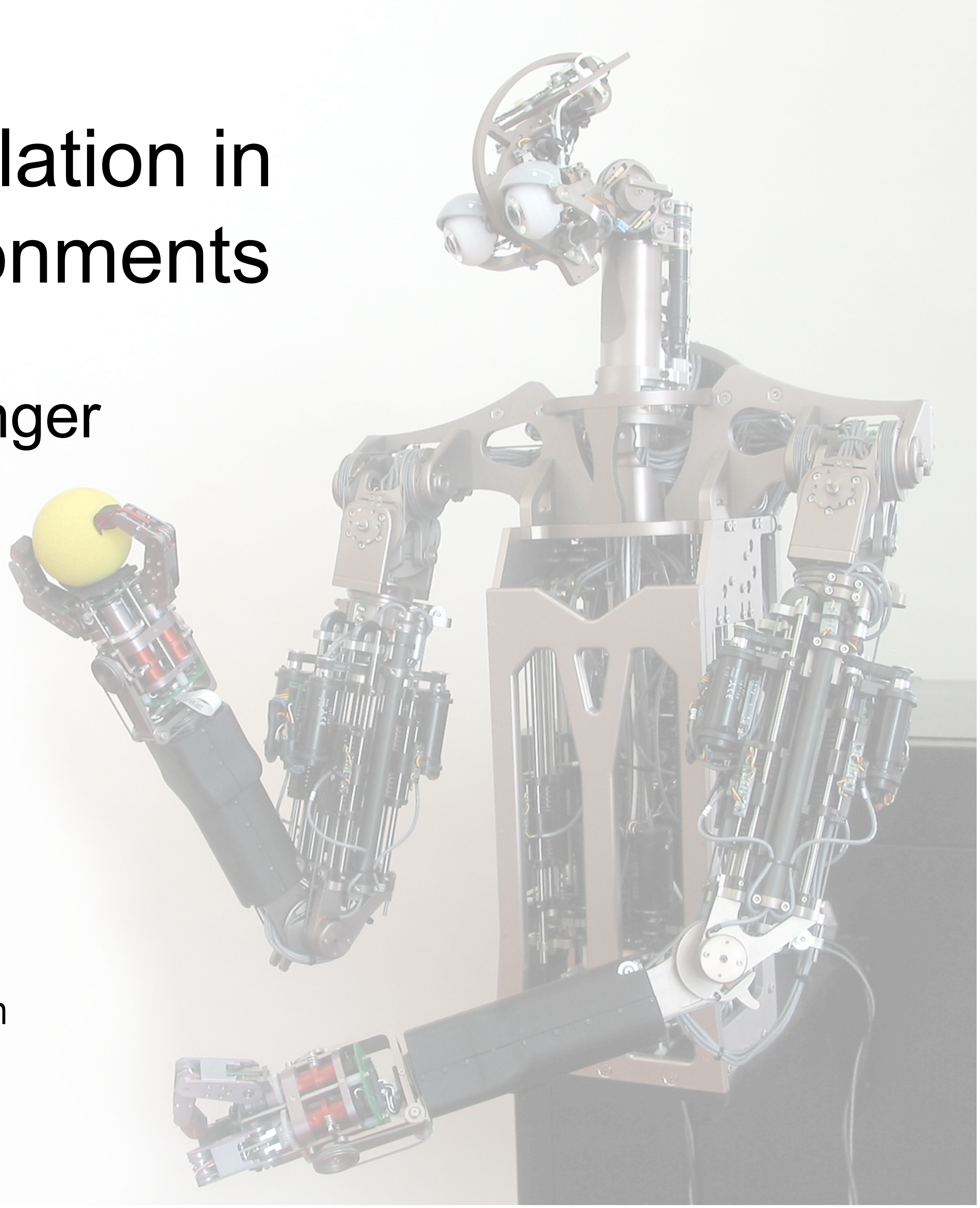
Robot Manipulation in Human Environments

Aaron Edsinger



CSAIL

Thesis committee
Rod Brooks, Daniela Rus, Rod Grupen

MIT EECS thesis defense
12.22.2006

Why manipulation in human environments?

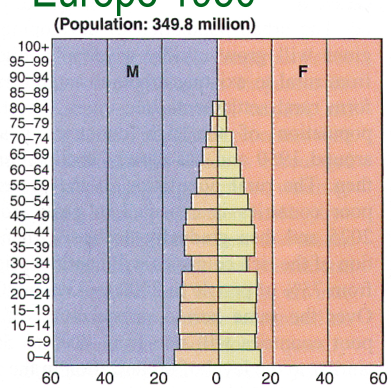
Robots that can work with people could…

Social	Extend the time an elderly person can live at home
Economic	Provide assistance to a worker on an assembly line
Laziness	Help with household chores

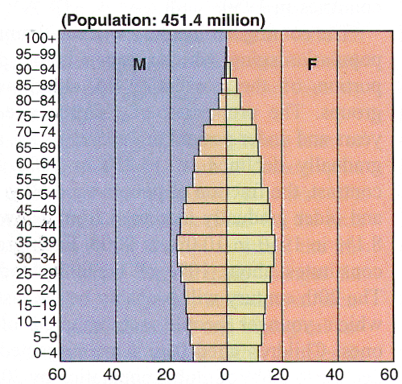
Changing Demographics

Worldwide shortage of qualified nurses…

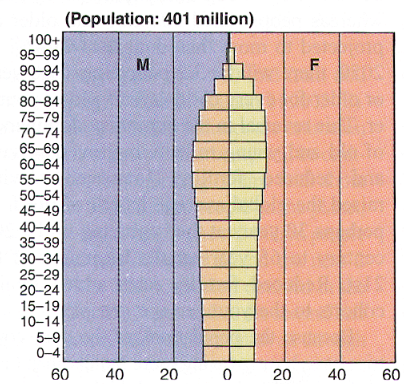
Europe 1950



2000

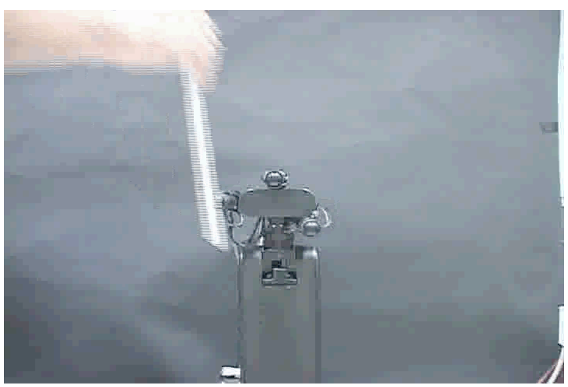


2050

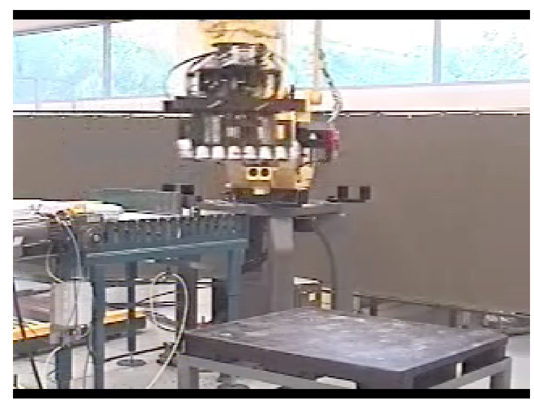


Where we are today…

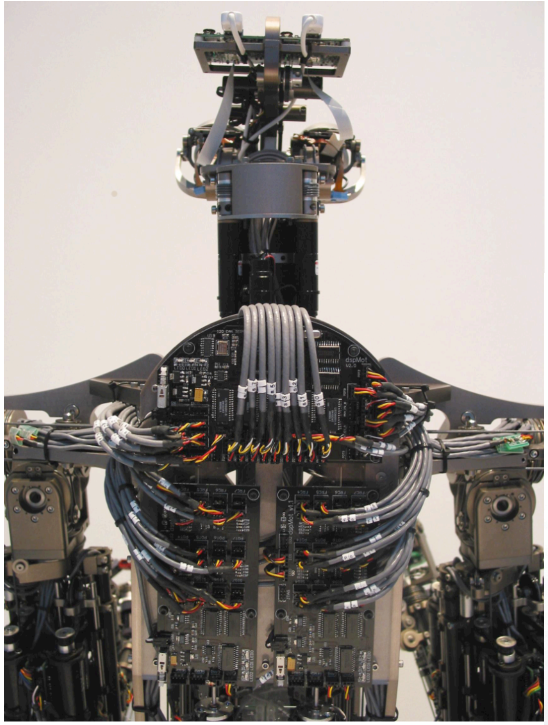
At, and beyond, human levels in specialized domains

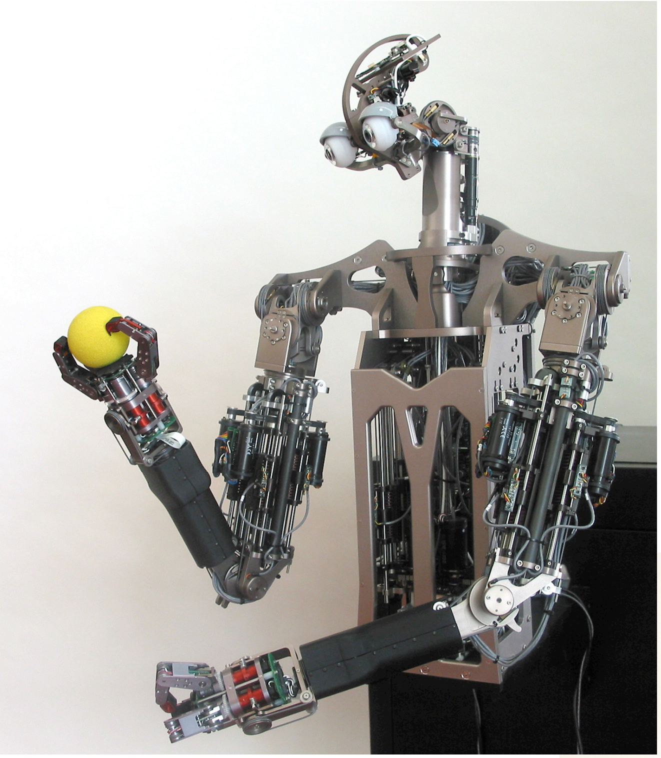


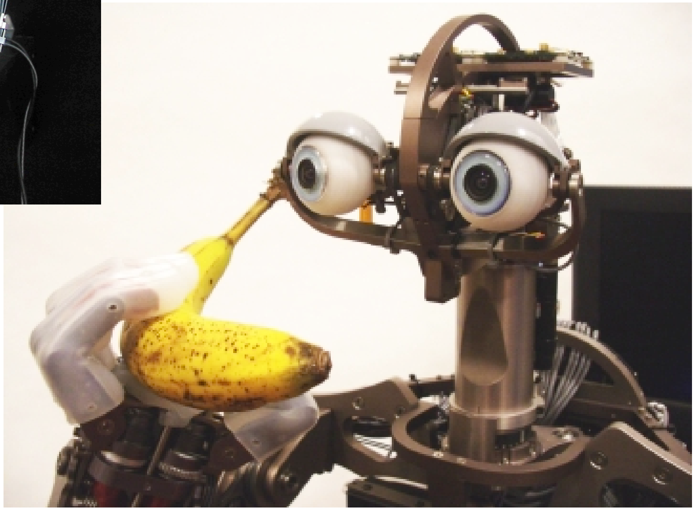
Dynamic Pen Spinning Using a High-speed Multifingered Hand with High-speed Tactile Sensor
(Ishihara, 2006)



Domo







What does Domo do?

Contributions

- Real robot
    - Force sensing and compliance
    - Intrinsic safety
    - Single, integrated behavior system

- Strategies for human environments
    - Let the body do the thinking
    - Cooperative manipulation
    - Task relevant features

- Accomplish useful, everyday tasks
    - Dynamics and variability
    - No object models

Collaborators

Charles Kemp

Jeff Weber

Roadmap

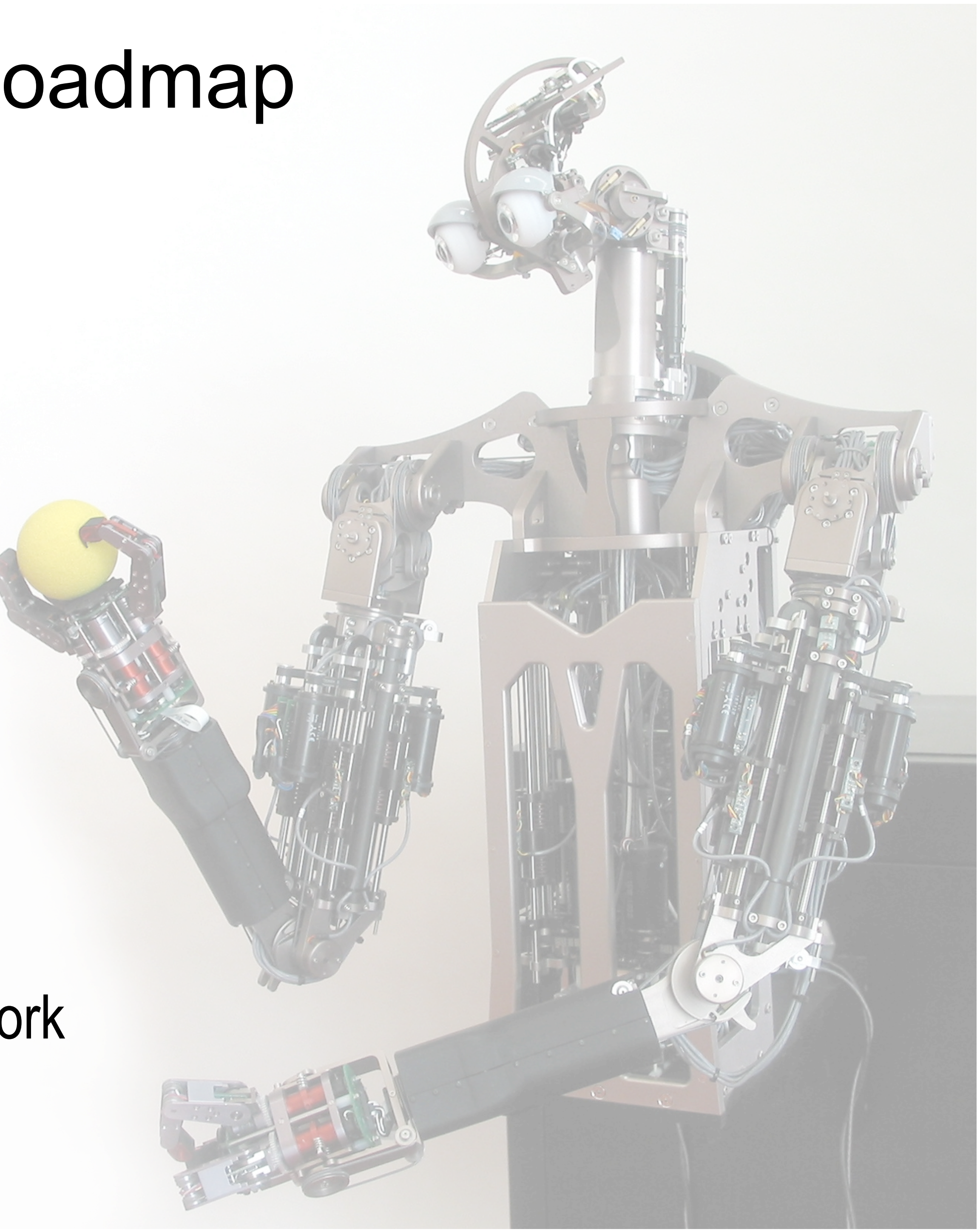
- Approach

- Robot design
- Visual system
- Control architecture

- Working with object tips
- Working with people
- Manual skills

- Helping with chores

- Conclusions and future work



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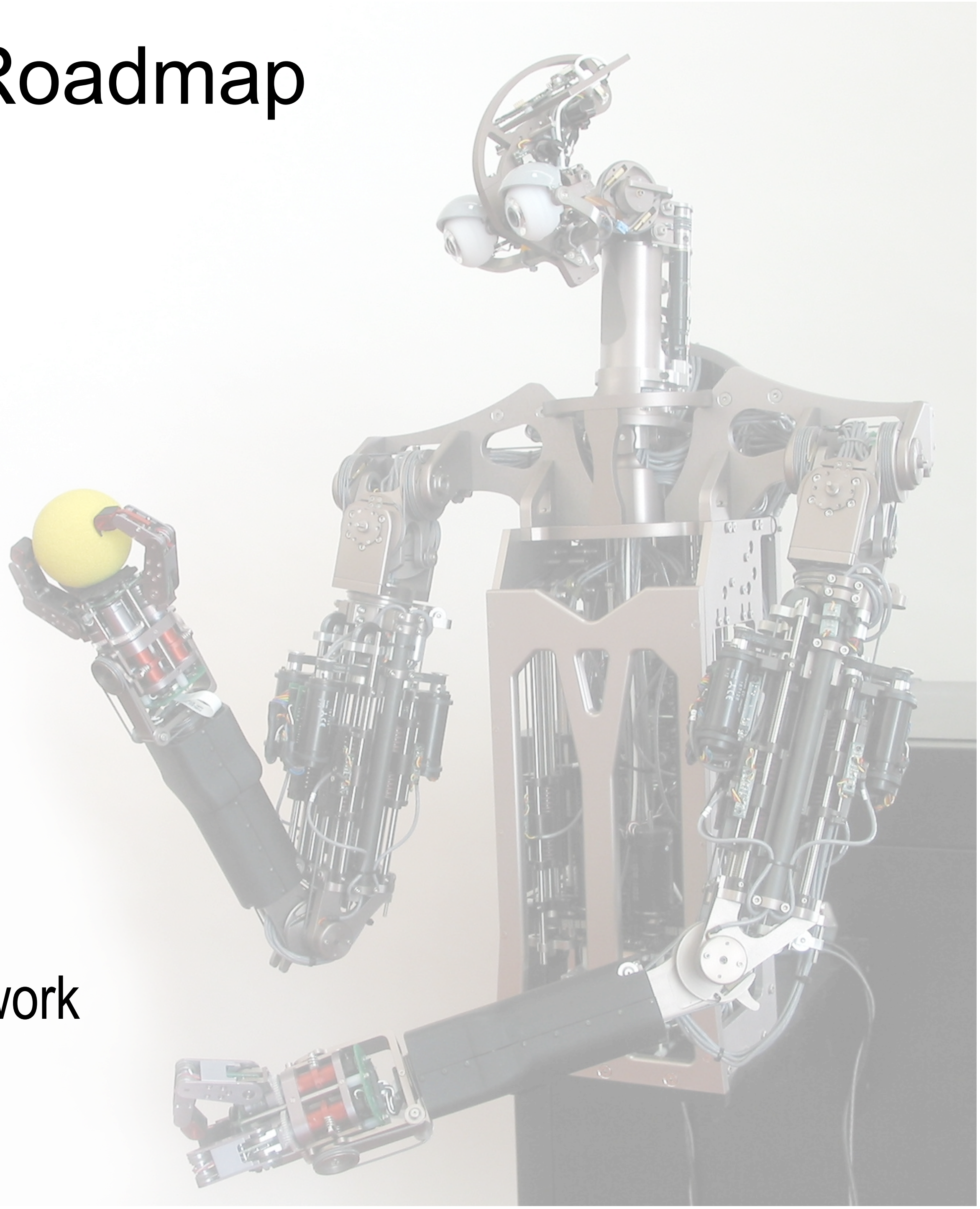
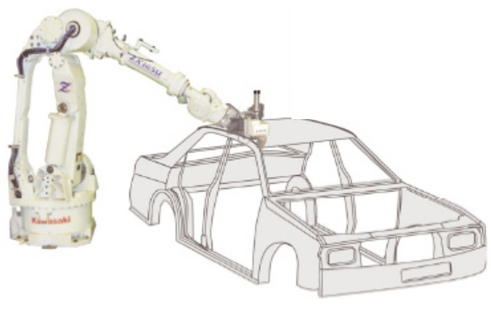
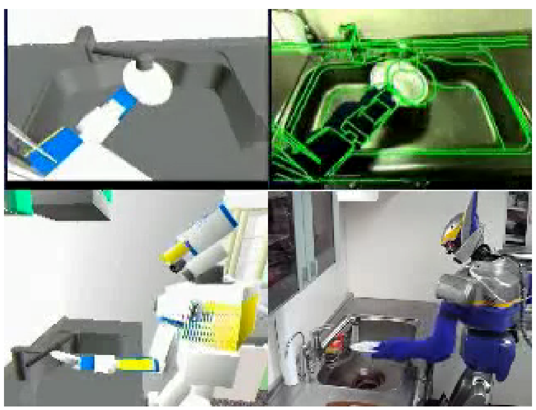




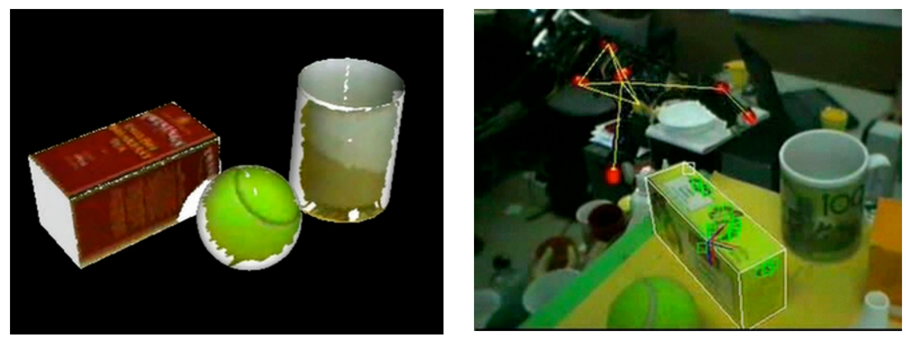
Controlled environments

Adapt the world to the robot

- World can be sensed and described with a 3D model
- Actions are mostly pre-planned
- Sensing within engineered constraints



Vision Based Behavior Verification System of Humanoid Robot for Daily Environment Tasks (Okada et al., 2006)



Robust Perception and Control for Humanoid Robots in Unstructured Environments Using Vision (Taylor, 2004)

Human environments

Adapt the robot to the world

If it works here … will it work here as well?

Uncertainty

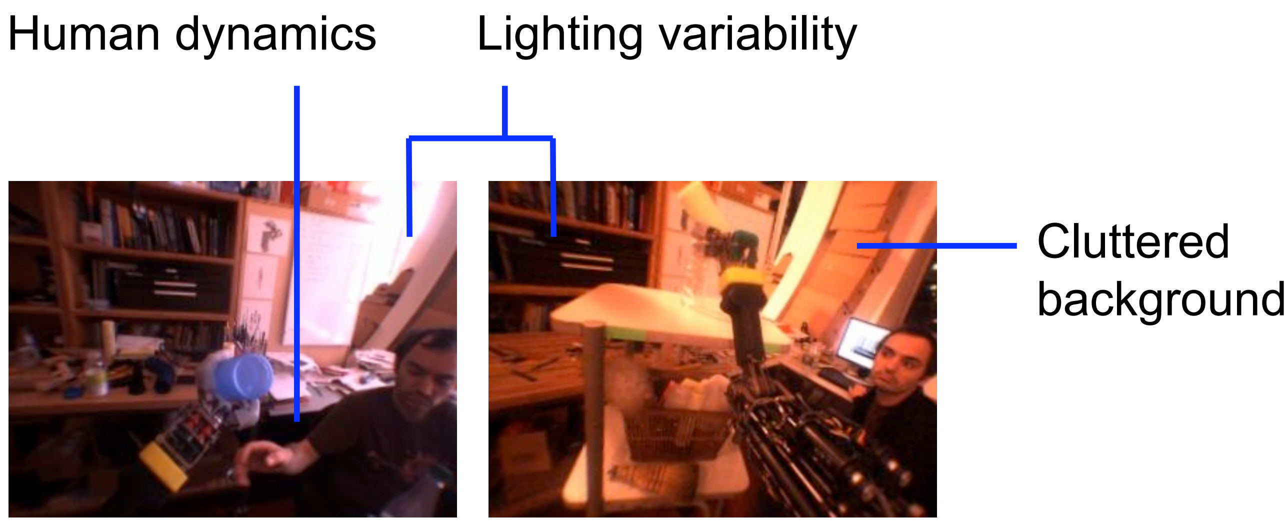
Sensing

- Beyond control of the robot engineer
- Unknown dynamics and variation

- Sensory noise and clutter
- Piecemeal view of the world

Human environments

Scope of work



What we do…

- Variety of everyday objects
- Variability in lighting
- Human dynamics
- Cluttered background
- No 3D object models
- No environment engineering

What we don't do…

- Naïve collaborators
- Multiple environments
- Autonomous grasping
- Autonomous task-planning
- Differing classes of objects

Strategies for human environments

- Let the body do the thinking
  - robot as more than a passive observer
- Cooperative manipulation
  - accomplish tasks as a human-robot team
- Task Relevant Features
  - structure in everyday objects and environments

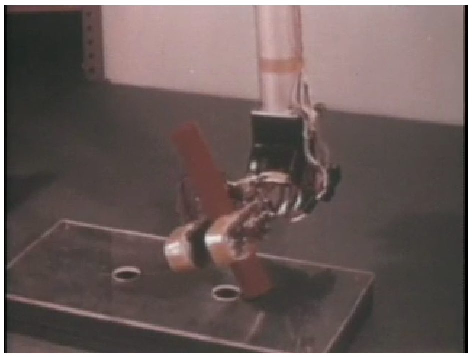
Let the body do the thinking

Compensatory actions under uncertainty

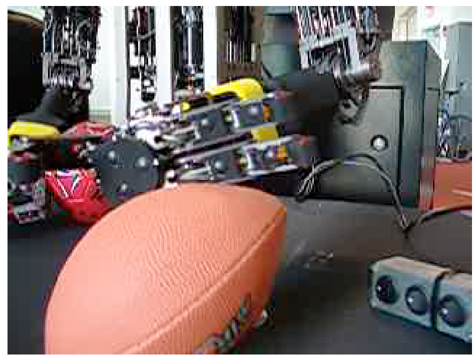
- Use arms as feelers in the dark
- Stiffen arm before inserting a key
- Rest a cup on a table before pouring
- Brace a hand on table while writing

Let the body do the thinking

Leverage compliance to reduce geometric uncertainty



(STANFORD, 1959)



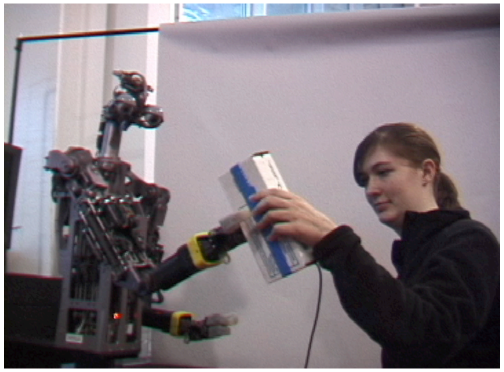
A body of human form can:

- work with human tools
- view countertops and shelves
- generate social cues

Cooperative manipulation

Manipulation as team effort

- Leverage human perception and planning
- Exploit natural social cues
    - Eye gaze
    - Reaching
    - Physical contact
- Smooth path to autonomy

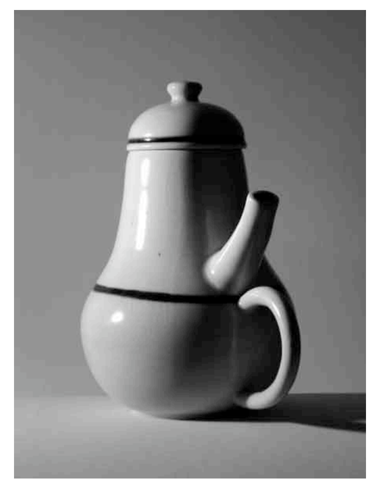


Task relevant features

Carefully select the aspects of the world that are to be perceived and acted upon…

1. Commonalities in everyday objects
2. Use sparse perceptual features
3. Features describe task, not object
4. Generalize across objects
5. Motor equivalence

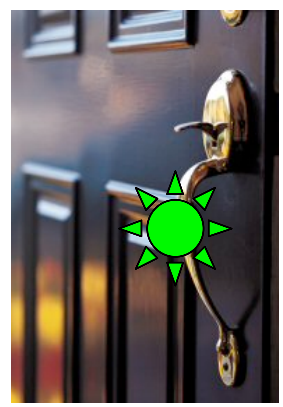
Learning to Grasp Novel Objects Using Vision
(Saxena et al., 2006)

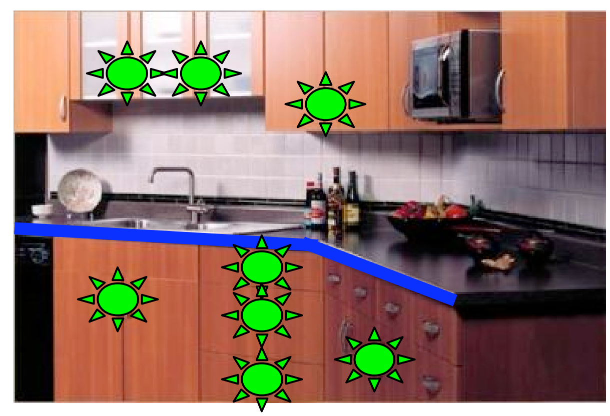


The Design of Everyday Things,
(Norman, 1990)

Task relevant features

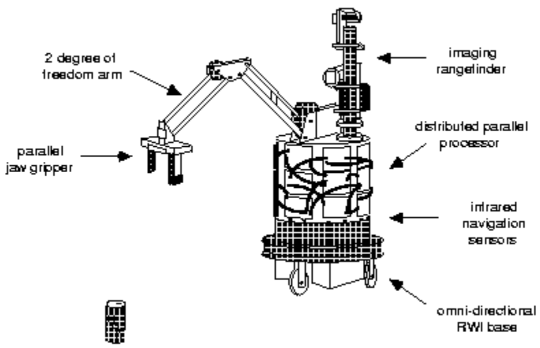
Carefully select the aspects of the world that are to be perceived and acted upon…





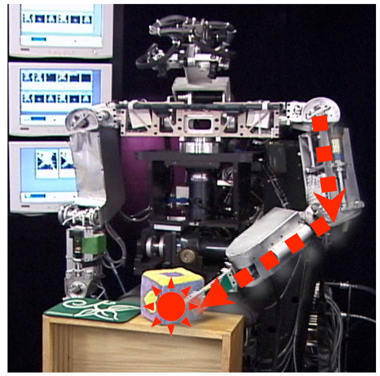
Pieces of the puzzle…

Exploiting environment structure



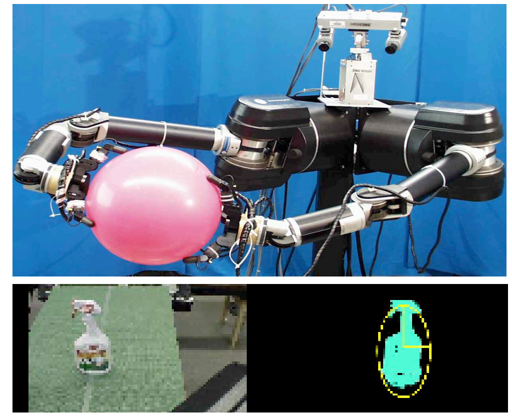
A Behavior Based Arm Controller
(Connell, 1989)

Using action to assist perception



Better Vision Through Manipulation
(Metta and Fitzpatrick, 2003)

Learning to grasp everyday objects



Learning and Generalizing Control-Based Grasping and Manipulation Skills
(Platt, 2006)

Sparse features for grasping

Learning to Grasp Novel Objects Using Vision
(Saxena et al., 2006)

Working with people and tools

Building an Autonomous Humanoid Tool User
(Bluethmann et al., 2004)

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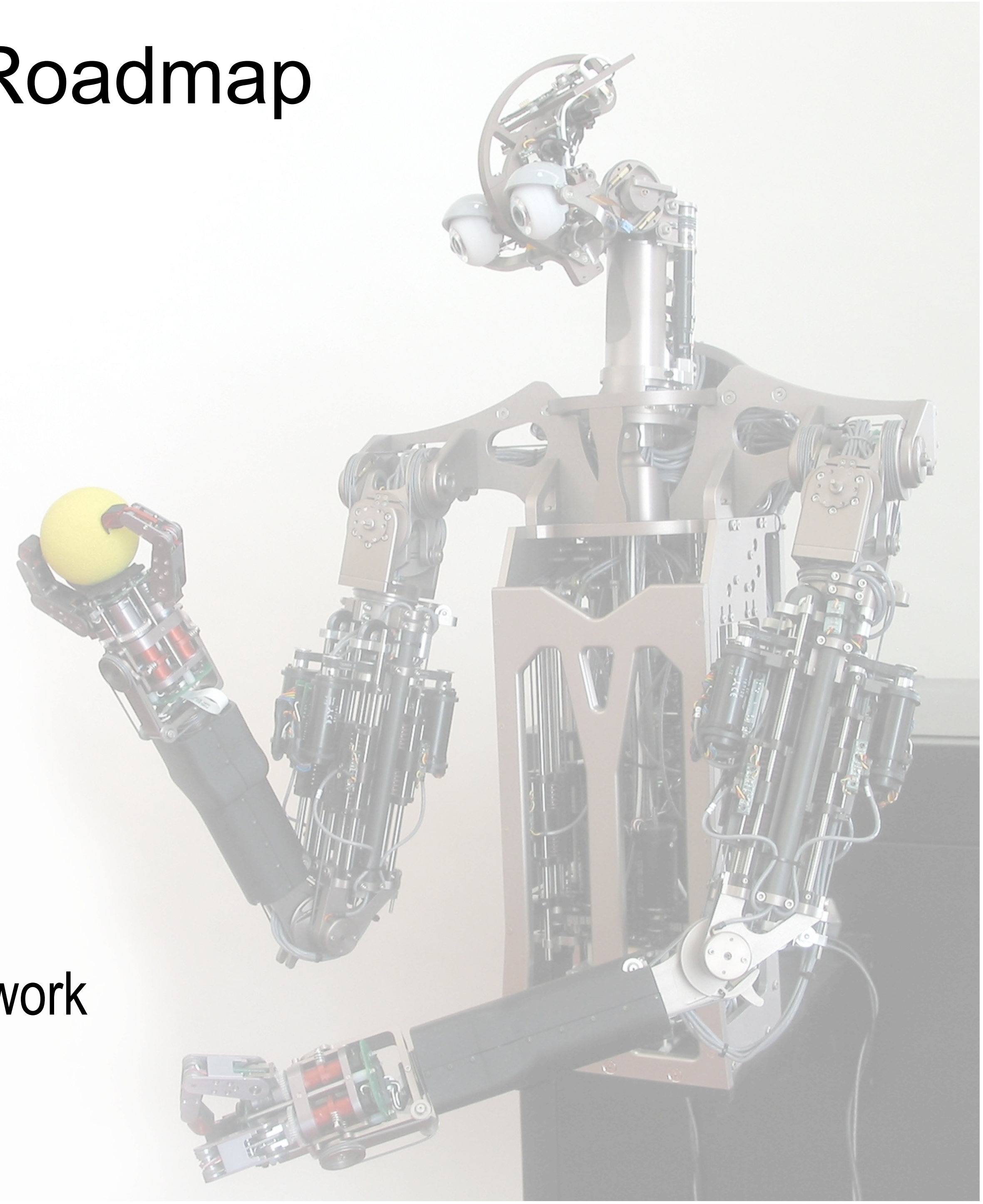
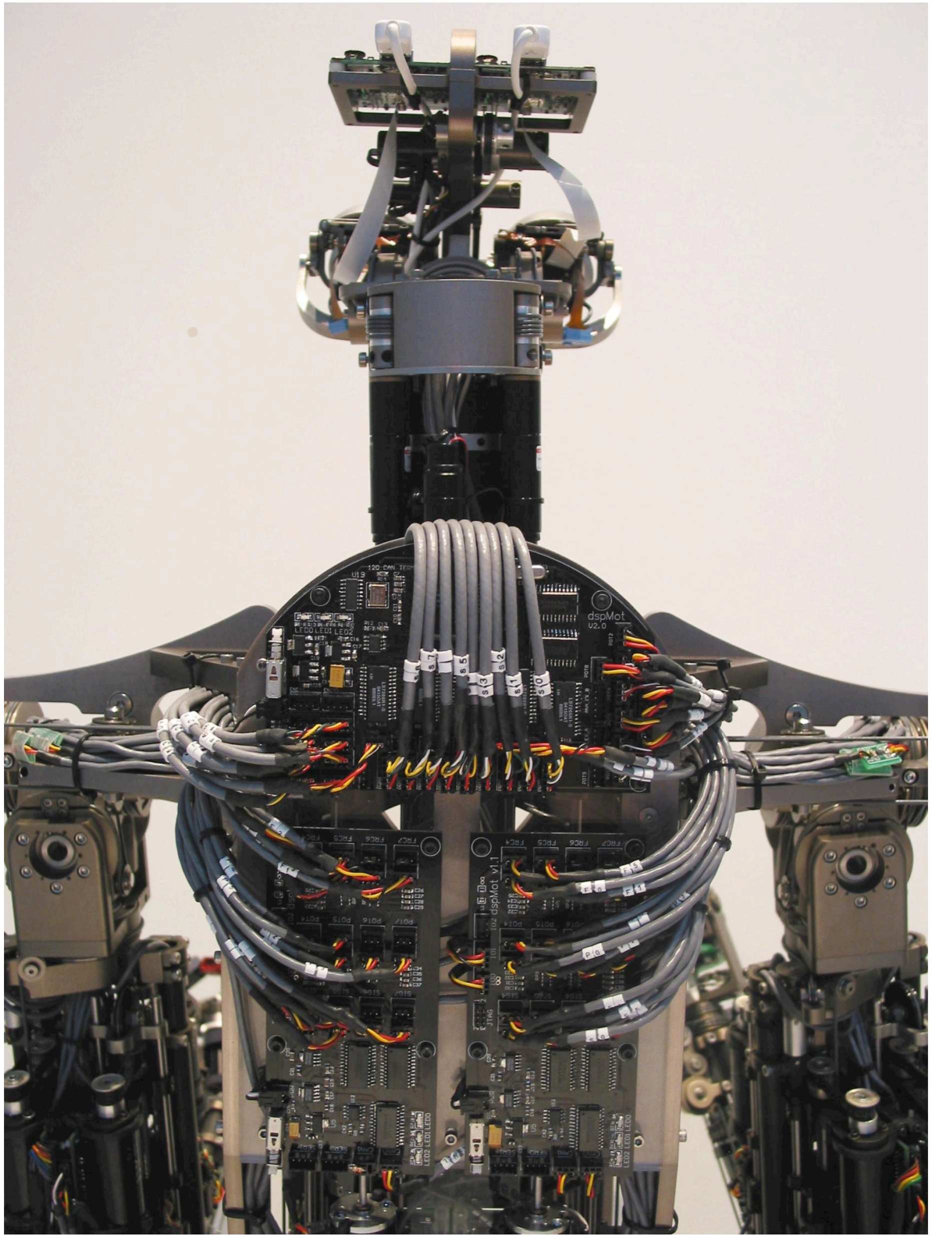
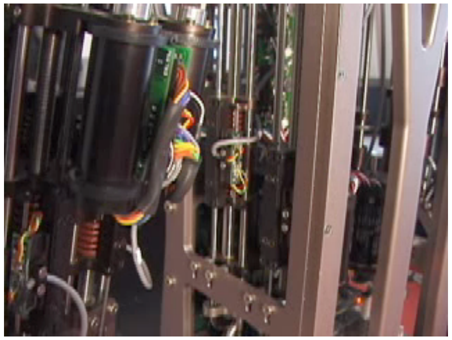




Domo

- 29 Degrees-of-Freedom
  - 7 DOF head
  - 2 DOF SEA neck
  - 6 DOF SEA arms
  - 4 DOF SEA hands
- Passive Compliance
- Force sensing
- 12 Linux PCs

Domo: A Force Sensing Humanoid Robot
for Manipulation Research
(Edsinger and Weber, 2004)



Series Elastic Actuators

(Pratt and Williamson, 1995)

Impedance above closed-loop bandwidth

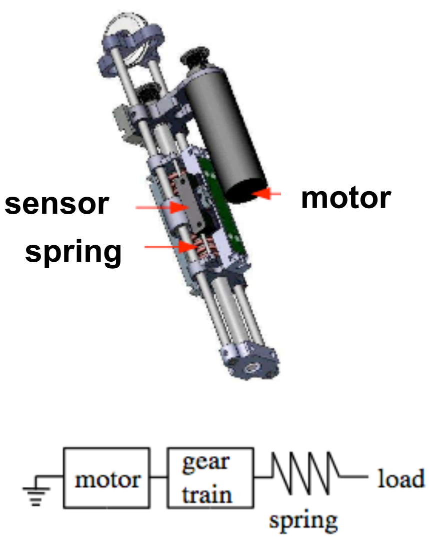
SEA

$$\frac{F_{load}(s)}{X_{load}(s)} = K_s$$

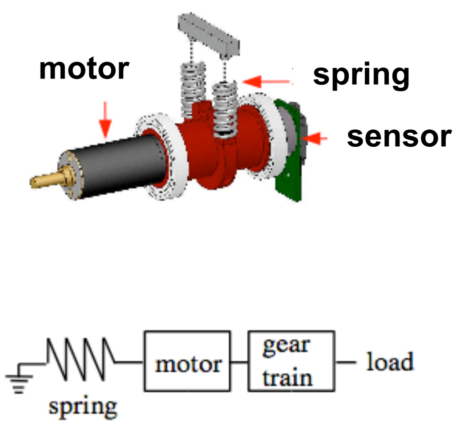
Traditional

$$\frac{F_{load}(s)}{X_{load}(s)} = s^2 N_{motor}^2 I_{motor}$$

Arms and neck

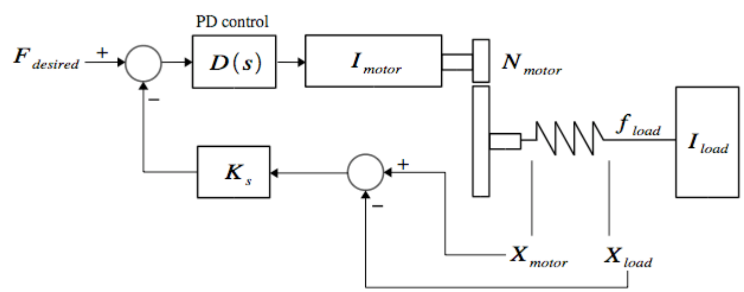


Hands

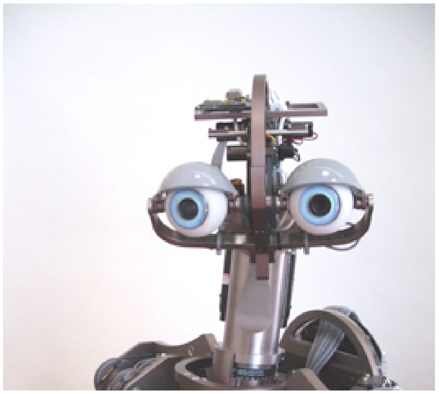


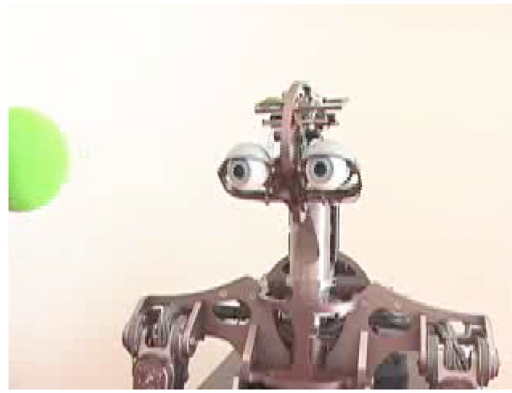
Impedance

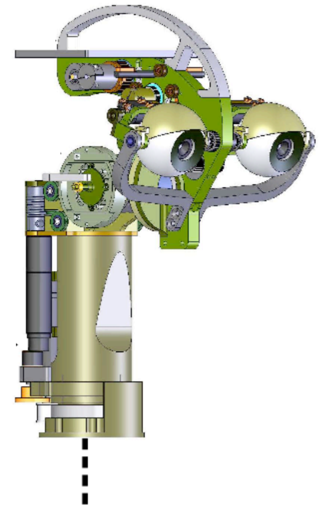
$$\frac{F_{load}(s)}{X_{load}(s)} = \frac{s^2 N_{motor}^2 I_{motor}}{\frac{s^2 N_{motor}^2 I_{motor}}{K_s} + 1 + N_{motor} D(s)}$$

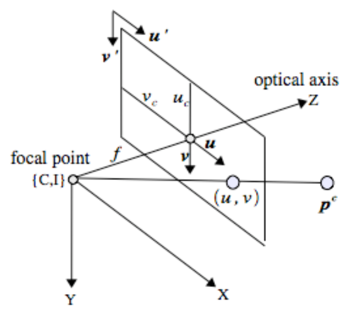


Head









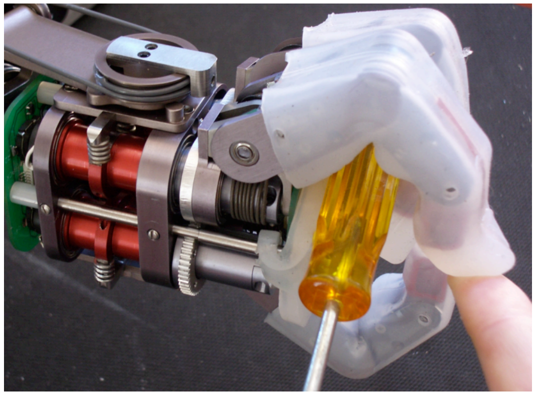
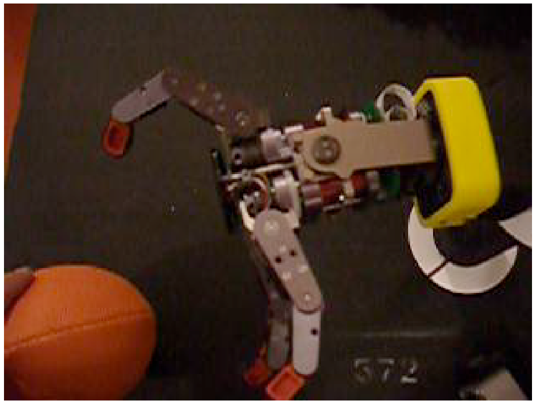
Calibrated camera model

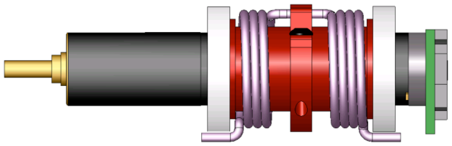
- 9 DOF
- SEA Neck
- Synchronized Firewire Cameras
- Gyroscope
- Encoders and potentiometers
- 1KHz DSP control
- Visual smooth-pursuit controller

Copy of the Mertz head, Designed by Jeff Weber

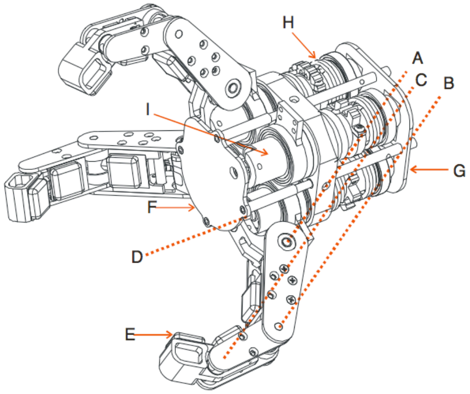
Mertz: A Quest for a Robust and Scalable Active Vision Humanoid Head Robot (Aryananda and Weber, 2004)

Hands

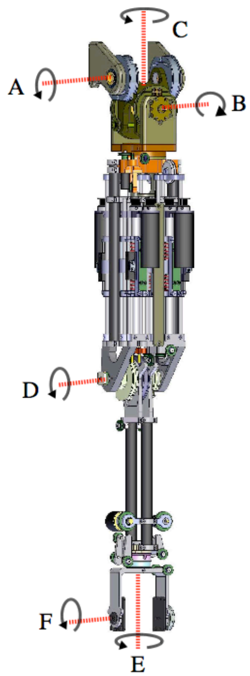


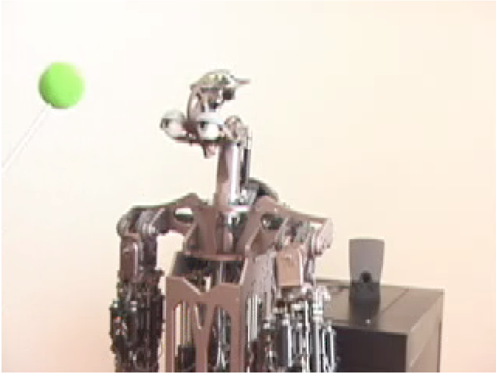
- 4 DOF
- Series Elastic Actuators
- Force and angle sensing
- 1KHz DSP control
- 0.4 kg
- Compliant skin
- Compliant fingertips



Design of a compliant and Force Sensing Hand for a Humanoid Robot (Edsinger, 2004)

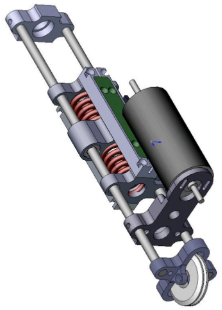
Lightweight compliant manipulators

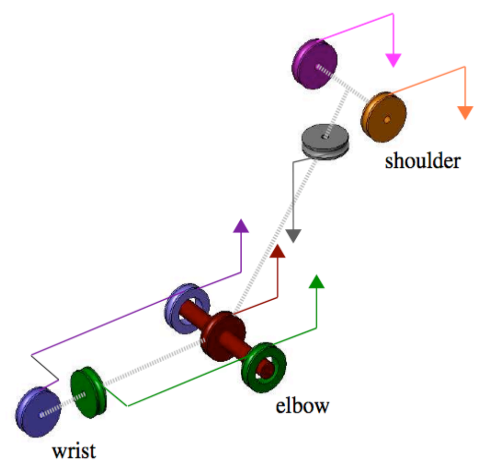




Controllers for:

- •Joint Force
- •Gravity compensation
- •Joint Angle
- •Virtual spring
- •Inverse kinematics



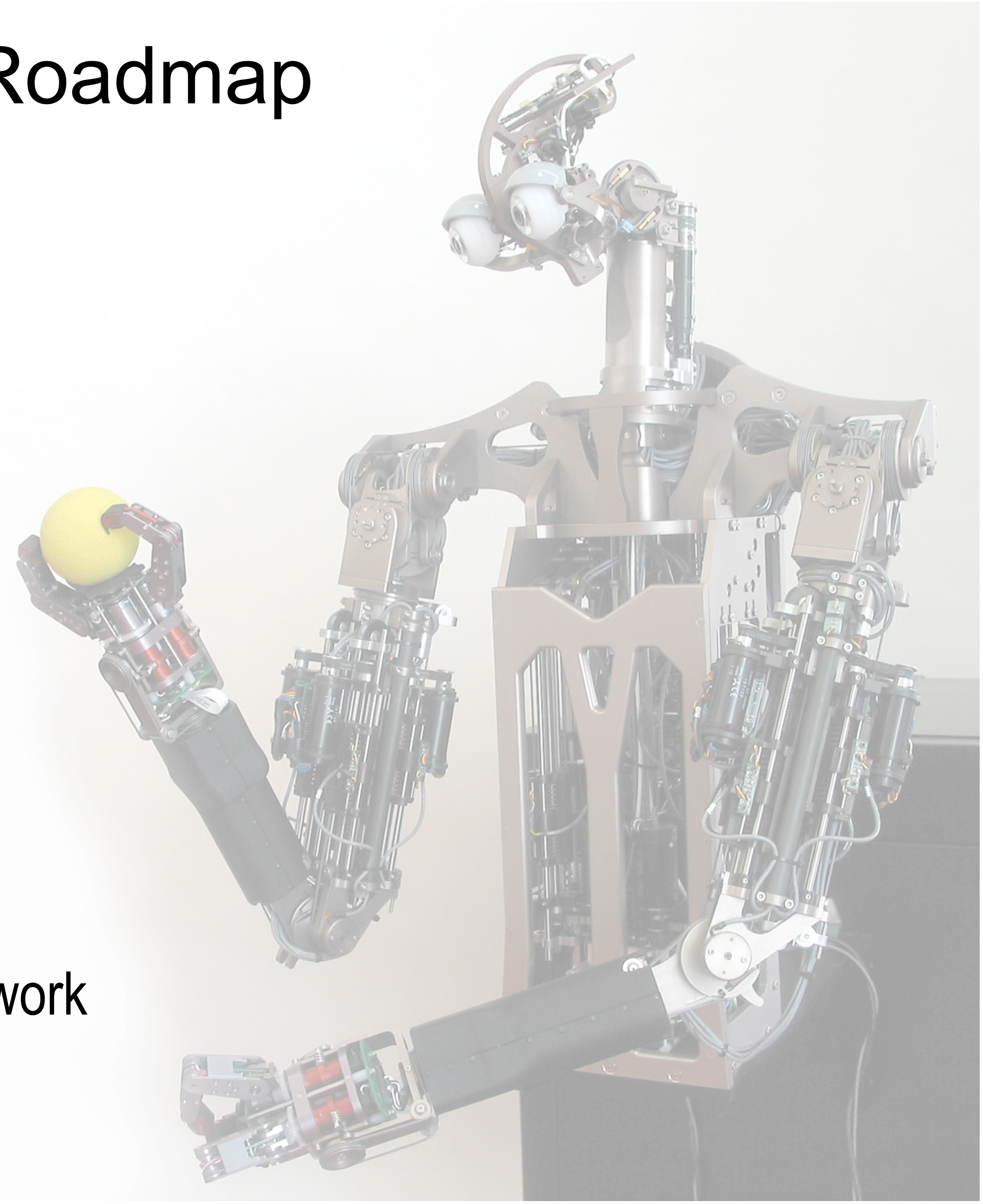


Cable routing

- •6 DOF
- •Cable drive
- •Series Elastic Actuators
- •Force and angle sensing
- •1KHz DSP control
- •2.2 kg
- •Intrinsic safety
- •2 kg payload

Design in collaboration with Jeff Weber

Roadmap



•Approach

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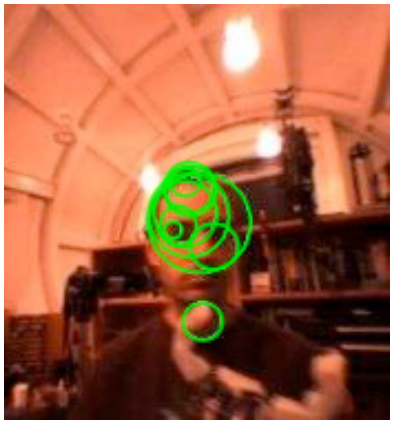
•Visual system
•Control architecture

•Working with object tips
•Working with people
•Manual skills

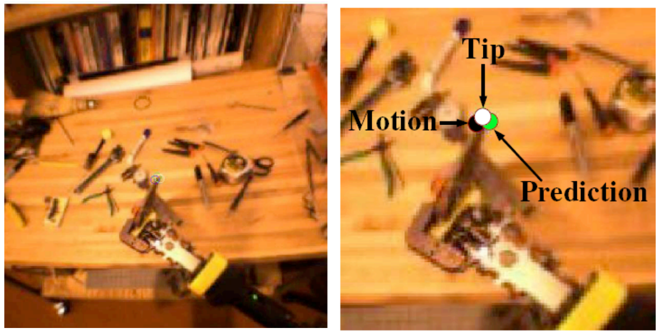
•Helping with chores

•Conclusions and future work

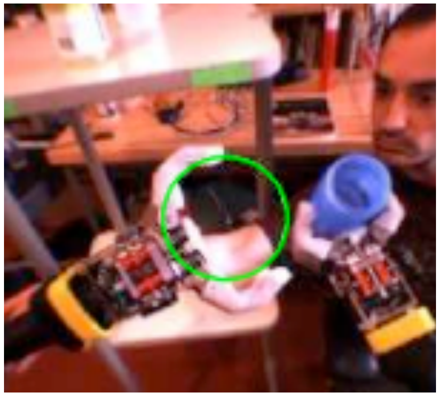
Using motion cues…



Regions of interest



Robust to lighting and clutter

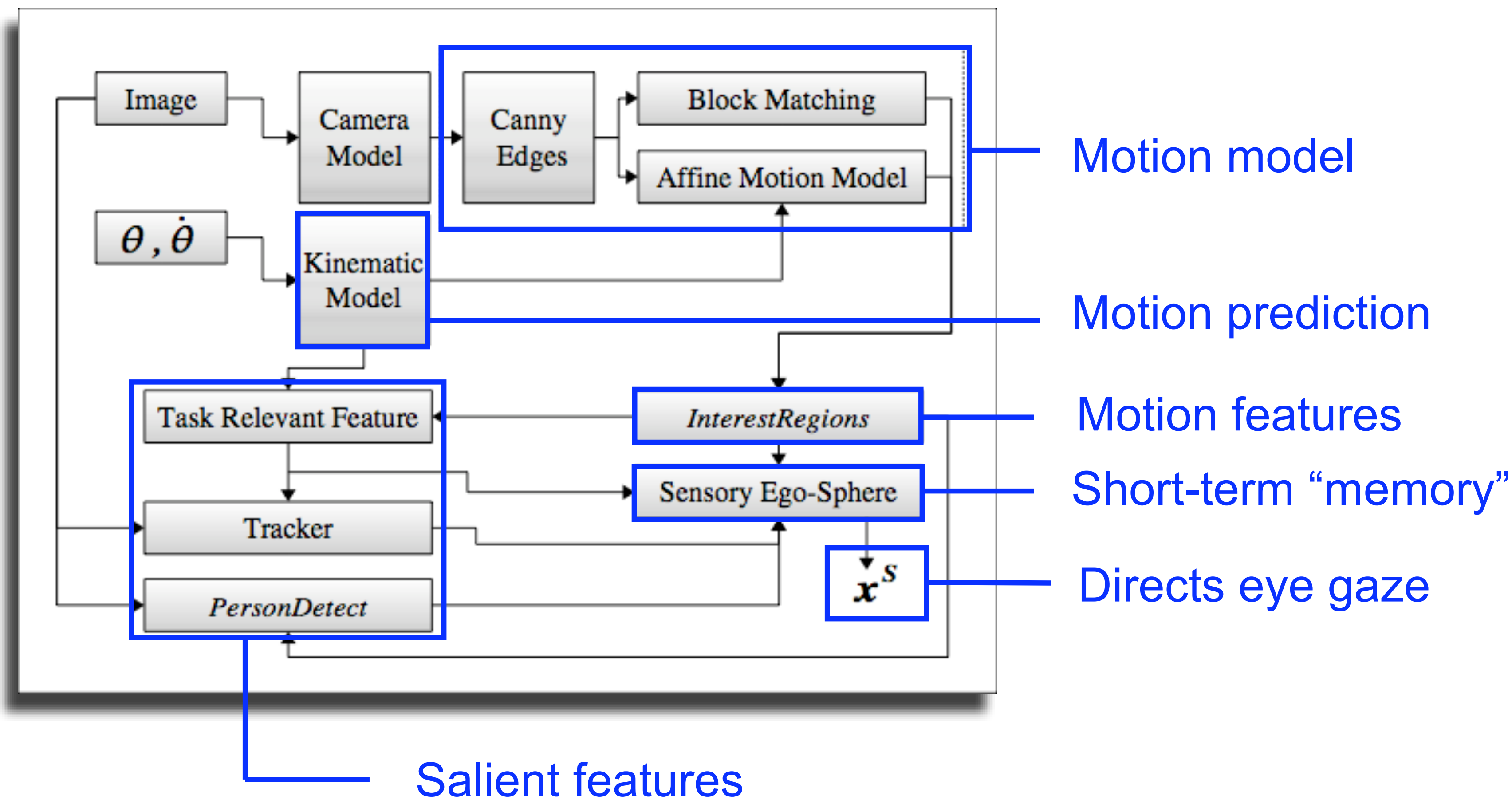


Generating motion to assist perception

Predictions to increase salience

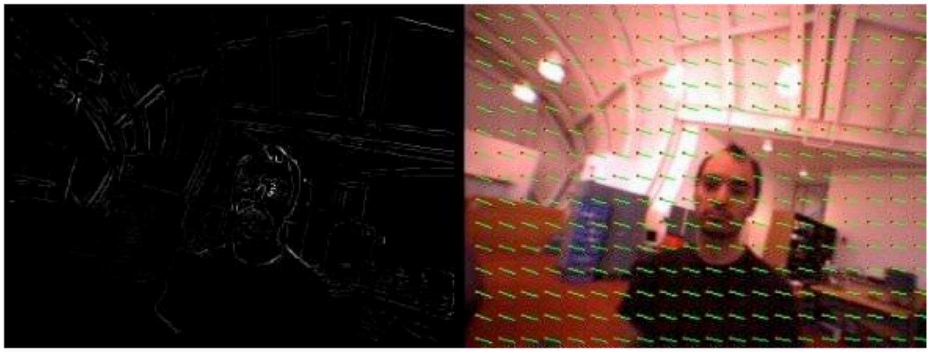
Visual attention system

Consolidate perceptual streams into a single spotlight of attention



Affine motion model

Work by Charles Kemp



$$\begin{bmatrix} u_2 \\ v_2 \end{bmatrix} = \underbrace{\begin{bmatrix} a_1 & a_2 & a_3 \\ a_4 & a_5 & a_6 \end{bmatrix}}_{A} \begin{bmatrix} u_1 \\ v_2 \\ 1 \end{bmatrix}$$

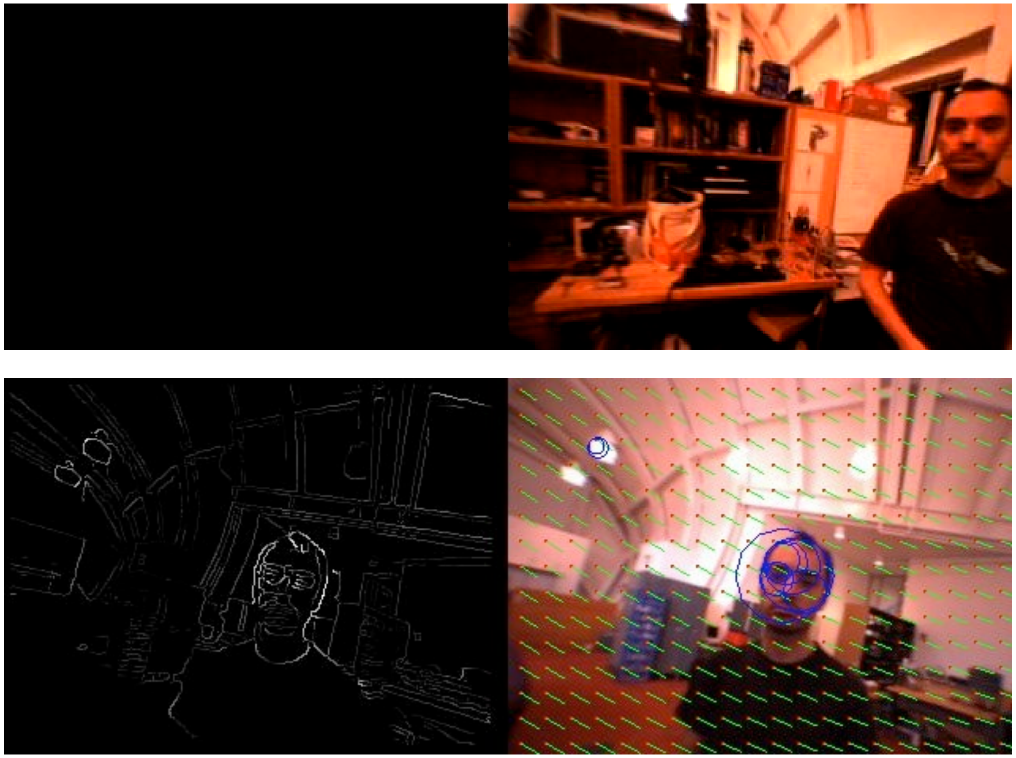
- Estimate global motion of edges (A)
- Select for edges that violate model

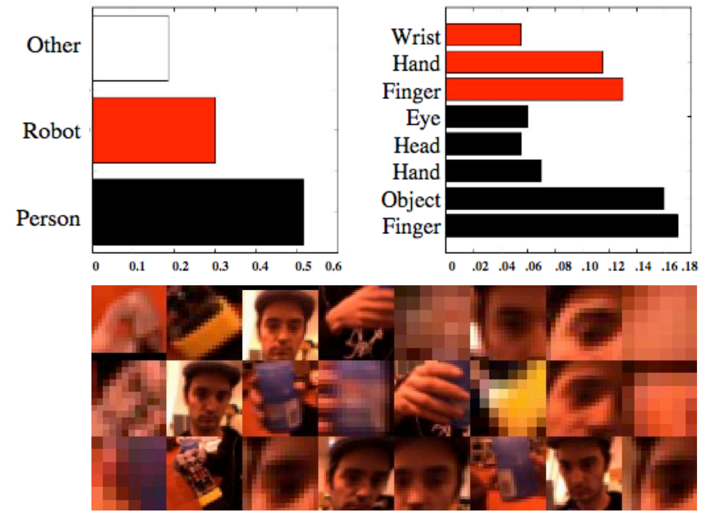
Generates weighted edge map of foreground motion

1. Canny edge detector on consecutive images
2. Block matching to estimate translation of each edge
3. Compute covariance matrix C of block matching error for each edge
4. Fit model A to translations when weighted by C (weighted linear-least-squares)
5. Iterate the fitting process
6. Weight each edge by how well translation fits A (Mahalanobis distance)

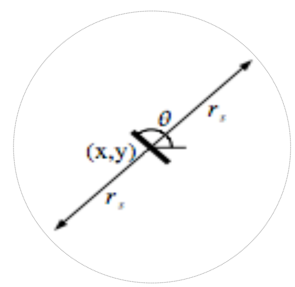
Interest regions

Work by Charles Kemp





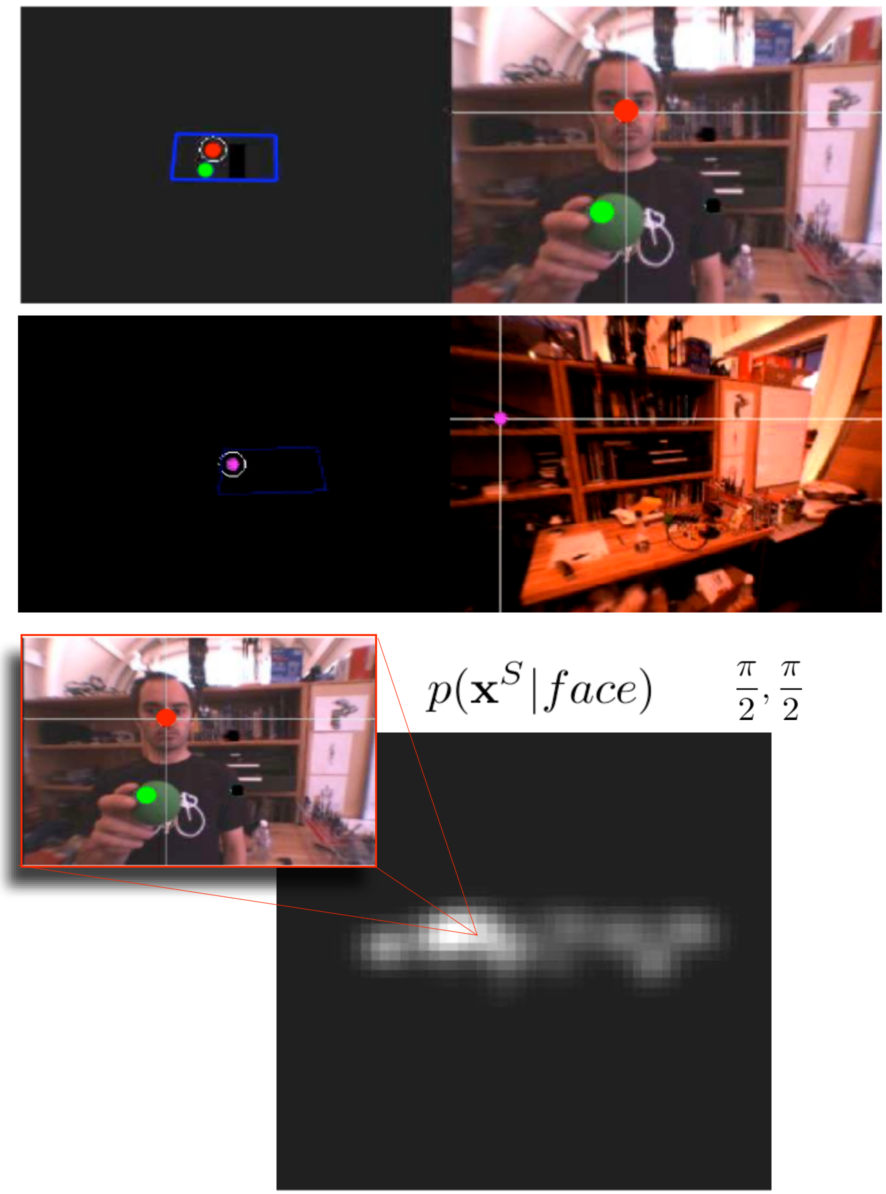
Selects regions important for interaction and manipulation



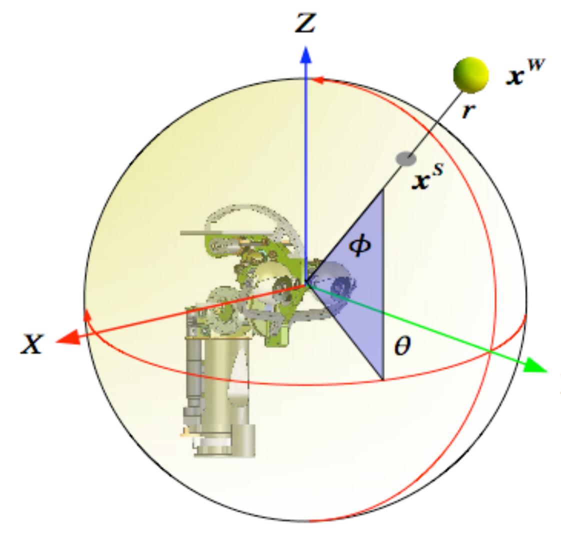
Convex edges define circular region in given scale-space

- Weighted edge map from motion model
- Select strongest responding regions at multiple-scales

Sensory Ego-Sphere



The Sensory Ego-Sphere as a Short-Term Memory for Humanoids
(R. A. Peters et al., 2001)



$$\mathbf{x}^S = [\theta, \phi, r]$$

- Short term memory
- Improves stability
- Multi-modal registration
- Learn spatial distributions

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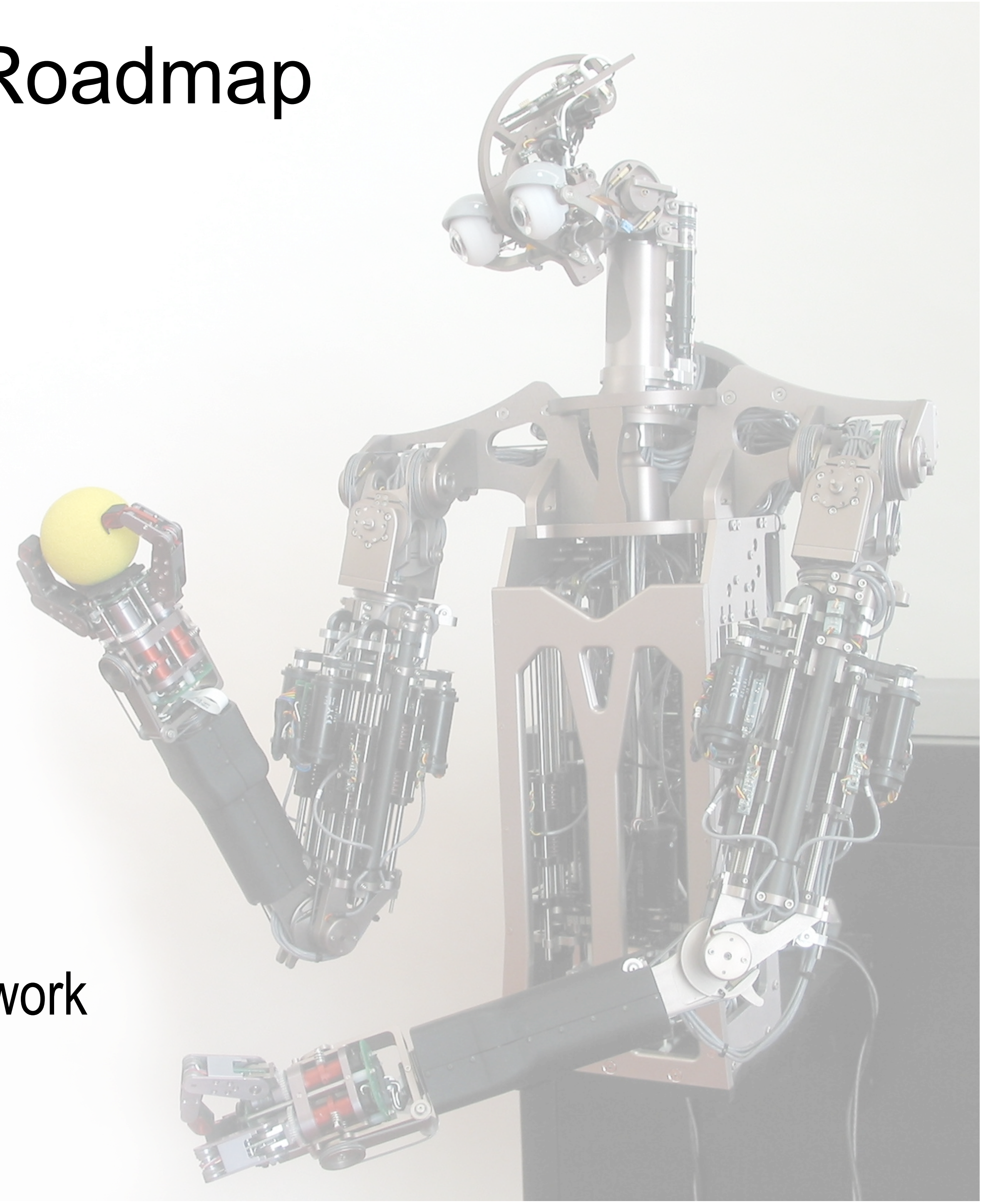
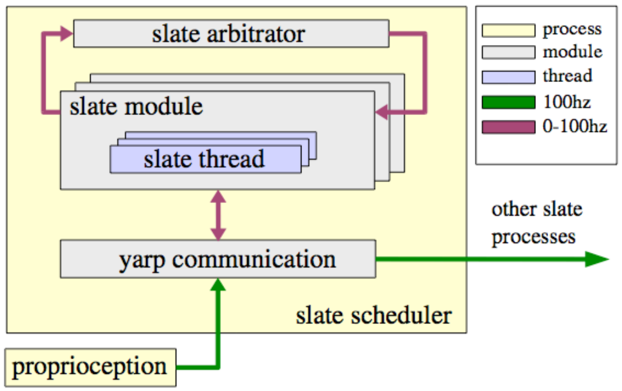


Slate

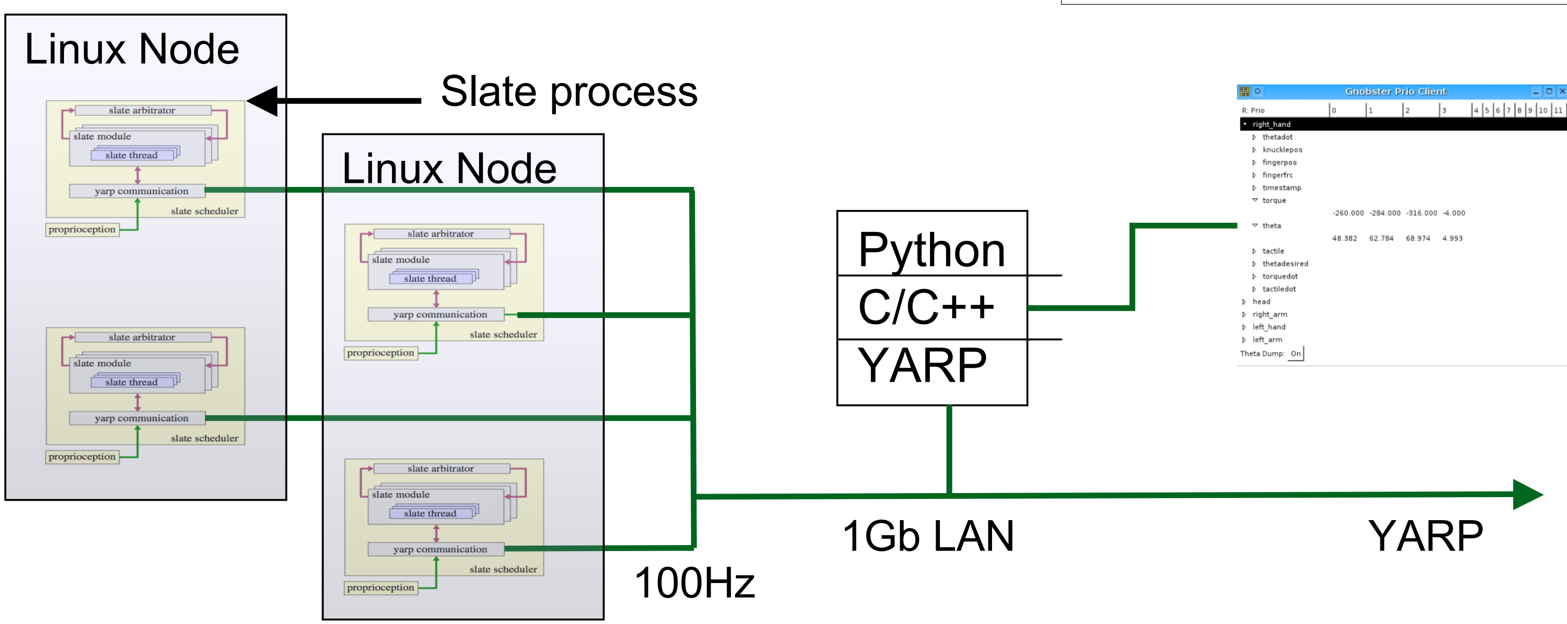
A tool for specifying time contingent behaviors



Components

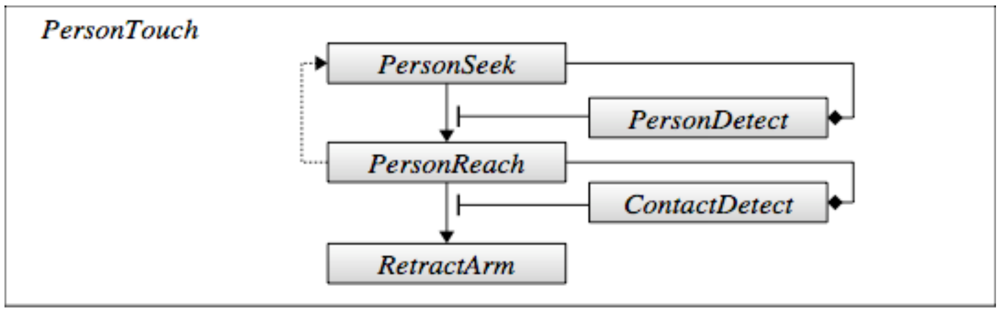
- •Scheduler
- •Modules ~= behaviors
- •Threads
- •Wires and Arbitrators
- •Monostables
- •FSAs with timing

- •Tools for rapid prototyping
- •Libraries for vision, learning



Designing manipulation tasks

Compose tasks through coordination of perception and control modules

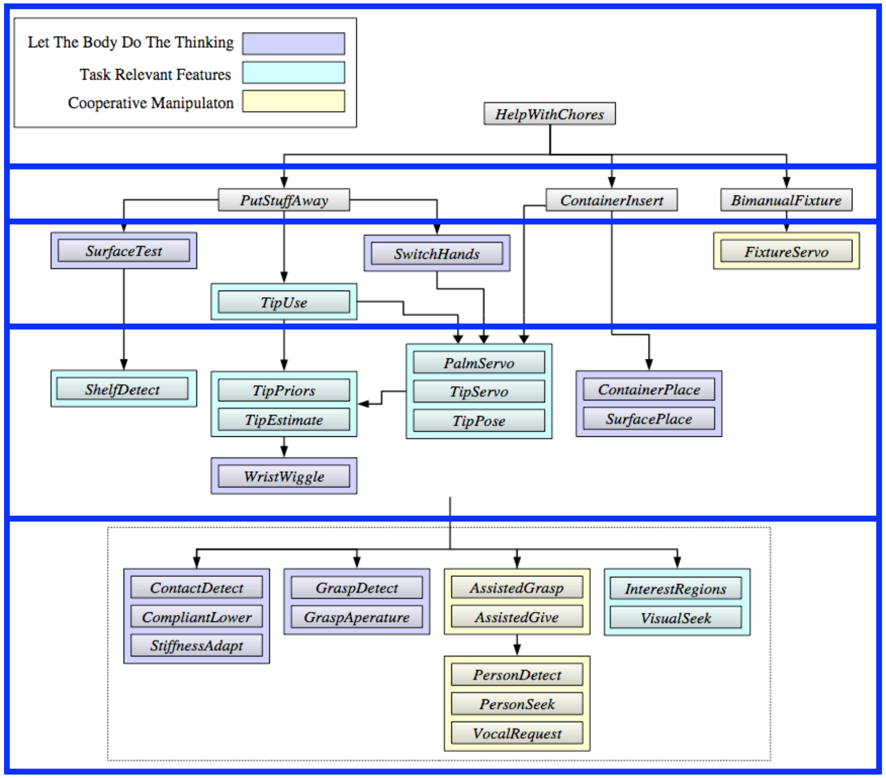


Module
- Local task knowledge
- Estimate readiness

Module interaction
- Adjust activation priorities
- Communicate through the world

Models and learning
- Simple prior models
- Control feedback to correct for model errors
- Offline learning for detectors

Task decomposition within Slate



Single, integrated system

Integrated tasks

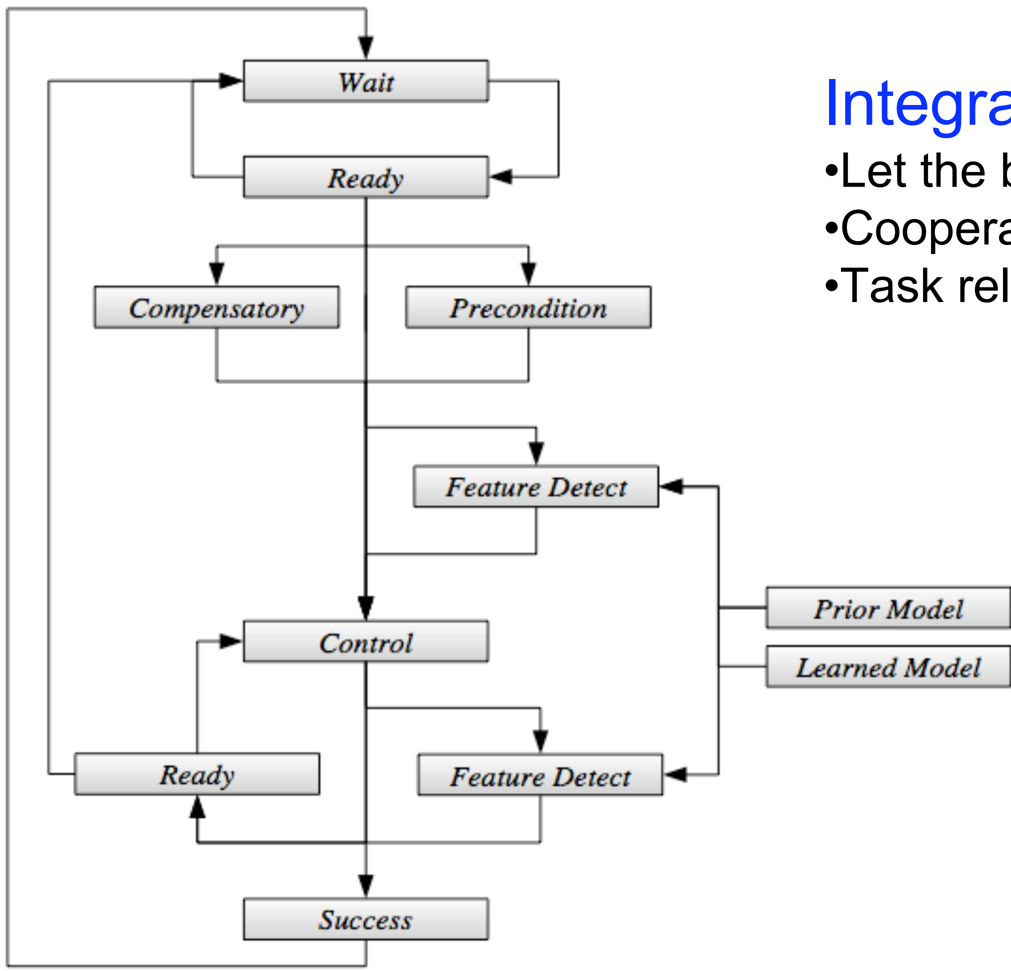
Manual skills

Task relevant features
Compensatory actions

Detectors and motor primitives

Main Process
125 Threads, 40 Wires, 35 FSAs, 10 Arbitrators

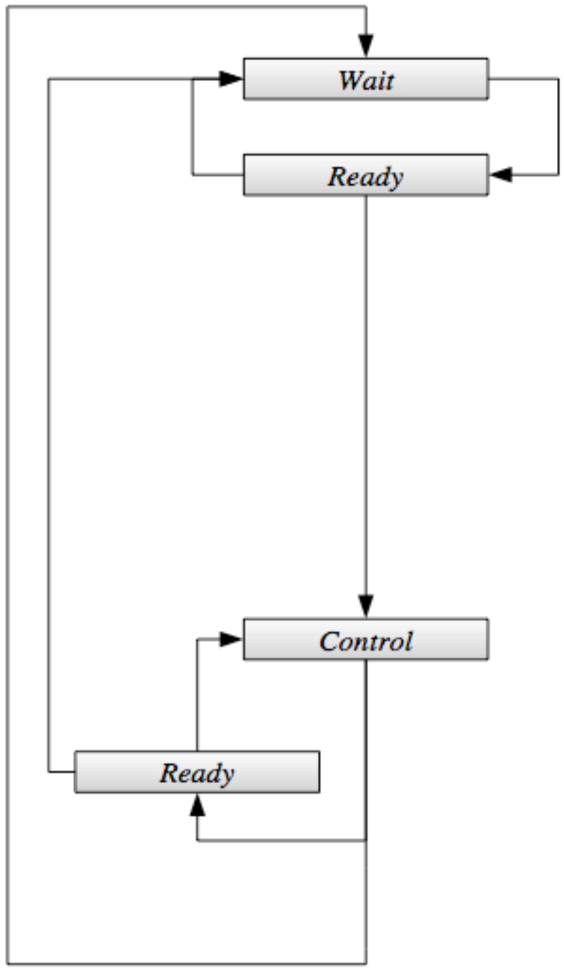
Manual skill algorithm



Integration

- Let the body do the thinking
- Cooperative manipulation
- Task relevant features

Manual skill algorithm

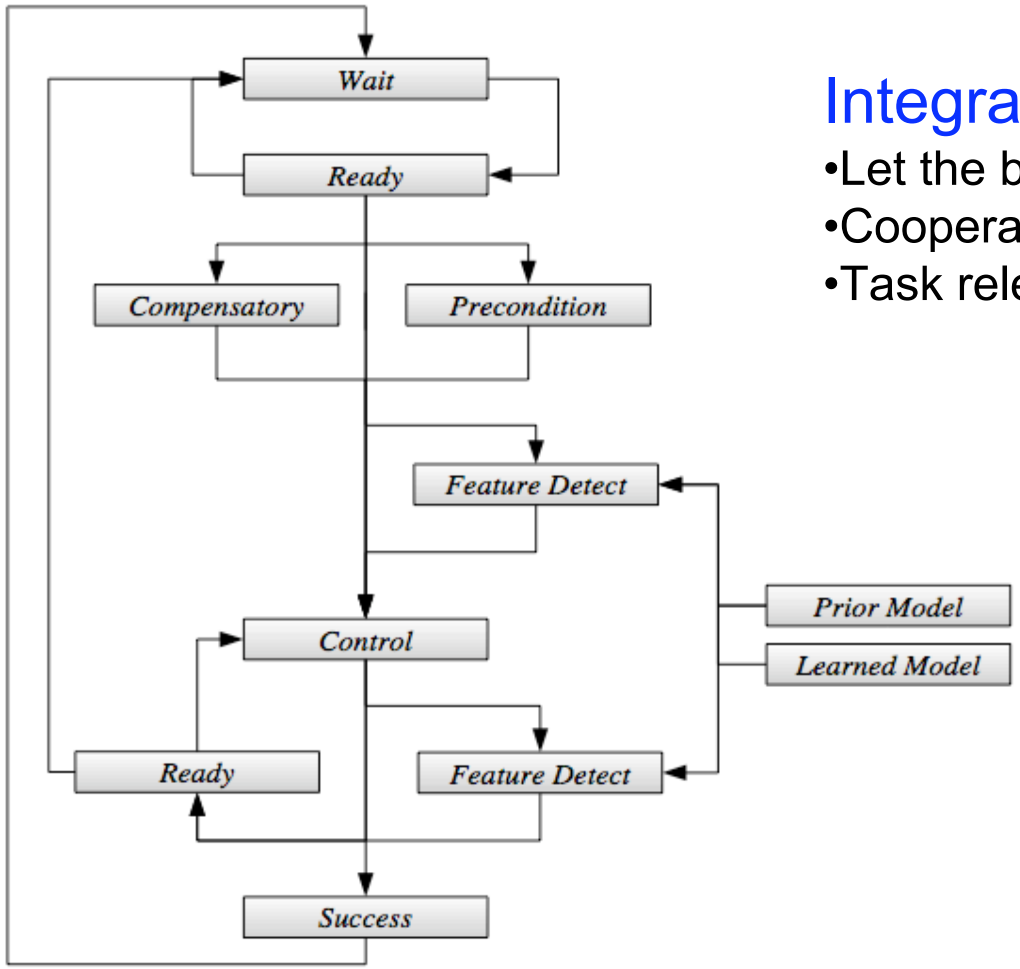


Integration

- Let the body do the thinking
- Cooperative manipulation
- Task relevant features

Basic control loop

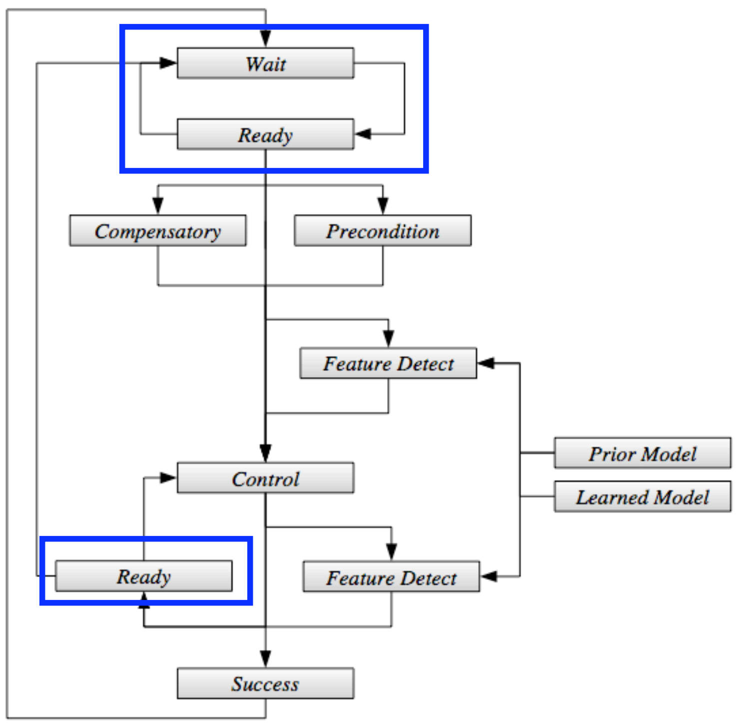
Manual skill algorithm

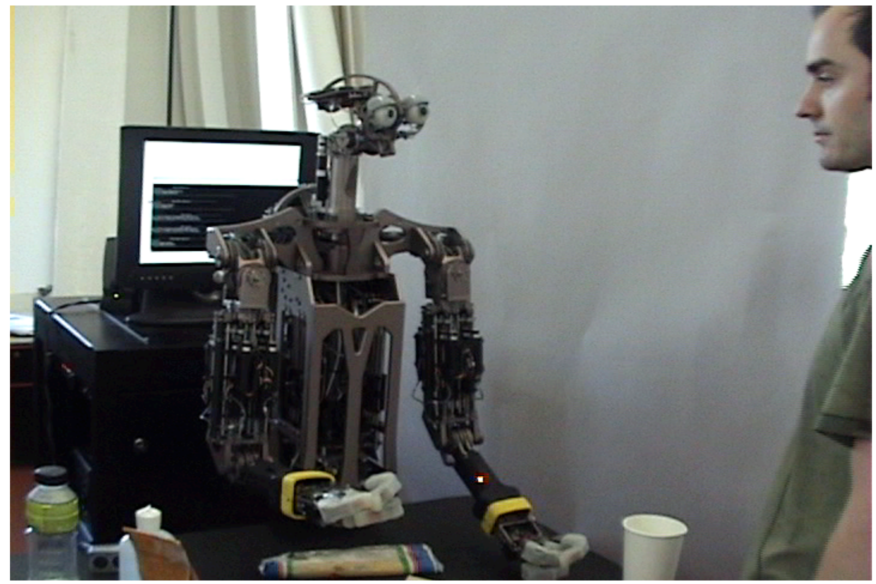


Integration

- Let the body do the thinking
- Cooperative manipulation
- Task relevant features

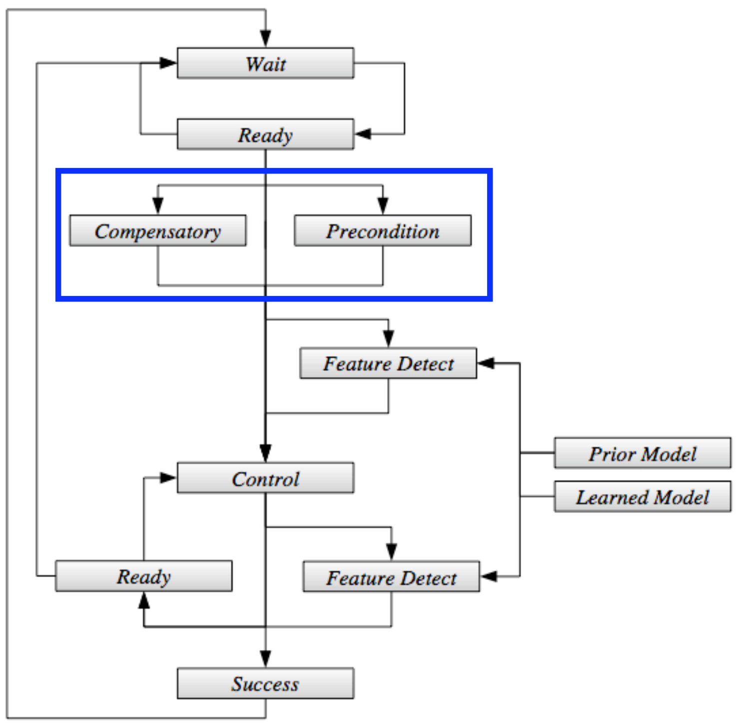
Example: Bimanual insertion task

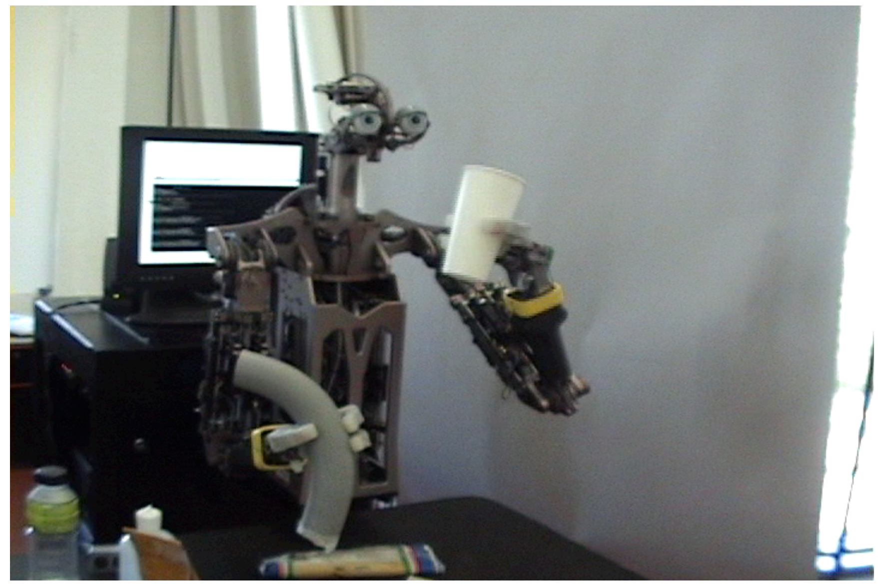




- Activation of modules that create readiness
- Monitor readiness

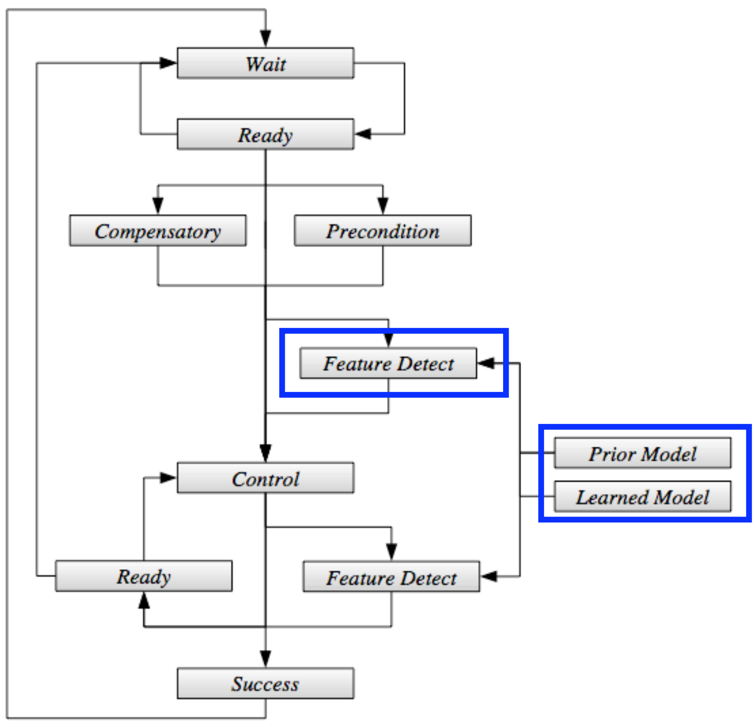
Example: Bimanual insertion task

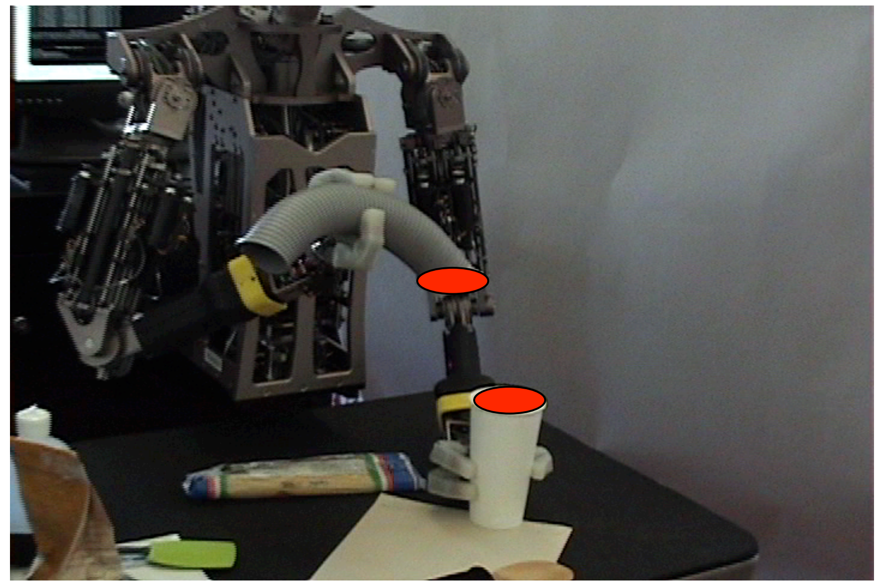




- Prepare body to assist perception
- Take action to reduce uncertainty

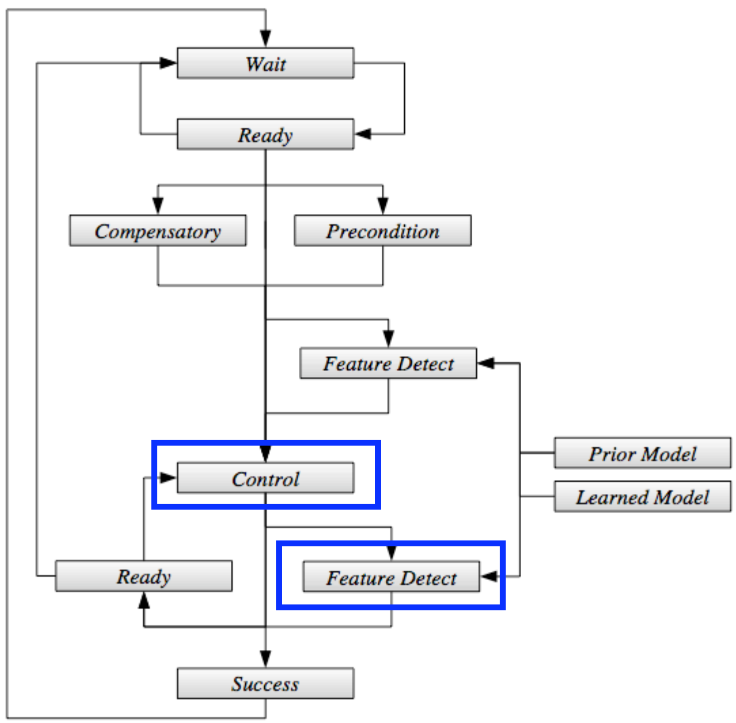
Example: Bimanual insertion task

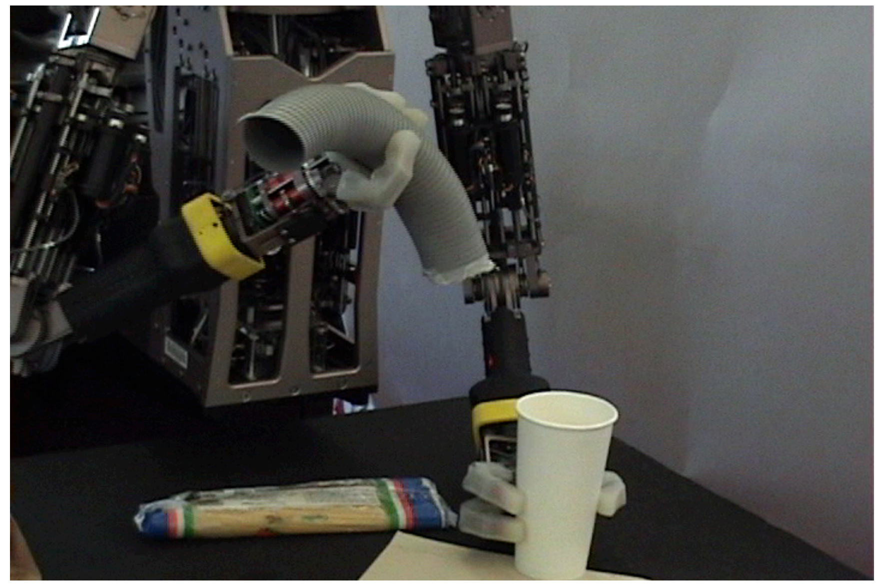




- Detect task relevant features
- Use learned models in detectors

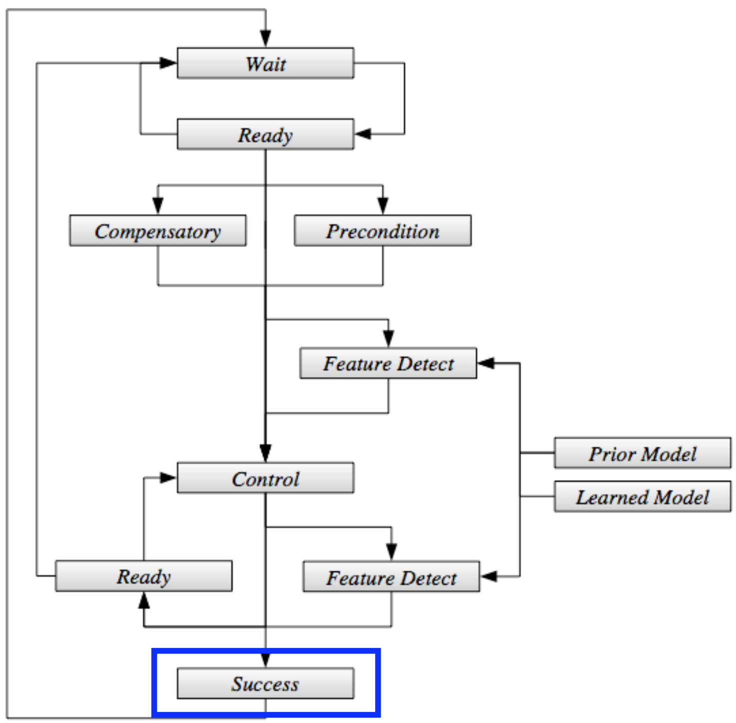
Example: Bimanual insertion task

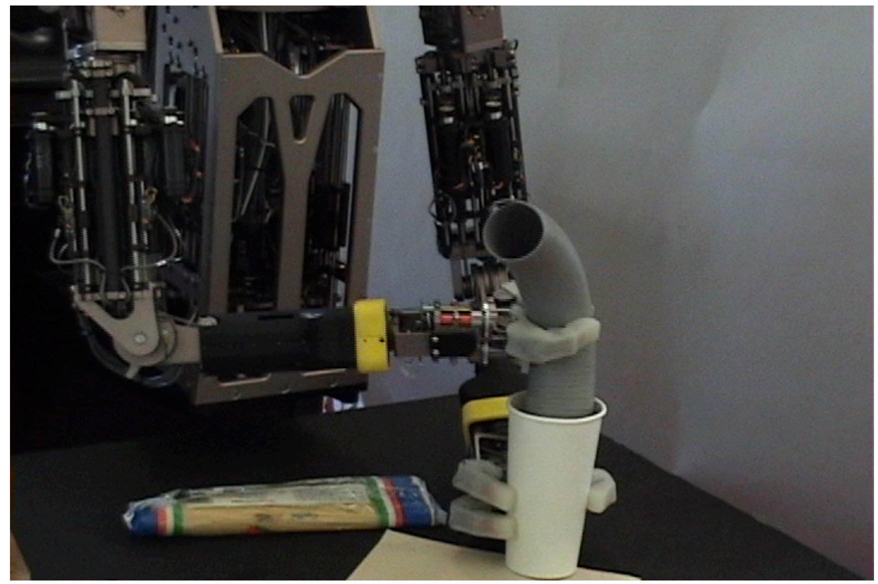




- Control feature
- Include perceptual feedback

Example: Bimanual insertion task





Detect controller success

Roadmap

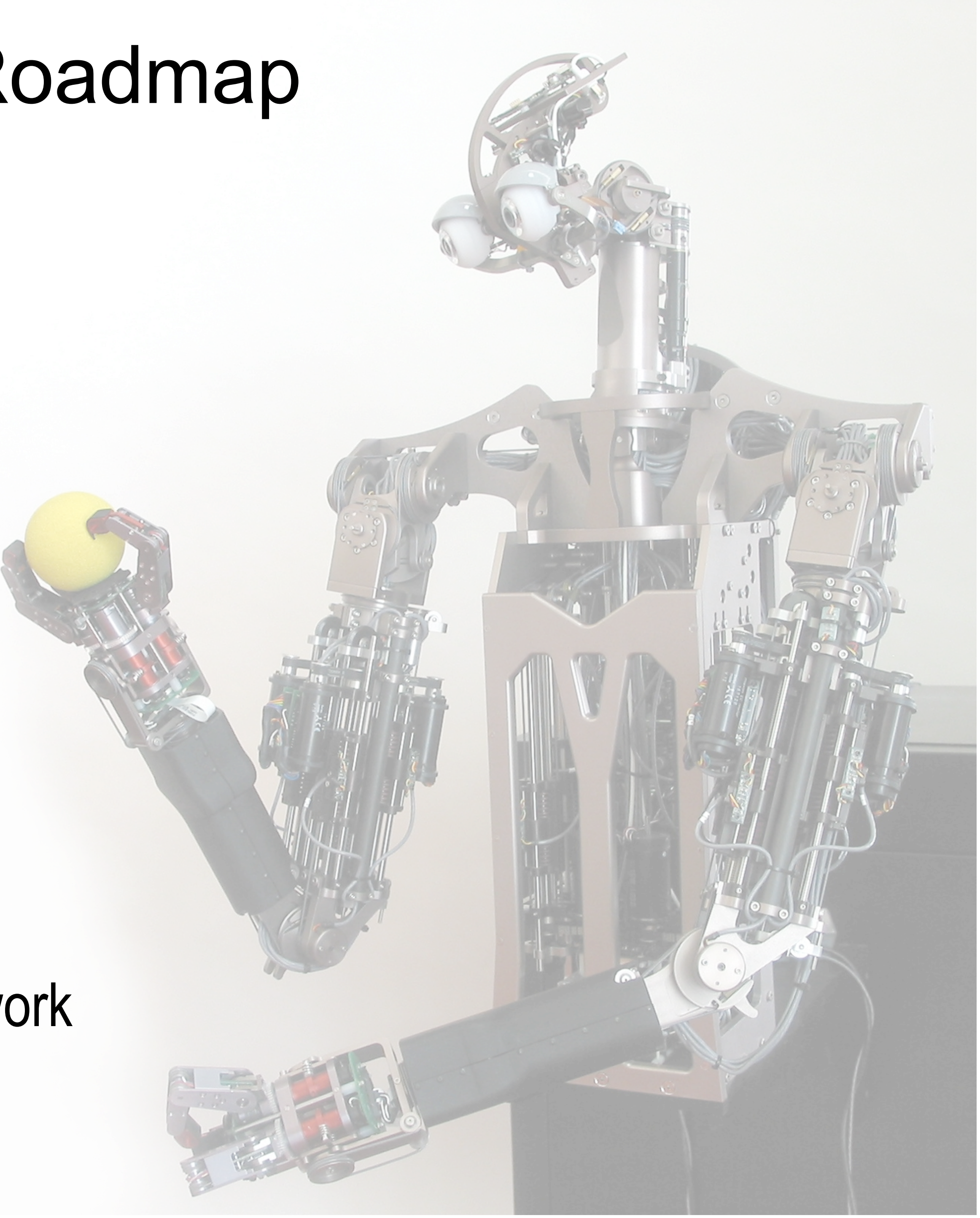
•Approach

•Robot design
•Visual system
•Control architecture

•Working with object tips
•Working with people
•Manual skills

•Helping with chores

•Conclusions and future work



The task relevant tip

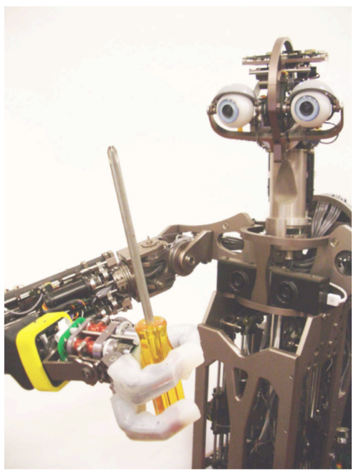
Detect and control the distal tip of a wide range of everyday objects

Why the prevalence of the tip?

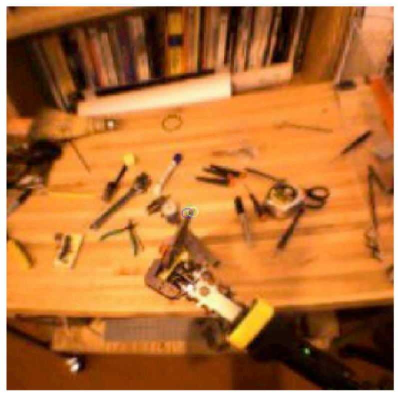
- •Single point of attention
- •Improves visual observation by reducing occlusions
- •Localize interaction forces
- •Natural extension of controlling hand and finger

The task relevant tip

Goal: quickly localize and control the tip
of an unknown object

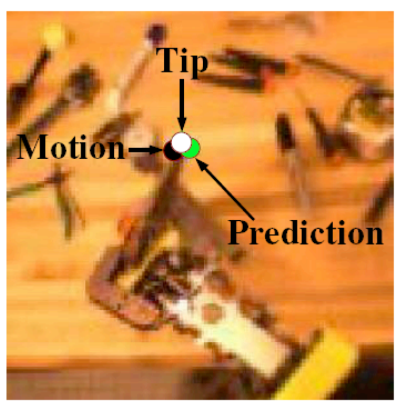


A

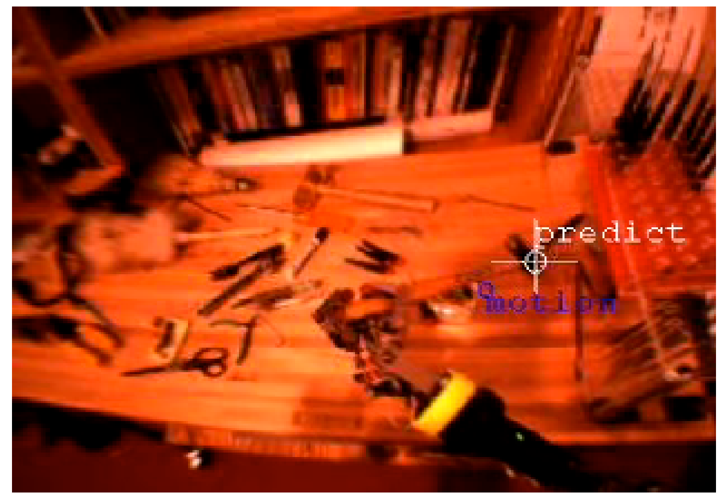


B

C



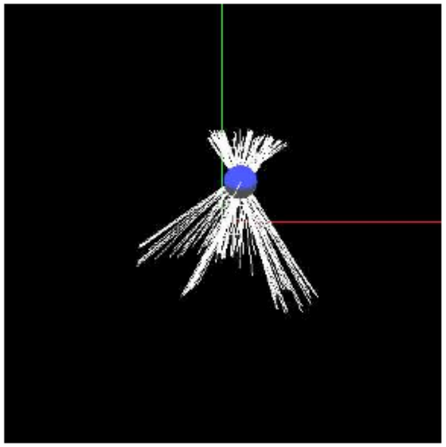
D

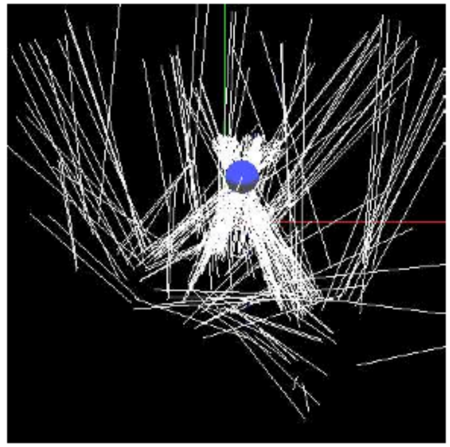


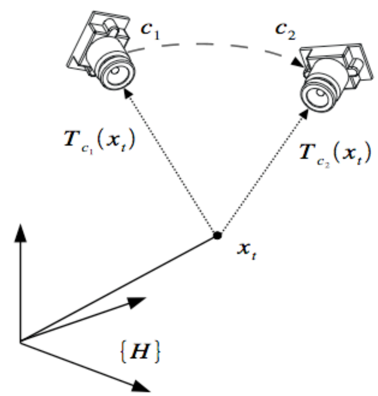
Tip detected as the fastest
moving convex edge in image

Work with Charles Kemp

Estimating the tip location







$$\mathrm{p}(\mathrm{x}_t | \mathbf{d}_1 \ldots \mathbf{d}_n, c_1 \ldots c_n) = \frac{p(\mathbf{d}_1 \ldots \mathbf{d}_n | \mathbf{x}_t, c_1 \ldots c_n) p(\mathbf{x}_t, c_1 \ldots c_n)}{p(\mathbf{d}_1 \ldots \mathbf{d}_n, c_1 \ldots c_n)}$$

3D tip location

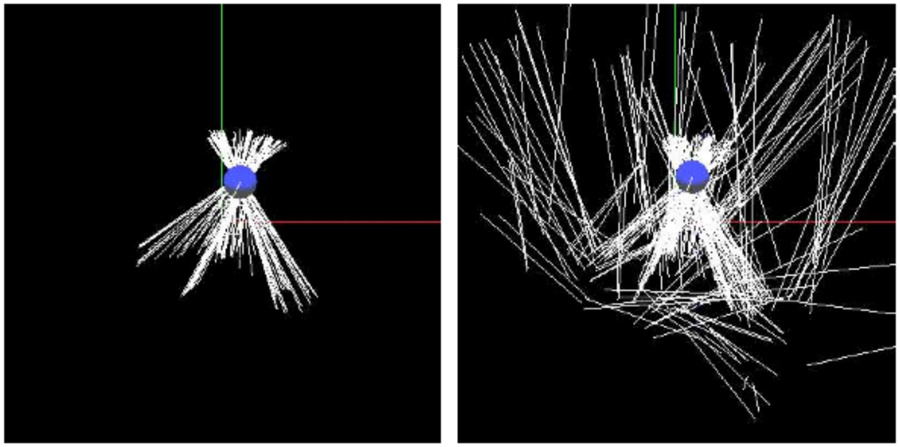
Detections

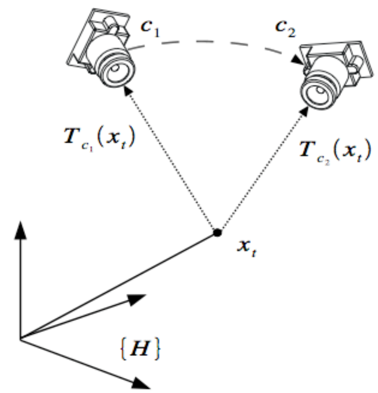
Kinematic configurations

Bayes rule

Work with Charles Kemp

Estimating the tip location





$$\mathrm{p}(\mathrm{x}_t | \mathbf{d}_1 \ldots \mathbf{d}_n, c_1 \ldots c_n) = \frac{p(\mathbf{d}_1 \ldots \mathbf{d}_n | \mathbf{x}_t, c_1 \ldots c_n) p(\mathbf{x}_t, c_1 \ldots c_n)}{p(\mathbf{d}_1 \ldots \mathbf{d}_n, c_1 \ldots c_n)}$$

Maximum likelihood

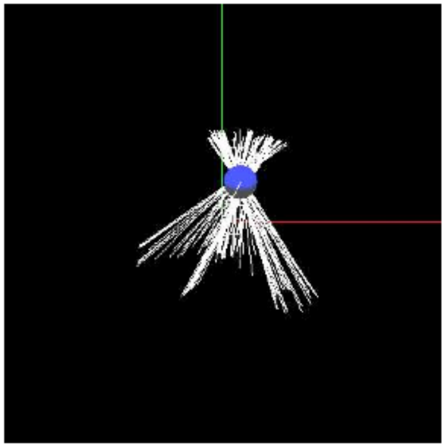
$$\begin{aligned} \widehat{\mathbf{x}}_t &= \mathrm{Argmax}_{\mathbf{x}_t} \left(p(\mathbf{d}_1 \ldots \mathbf{d}_n | \mathbf{x}_t, c_1 \ldots c_n) p(\mathbf{x}_t) \right) \\ &= \mathrm{Argmax}_{\mathbf{x}_t} \left(\log\left(p(\mathbf{x}_t)\right) + \sum_i \log \boxed{\left(p(\mathbf{d}_i | \mathbf{x}_t, c_i)\right)} \right) \end{aligned}$$

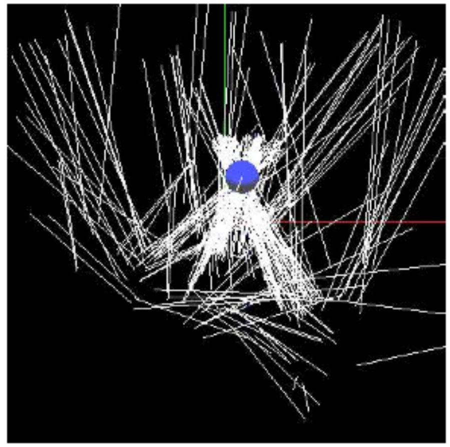
Uniform near hand

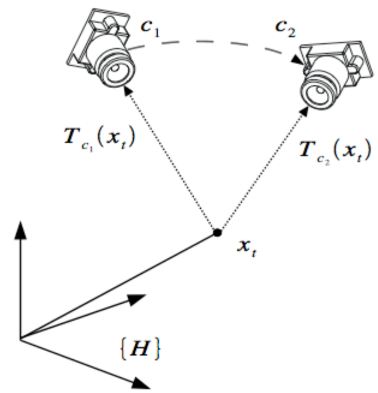
Solve in batch mode (N=50) using Nelder-Mead Simplex optimization

Work with Charles Kemp

Estimating the tip location







2D Gaussian error model in image

$$\boxed{\mathrm{p}(\mathrm{d}_i|\mathbf{x}_t, c_i)} = (1-m)\mathcal{N}_t(T_{c_i}(\mathbf{x}_t), \sigma_t^2 I)(\mathbf{d}_i) + m\mathcal{N}_f(0, \sigma_f^2 I)(\mathbf{d}_i)$$

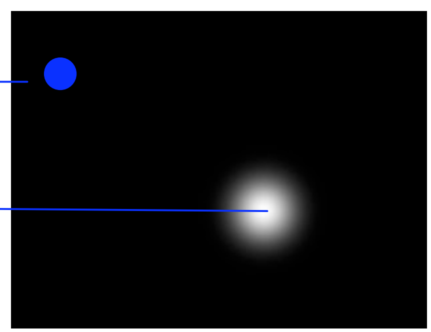
Mixing parameter

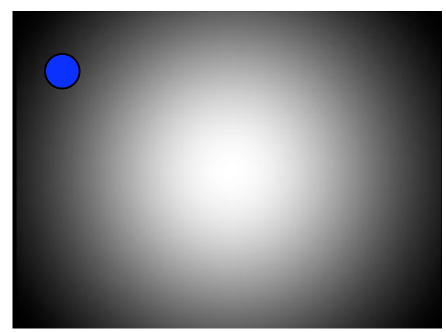
Gaussian at tip

Detection noise

d_i

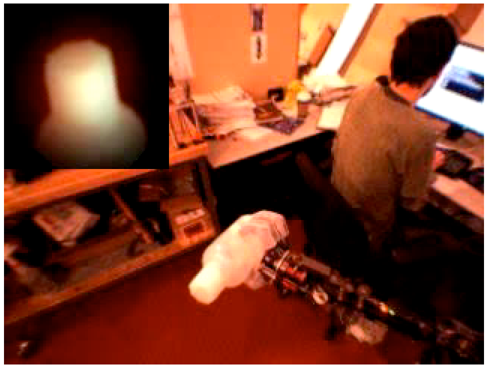
$T_{c_i}(\mathbf{x}_t)$





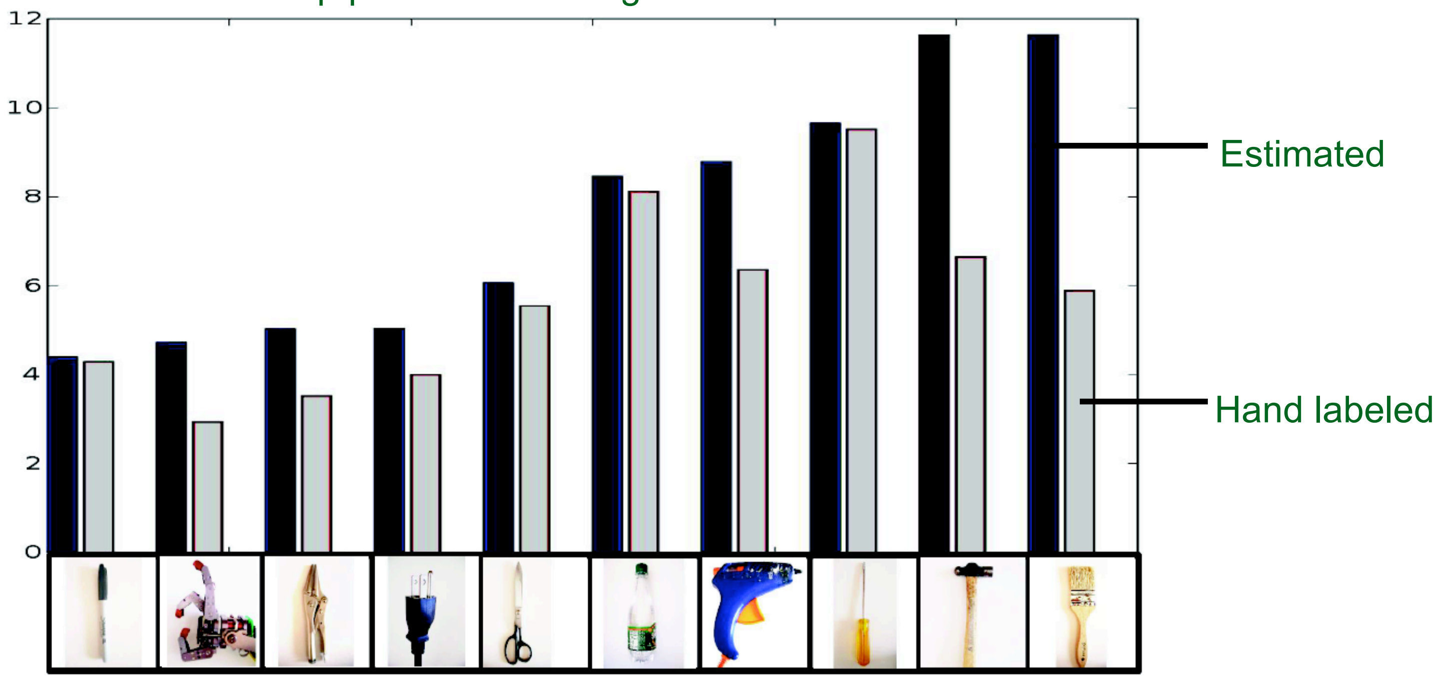
Work with Charles Kemp

Detecting tips of everyday tools

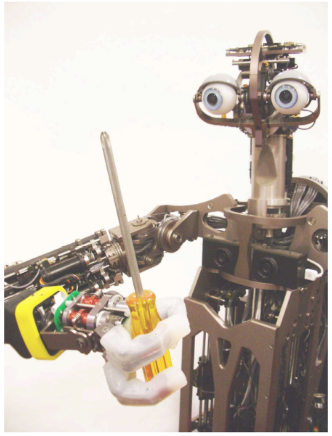


Robot Manipulation of Human Tools: Autonomous Detection and Control of Task Relevant Features (Kemp and Edsinger, 2005)

Pixel error of tip prediction in image



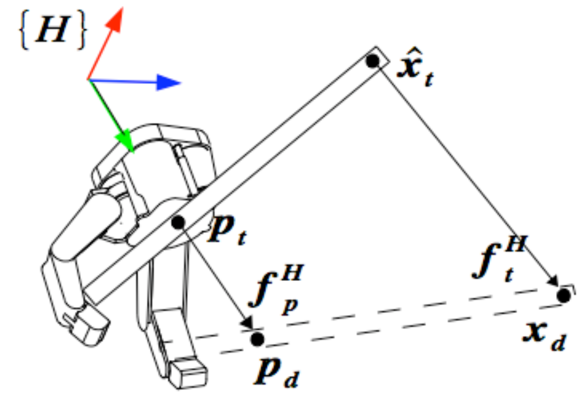
Work with Charles Kemp



Tip open-loop control

Virtual forces on object

$$\mathbf{f}_t^H \propto (\mathbf{x}_d - \widehat{\mathbf{x}}_t)$$
$$\mathbf{f}_p^H \propto (\mathbf{p}_d - \mathbf{p}_t)$$



Virtual force in hand frame

$$\mathbf{f}_t^H = \mathbf{K}_t \mathbf{M}(\mathbf{I}, \widehat{\mathbf{x}}_t) \begin{bmatrix} (\mathbf{x}_d - \widehat{\mathbf{x}}_t) & 0 & 0 & 0 \end{bmatrix}^T$$
$$\mathbf{f}_p^H = \mathbf{K}_p \mathbf{M}(\mathbf{I}, \mathbf{p}_t) \begin{bmatrix} (\mathbf{p}_d - \mathbf{p}_t) & 0 & 0 & 0 \end{bmatrix}^T$$

Virtual force in world frame

$$\mathbf{f}^W = \mathbf{M}({}^W\mathbf{R}^H, 0)\,(\mathbf{f}_t^H + \mathbf{f}_p^H)$$

Controller update rule

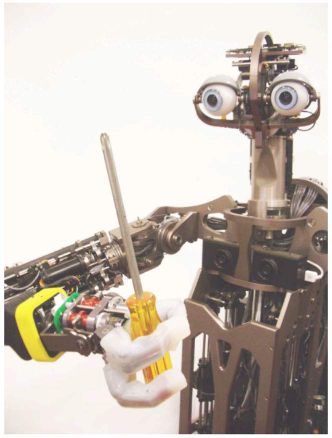
$$\boxed{\Delta\theta = \sigma \mathbf{J}^T \mathbf{f}^W}$$

Force moment transform

$$\mathbf{M}(\mathbf{R}, \mathbf{t}) = \begin{bmatrix} \mathbf{R} & 0 \\ P(\mathbf{t})\mathbf{R} & \mathbf{R} \end{bmatrix}$$

Cross product operator

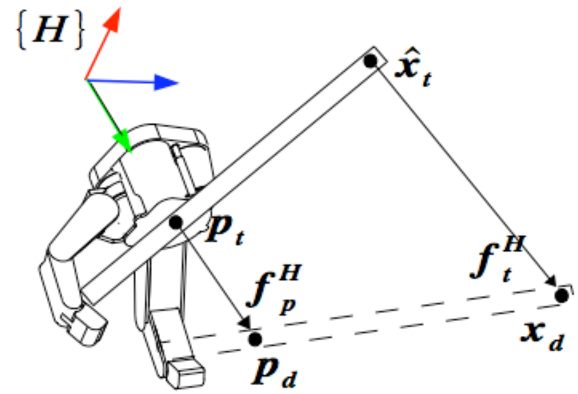
$$\mathbf{P}(\mathbf{t}) = \begin{bmatrix} 0 & -t_3 & t_2 \\ t_3 & 0 & -t_1 \\ -t_2 & t_1 & 0 \end{bmatrix}$$

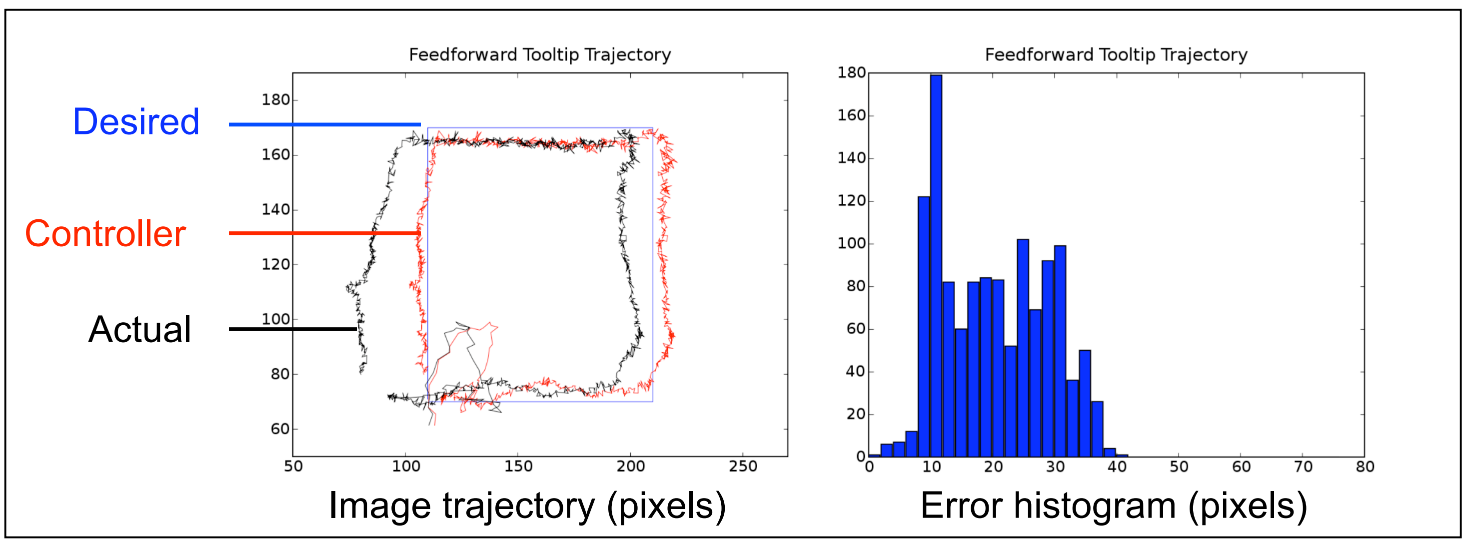


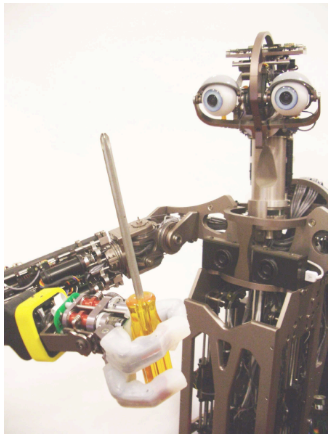
Tip open-loop control

Virtual forces on object

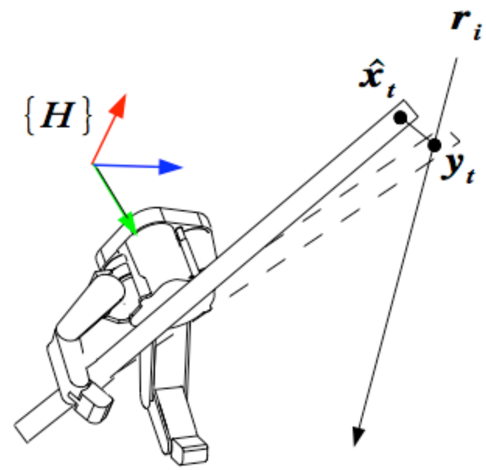
$$\mathbf{f}_t^H \propto (\mathbf{x}_d - \widehat{\mathbf{x}}_t)$$
$$\mathbf{f}_p^H \propto (\mathbf{p}_d - \mathbf{p}_t)$$







Tip servo control



Leverage strong prior on tip location

whenever the wrist rotates:

detect tip in image as $\mathbf{d}_i$

estimate probability is tip detection as $p(\mathbf{d}_i | \widehat{\mathbf{x}}_t, c_i)$

If $p(\mathbf{d}_i | \widehat{\mathbf{x}}_t, c_i) > \epsilon$:

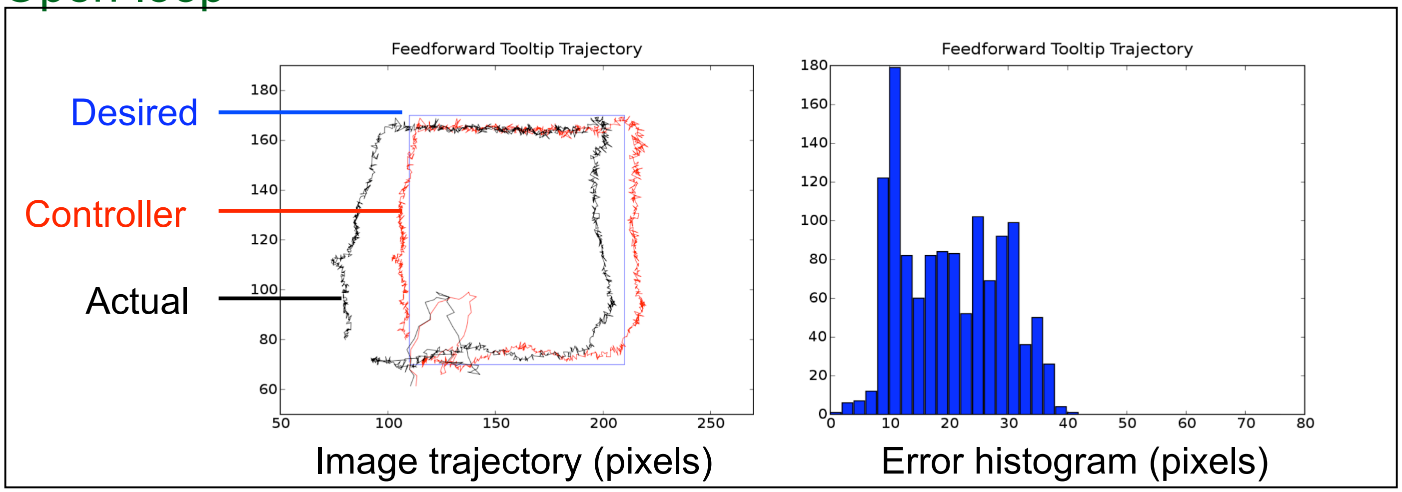
initialize block-matching visual tracker at $\mathbf{d}_i$

estimate tip location $\mathbf{y}_t$ using closest point of $\widehat{\mathbf{x}}_t$ to tracker ray $\mathbf{r}_i$

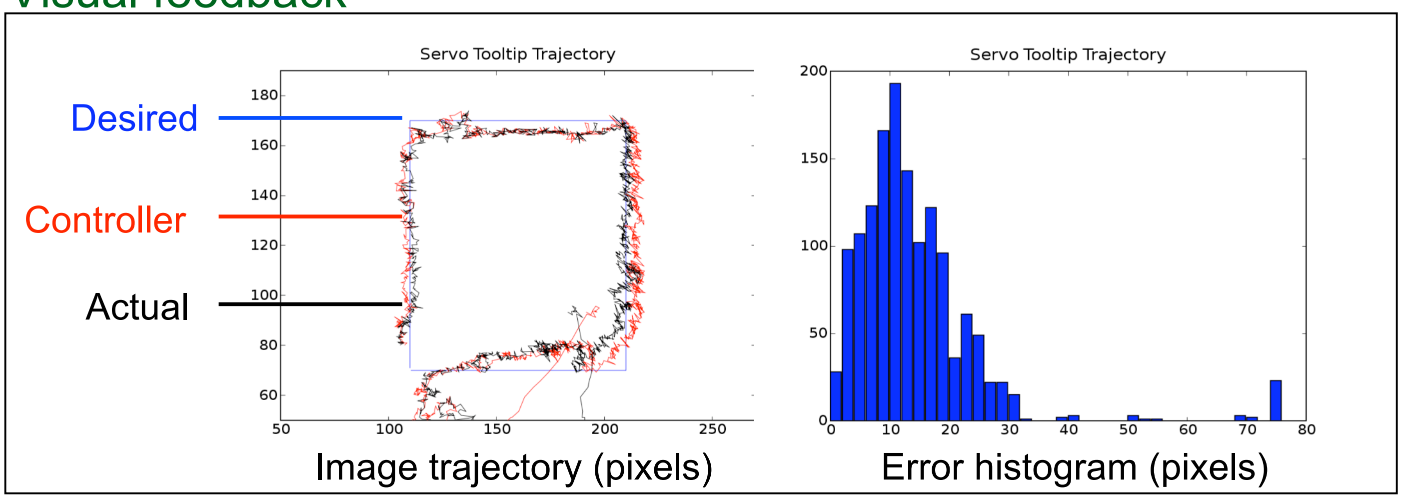
substitute $\mathbf{y}_t$ for $\widehat{\mathbf{x}}_t$ in the open-loop controller

Tip servo control

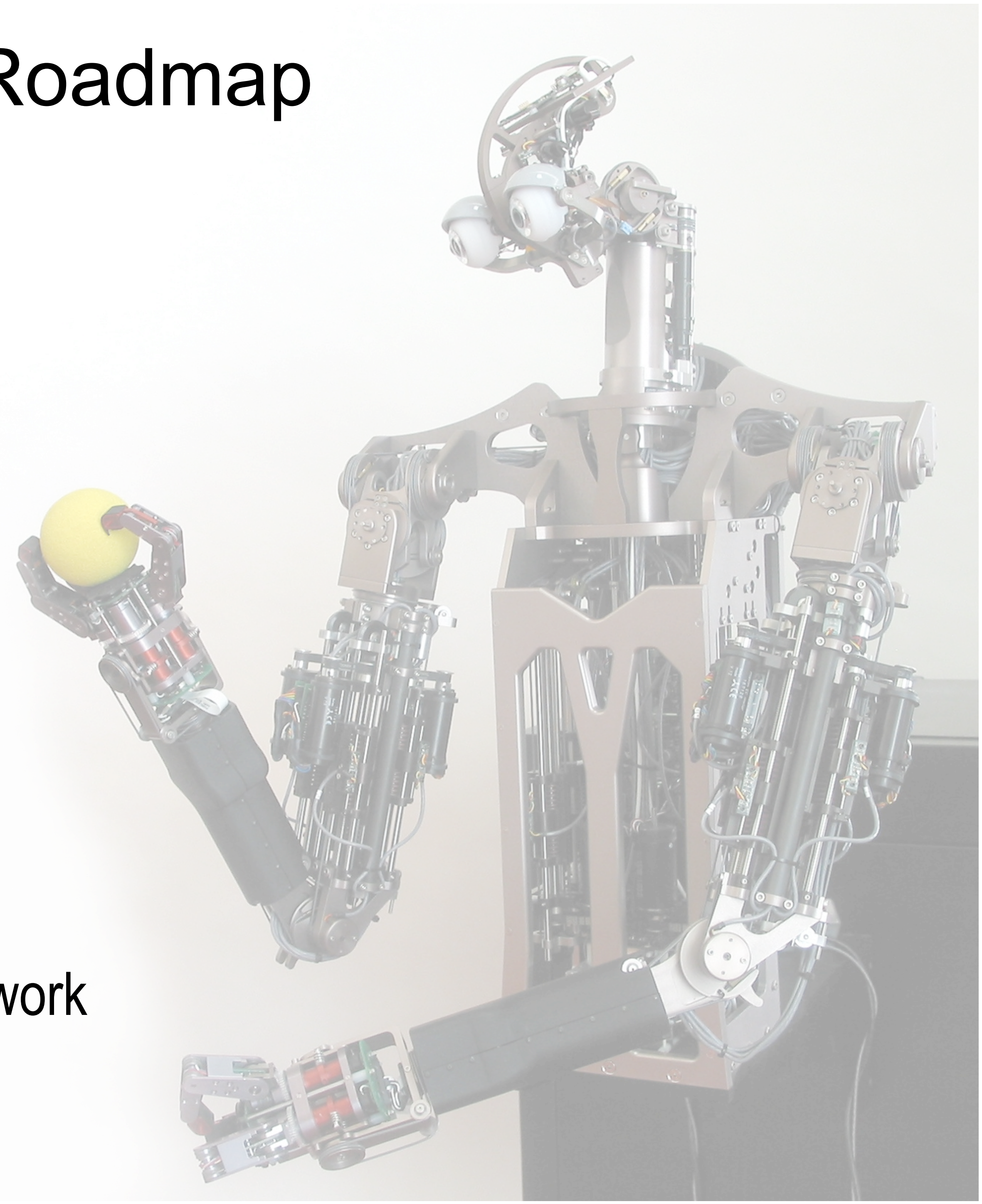
Open-loop



Visual feedback



Roadmap



- Approach

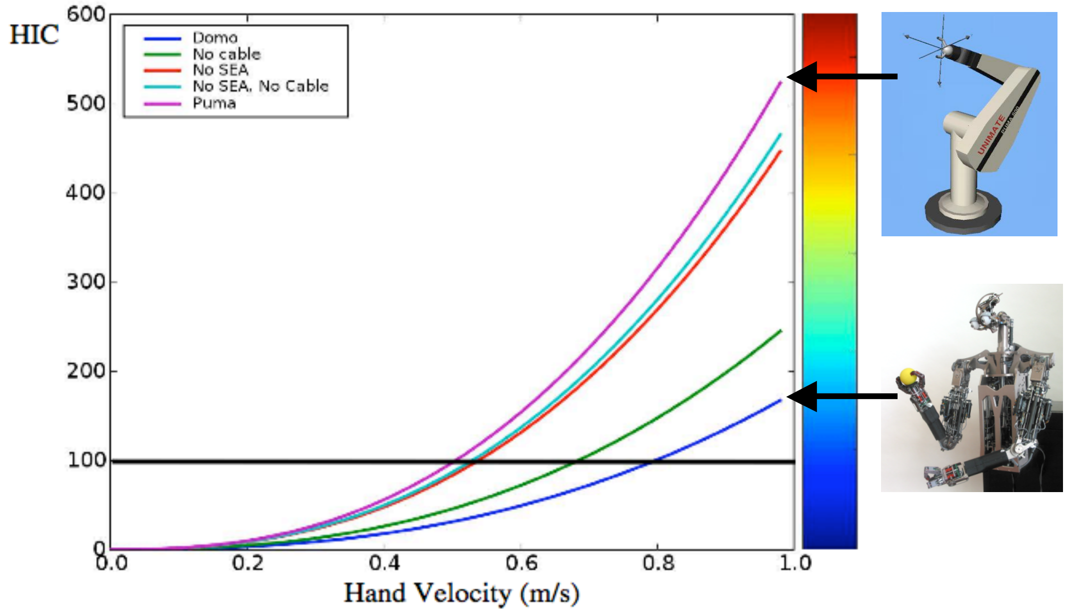
- Robot design
- Visual system
- Control architecture

- Working with object tips
- Working with people
- Manual skills

- Helping with chores

- Conclusions and future work

Intrinsic safety



Passive compliance lowers effective mass

The Head Injury Criterion

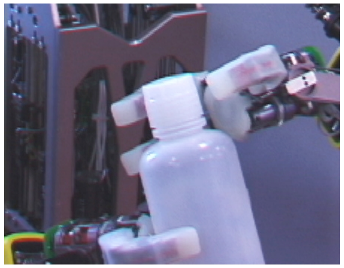
$$HIC = 2\left(\frac{2}{\pi}\right)^{\frac{3}{2}}\left(\frac{K_{cov}}{M_{oper}}\right)^{\frac{3}{4}}\left(\frac{M_{rob}}{M_{rob}+M_{oper}}\right)^{\frac{7}{4}} v_{max}^{\frac{5}{2}}$$

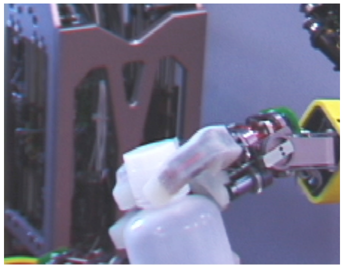
$$M_{rob} = M_{link} + \frac{K_s}{K_s+\gamma} M_{rot}$$

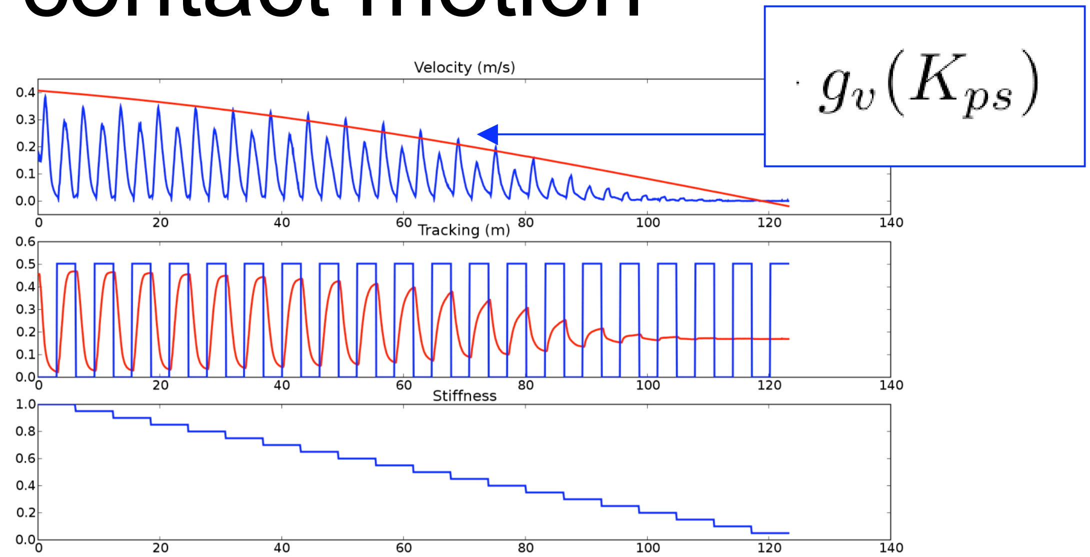
γ Rigid link stiffness

K_s Spring stiffness

Detecting contact motion







Arm stiffness:

$$\tau_{desired} = K_{ps}\left(PID(\theta_{desired},\,\theta)\right) - G(\boldsymbol{\Theta})$$

Learn velocity prediction:
(Support Vector Regression) $g_v(K_{ps})$

Signal contact when
prediction violation:

$$\left(\left\|\mathbf{J}\dot{\boldsymbol{\Theta}}\right\| - g_v(K_{ps})\right) > \epsilon \quad \text{and} \quad K_{ps} < 0.5$$

Detecting contact force

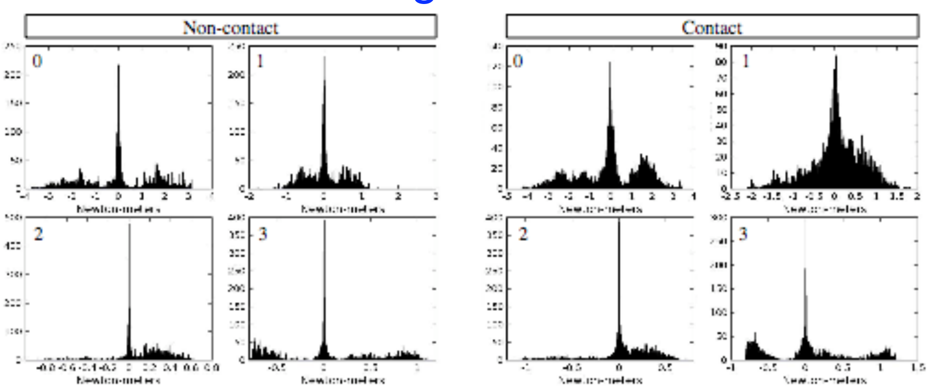
Joint space dynamic model

$$\tau_{dyn} = \mathbf{M}(\boldsymbol{\Theta})\ddot{\boldsymbol{\Theta}} + \mathbf{V}(\boldsymbol{\Theta}, \dot{\boldsymbol{\Theta}}) + \mathbf{G}(\boldsymbol{\Theta})$$
$$\approx \mathbf{M}(\boldsymbol{\Theta})\ddot{\boldsymbol{\Theta}} + \mathbf{G}(\boldsymbol{\Theta})$$

Prediction error

$$e = \tau_{dyn} - \tau_{sense}$$

Prediction error histograms

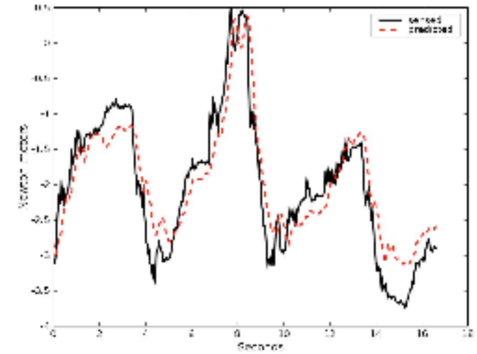


$p(e|no\_contact)$ $p(e|contact)$

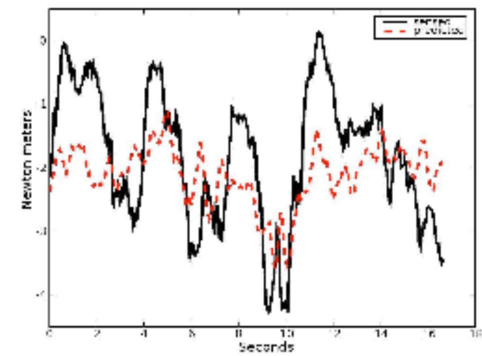
Signal contact when prediction violation:

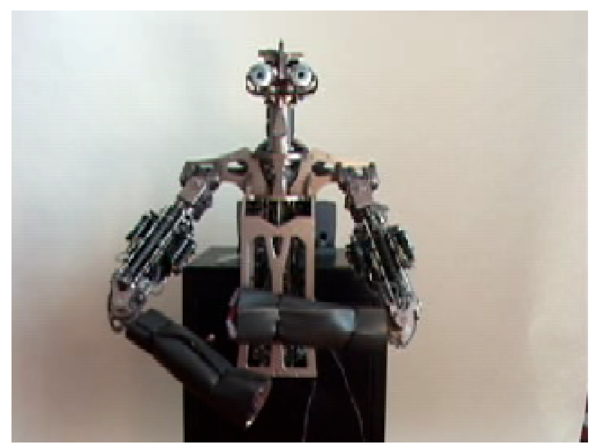
$$p(e|contact) > p(e|no\_contact)$$

No contact

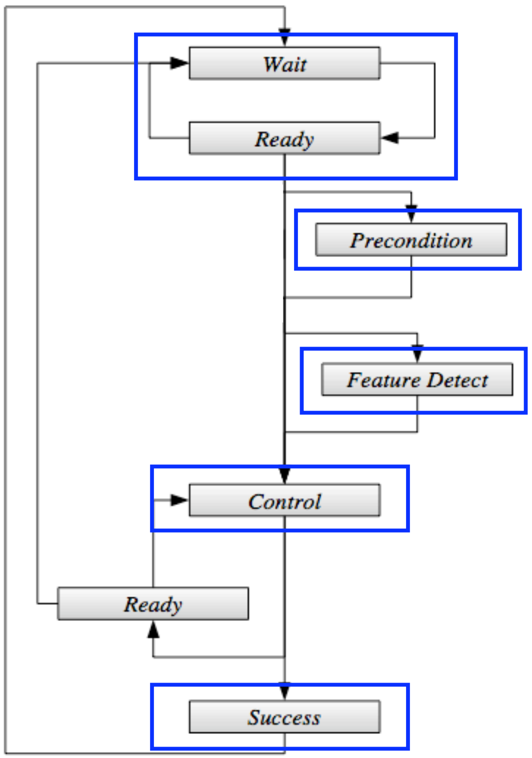


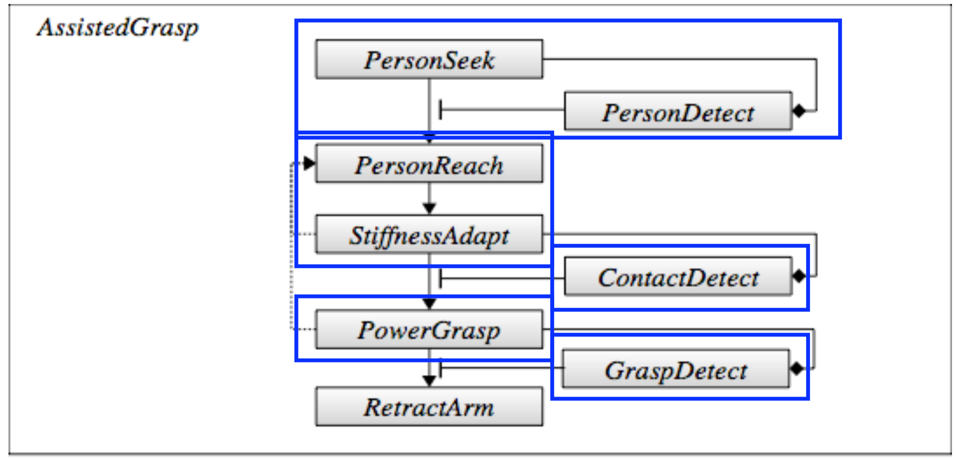
Contact





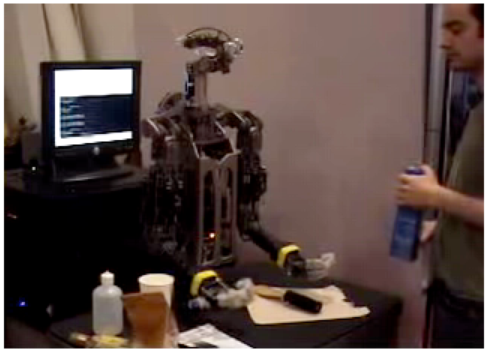
Assisted grasping

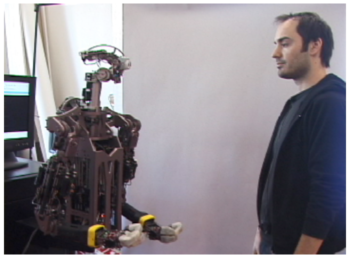


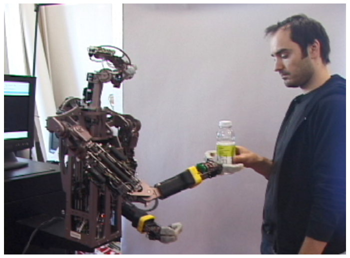


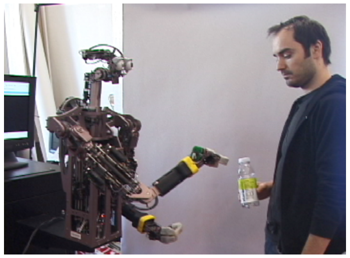
Social cues to request assistance

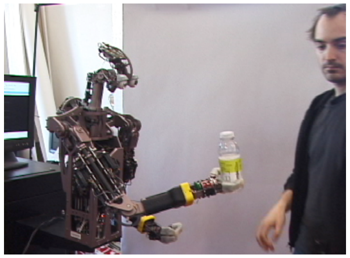
- Reach direction
- Eye contact
- Grasp preshape











Can we design naïve collaborators into a task?

Give and take experiment

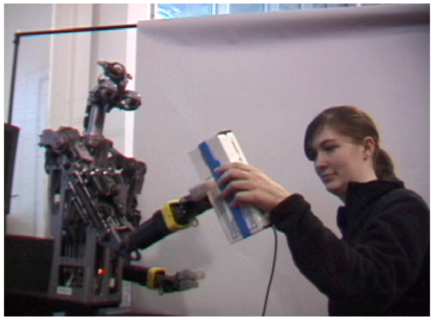
Will people give an object aligned with the robot's grasp?

Will people take an object when offered by the robot?

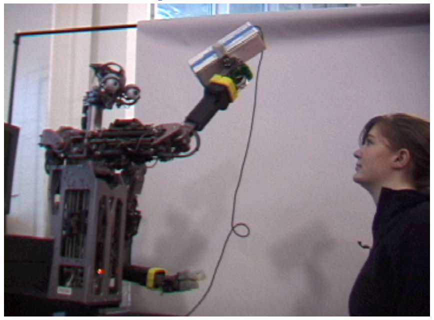
- •10 subjects
- •6 trials each
- •Naïve to task
- •Varied experience with robots
- •Incentive during release

Cues:
- •Voice "ok"
- •Eye-gaze
- •Reach direction
- •Reach length
- •Wrist orientation

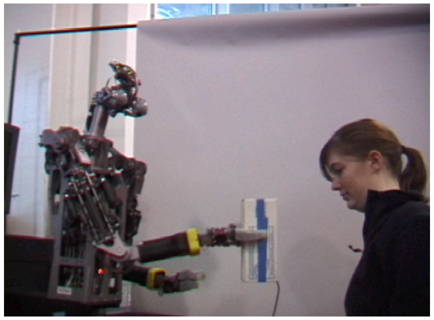
grasp box



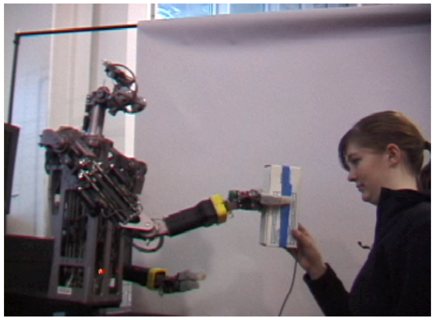
"inspection"



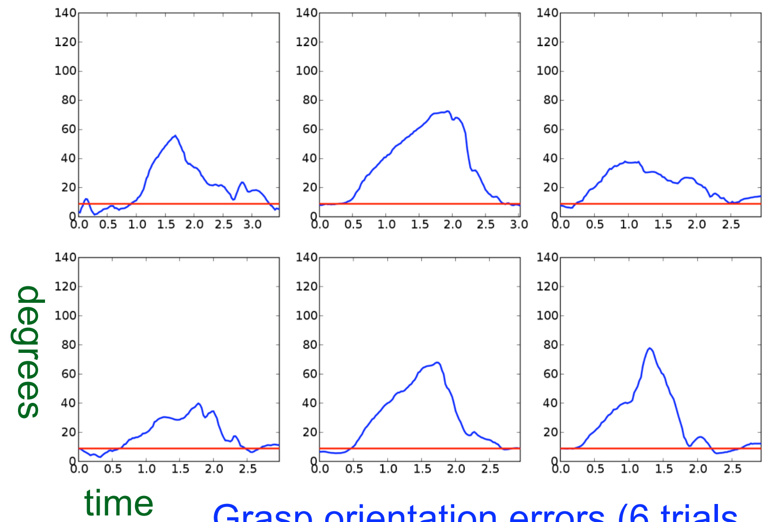
offer box



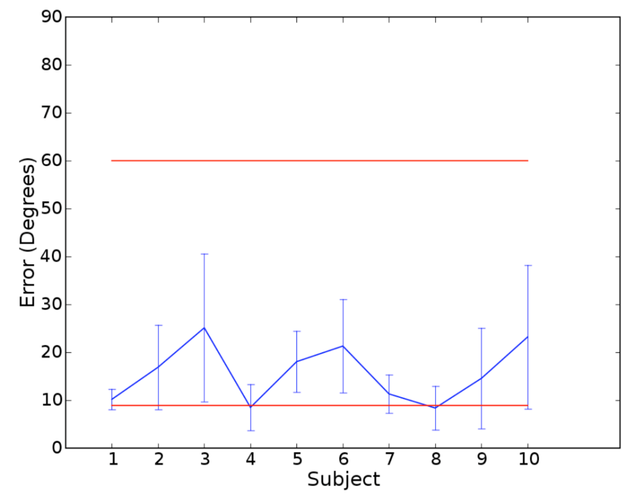
release box



Can we design naive collaborators into a task?



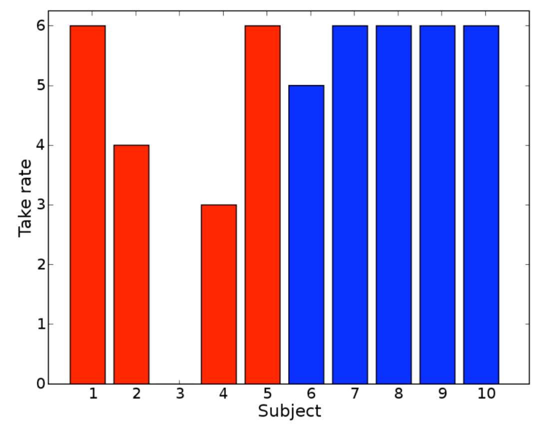
Grasp orientation errors (6 trials, one subject)



Mean grasp orientation errors (10 subjects)

- Very good at matching grasp
- Incentive increases likelihood of taking back
- Unrelated to expertise

Take-back rate (10 subjects)



Incentive NO YES

Roadmap

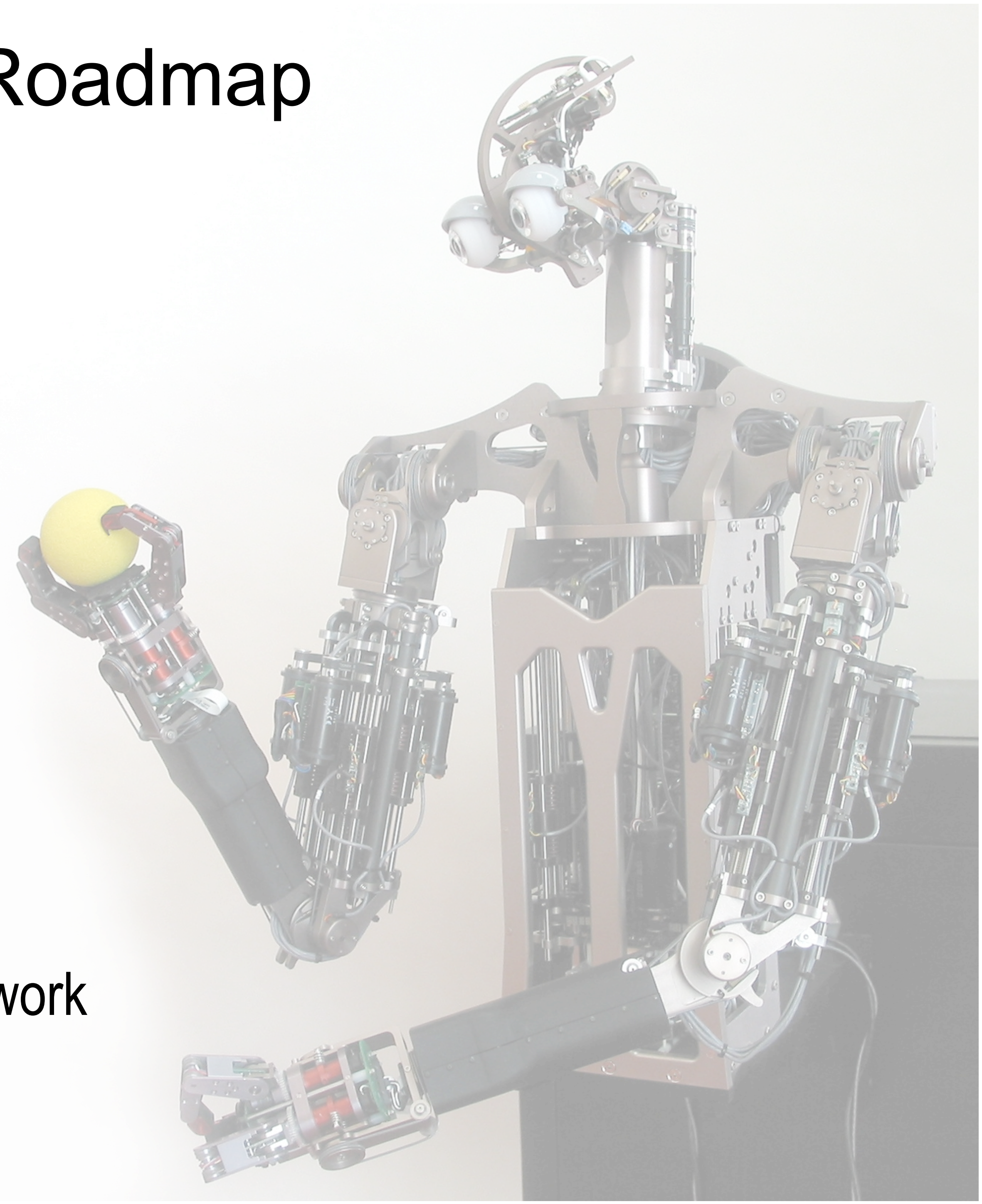
- Approach

- Robot design
- Visual system
- Control architecture

- Working with object tips
- Working with people
- Manual skills

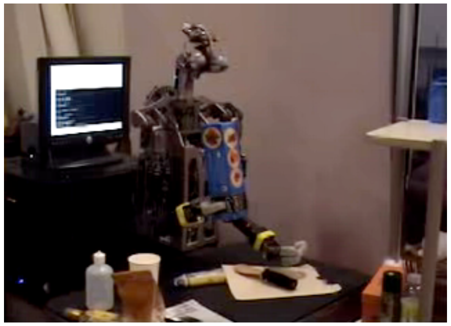
- Helping with chores

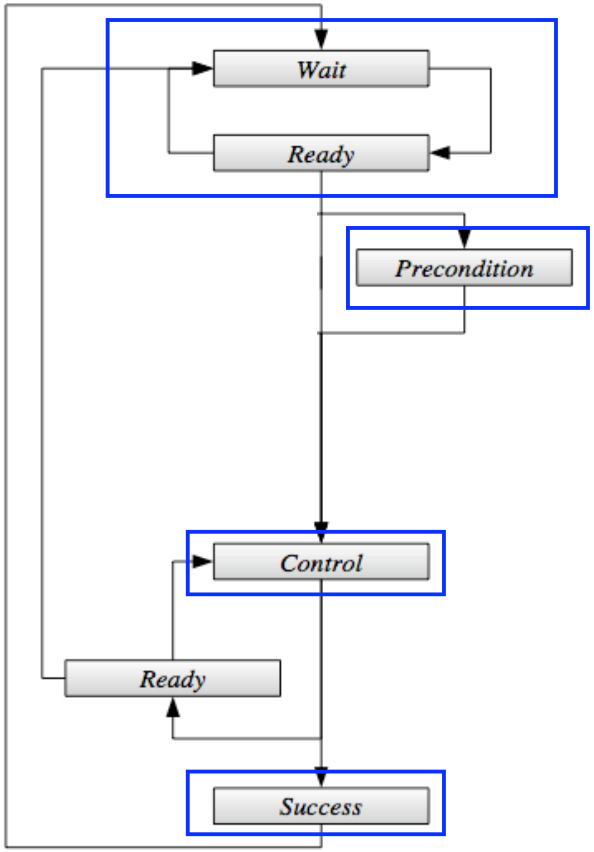
- Conclusions and future work



Reaching in the dark…

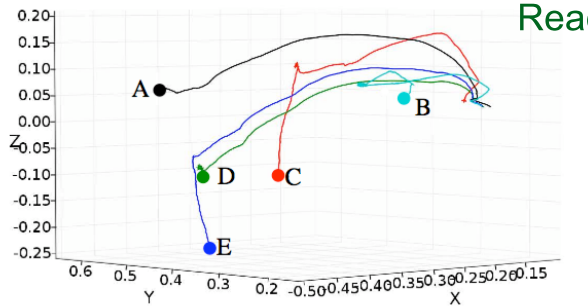
- •Uncertain detection of surface
- •Use body to verify location
- •Represent location in joint space

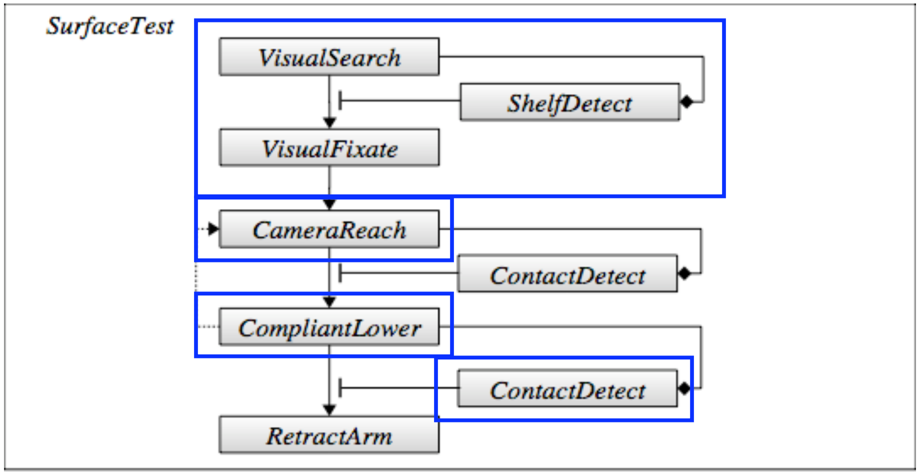




Vary shelf pose and height

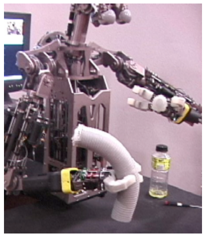
Reach trajectories

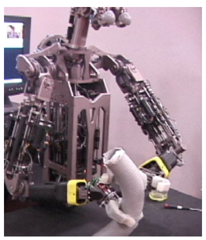


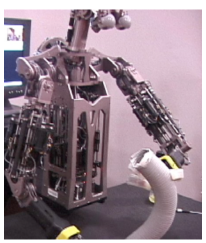


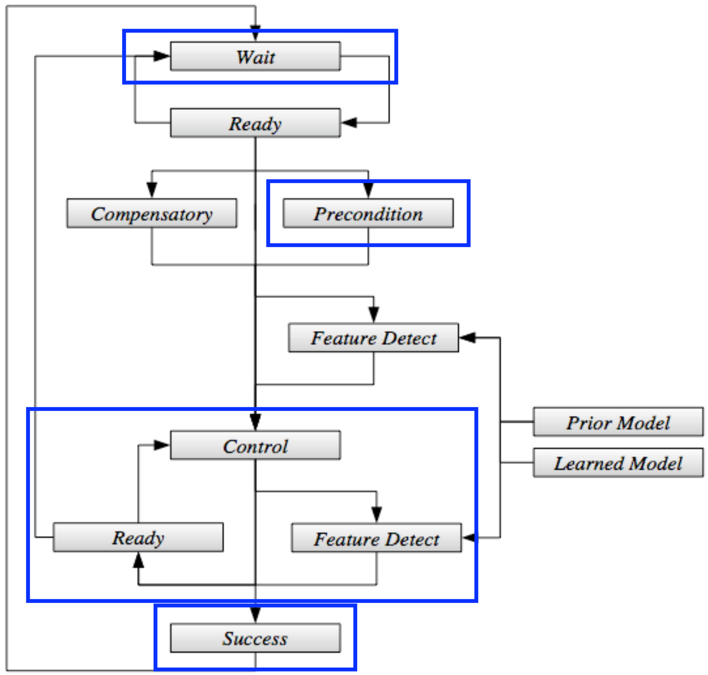
Switching hands

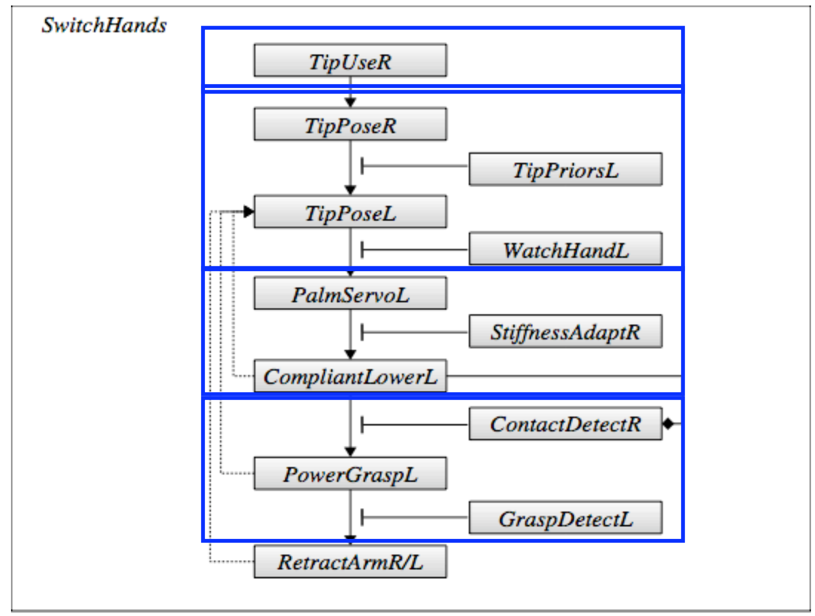
Expand the manipulation workspace

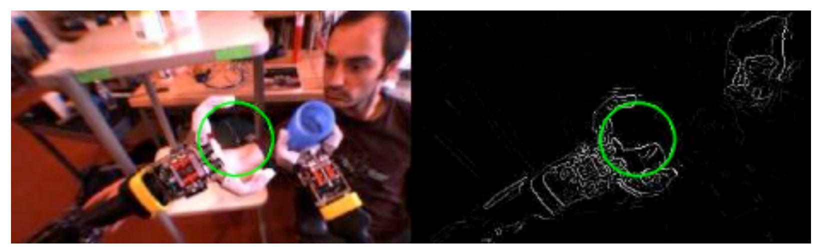






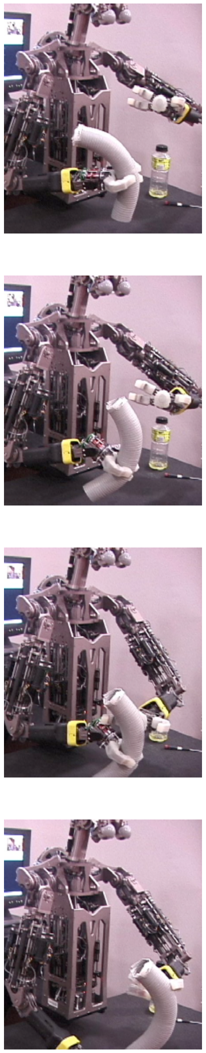




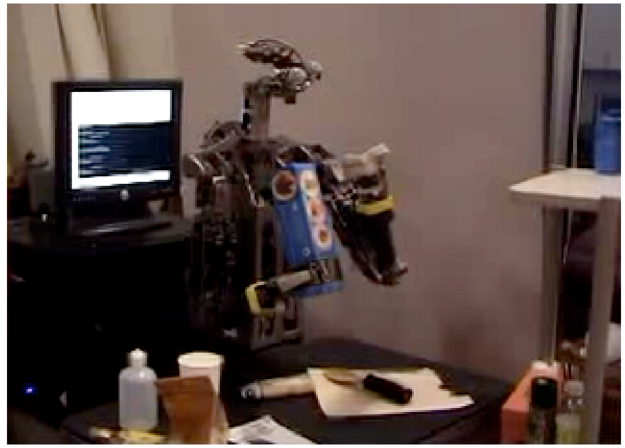


- Estimation of object tip
- Object realignment
- Visual servo of the palm
- Exploit compliance during contact

Switching hands

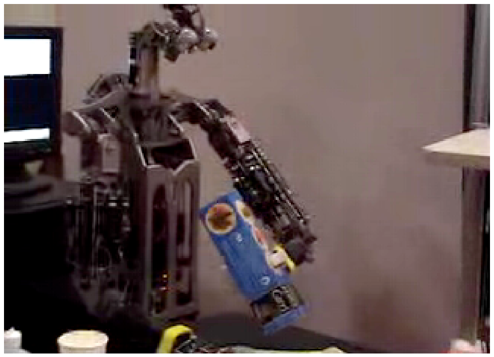


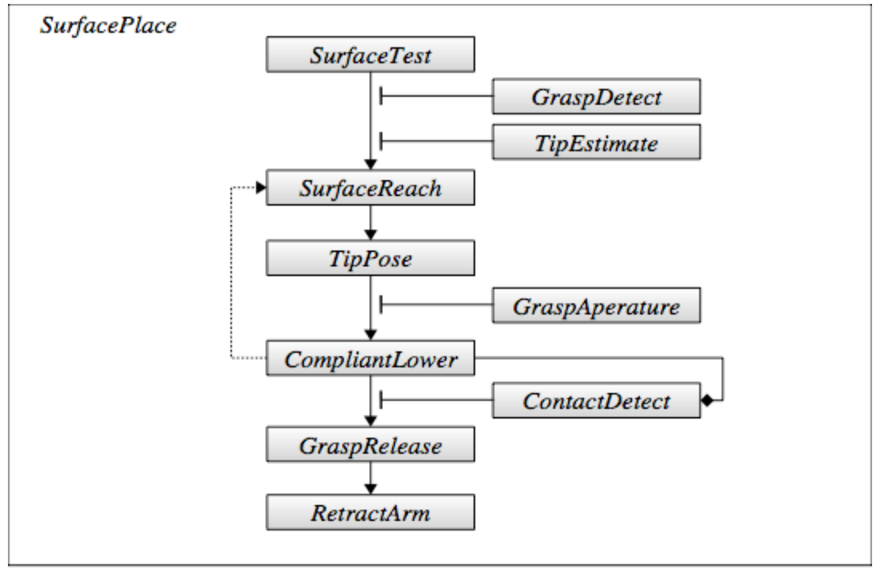
Expand the manipulation workspace



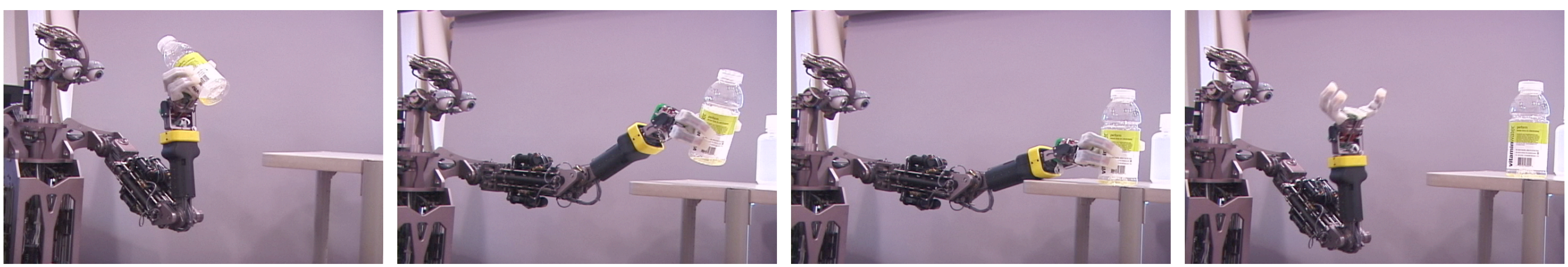
					
	A	B	C	D	E
SwitchHands	3/3	3/3	3/3	2/3	3/3
Open-loop	0/3	0/3	1/3	0/3	2/3

Placing objects on flat surfaces

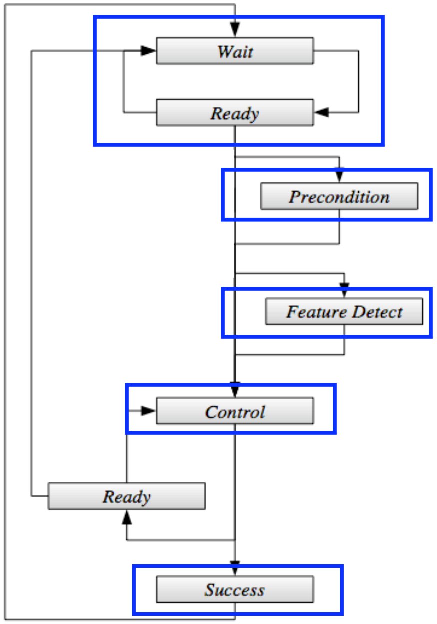


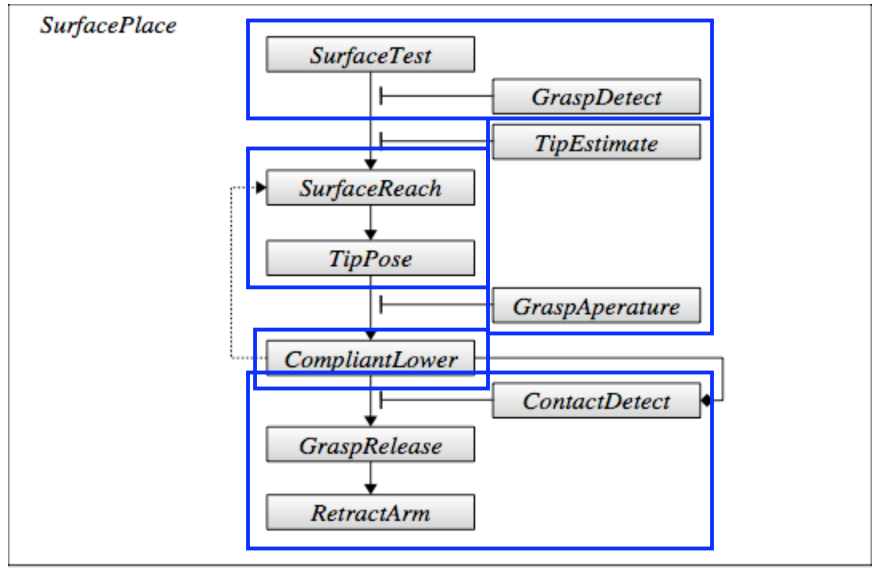


- Estimate placement stability
- Place upright or lying down
- Leverage compliance to self-align to surface



Placing objects on flat surfaces





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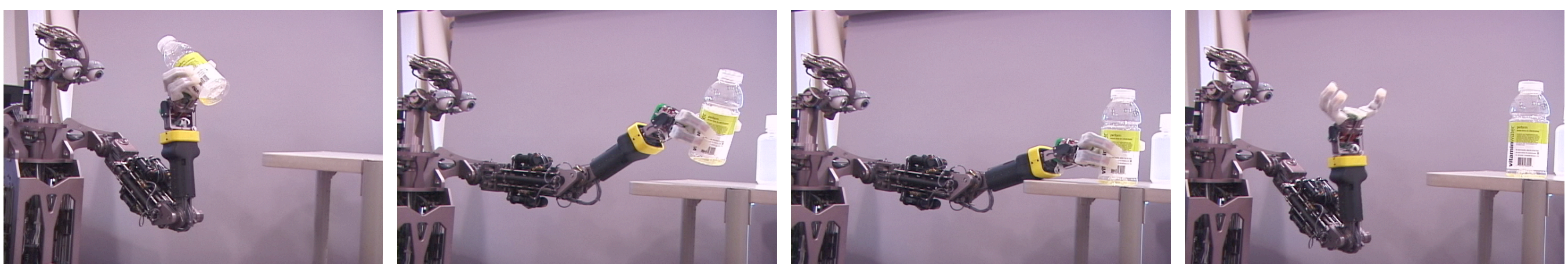


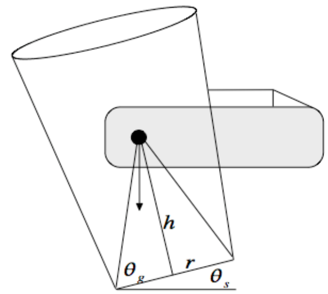
Placing objects on flat surfaces

Stability estimate

Object	η measured	η sensed
animal	0.48	0.50
box	1.15	0.82
large bottle	0.56	0.54
caddy	0.61	0.49
spoon	0.21	0.24
roller	0.29	0.26
broom	0.24	0.23
food tin	1.20	0.98
small bottle	0.57	0.49
duster	0.13	0.24
spray bottle	.36	.42

$$\eta = \frac{g_a(\mathbf{\Theta})}{||\mathbf{a}||}$$

Misalignment tolerance



$$\theta_s < \frac{\pi}{2} - tan^{-1}\frac{h}{r}$$

3 trials ea.

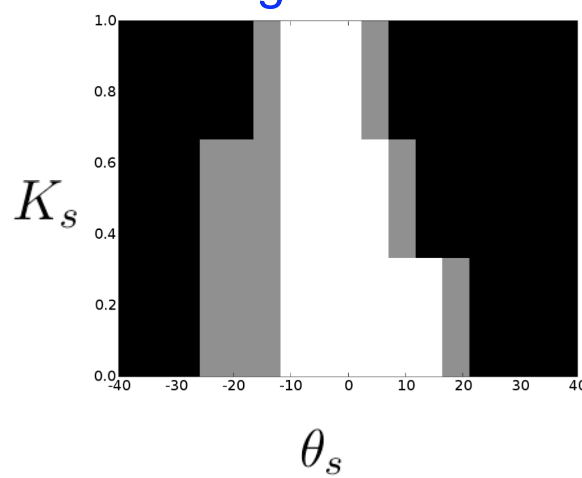
$$-40^\circ \leq \theta_s \leq 40^\circ$$

$$K_{ps} \in [0.0, 0.5, 1.0]$$

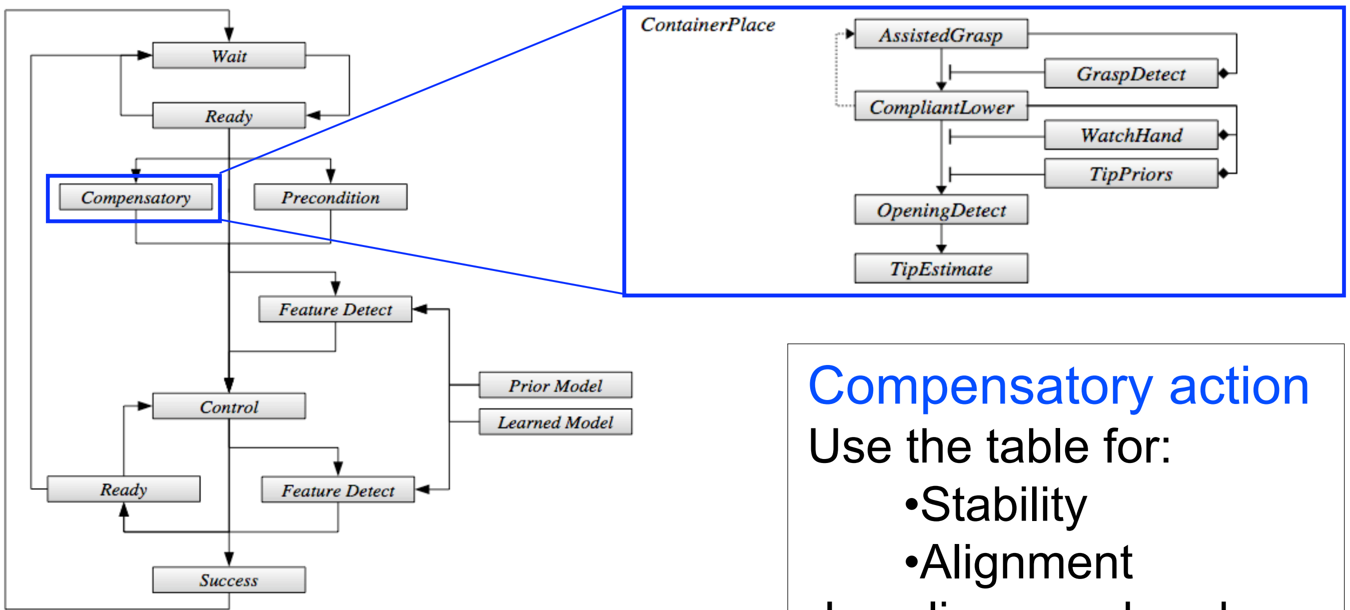
Predicted:

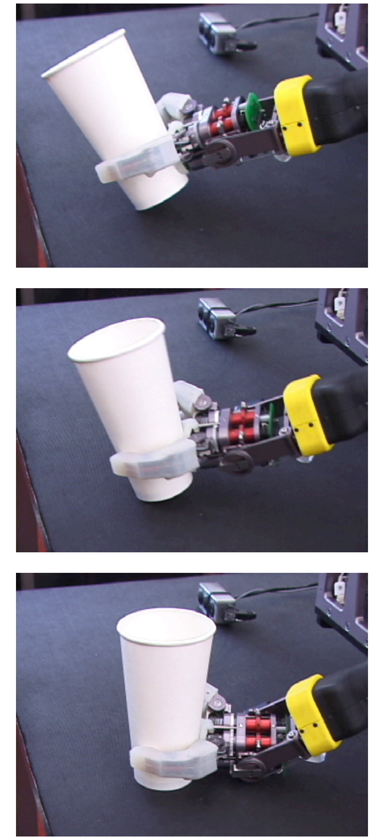
$$\theta_s = 21.2^\circ$$

Wrist stiffness v.s. misalignment



Finding an opening



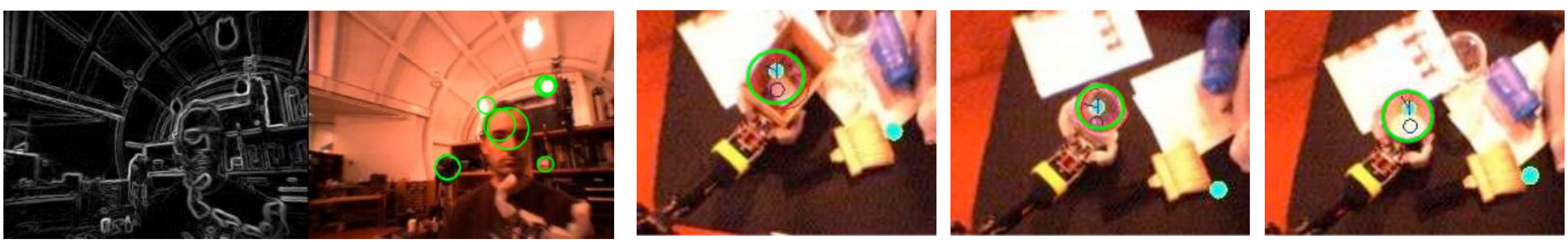


Compensatory action

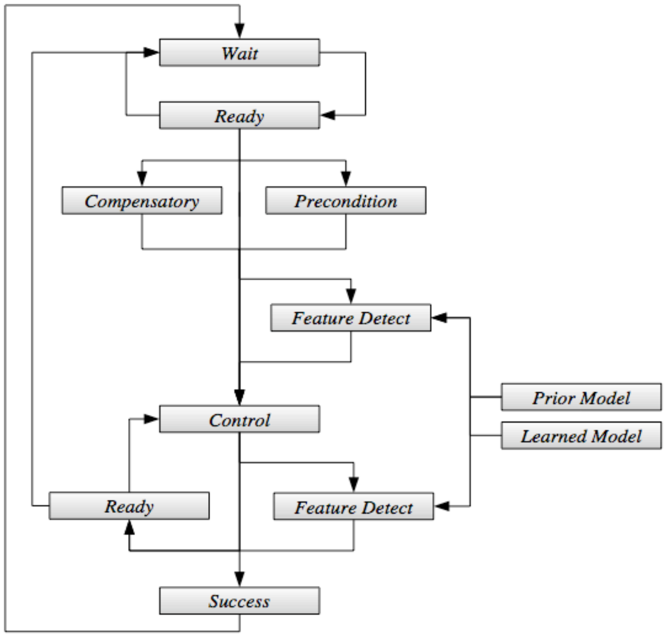
Use the table for:

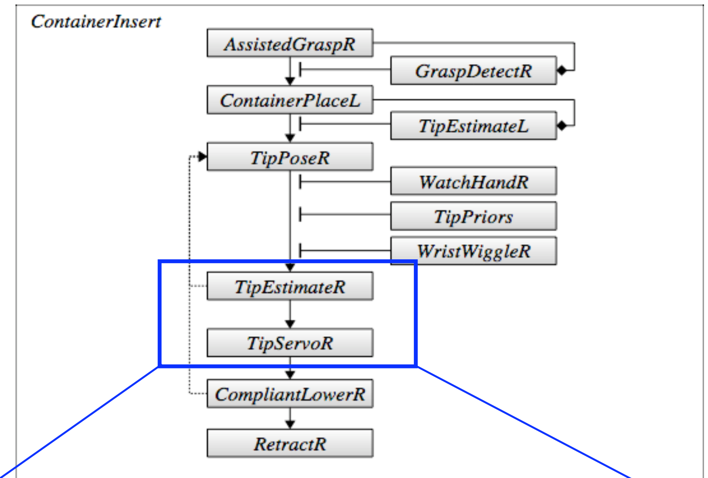
- Stability
- Alignment

- Localize near hand
- Detect convex edge

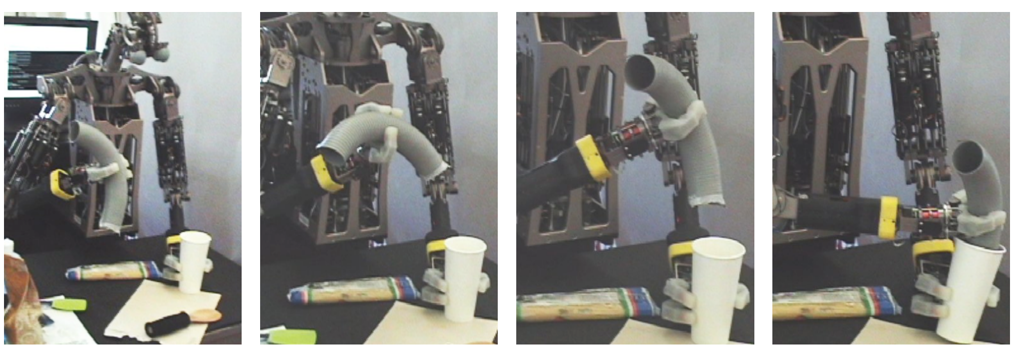


Bimanual insertion

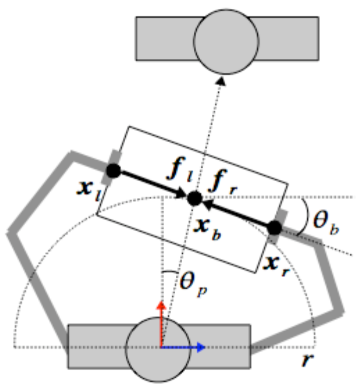


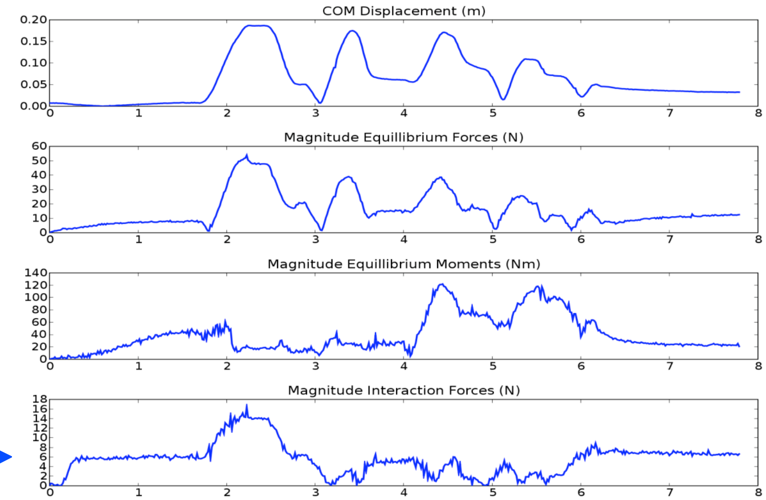


	Paper cup	Bowl	Box	Coffee mug	Jar
Mixing spoon	7/7	7/7	7/7	6/7	7/7
Water bottle	6/7				
Paint brush	6/7				
Paint roller	5/7				
Spoon (prior only)	1/7				



Bimanual fixture





Disturbance response

Right arm controller

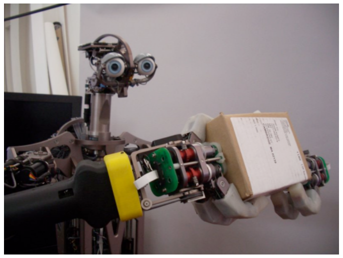
$$\hat{x}_r = \mathbf{x}_b + [\frac{d}{2}cos(\theta_p), \frac{d}{2}sin(\theta_p), 0]^T$$

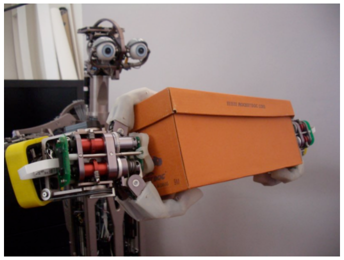
$$\mathbf{f}_r = -k_f(\mathbf{x}_r - \mathbf{x}_b)$$

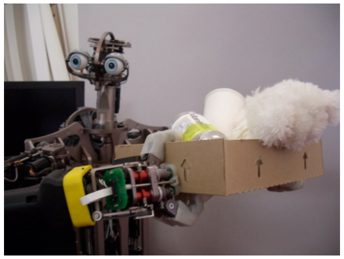
$$\Delta\theta_r = \sigma \mathbf{J}^T \mathbf{f}_r$$

Constant error creates “squeezing” force

$$\theta_{desired-r} = IK(\hat{x}_r) + \Delta\theta_r$$







Roadmap

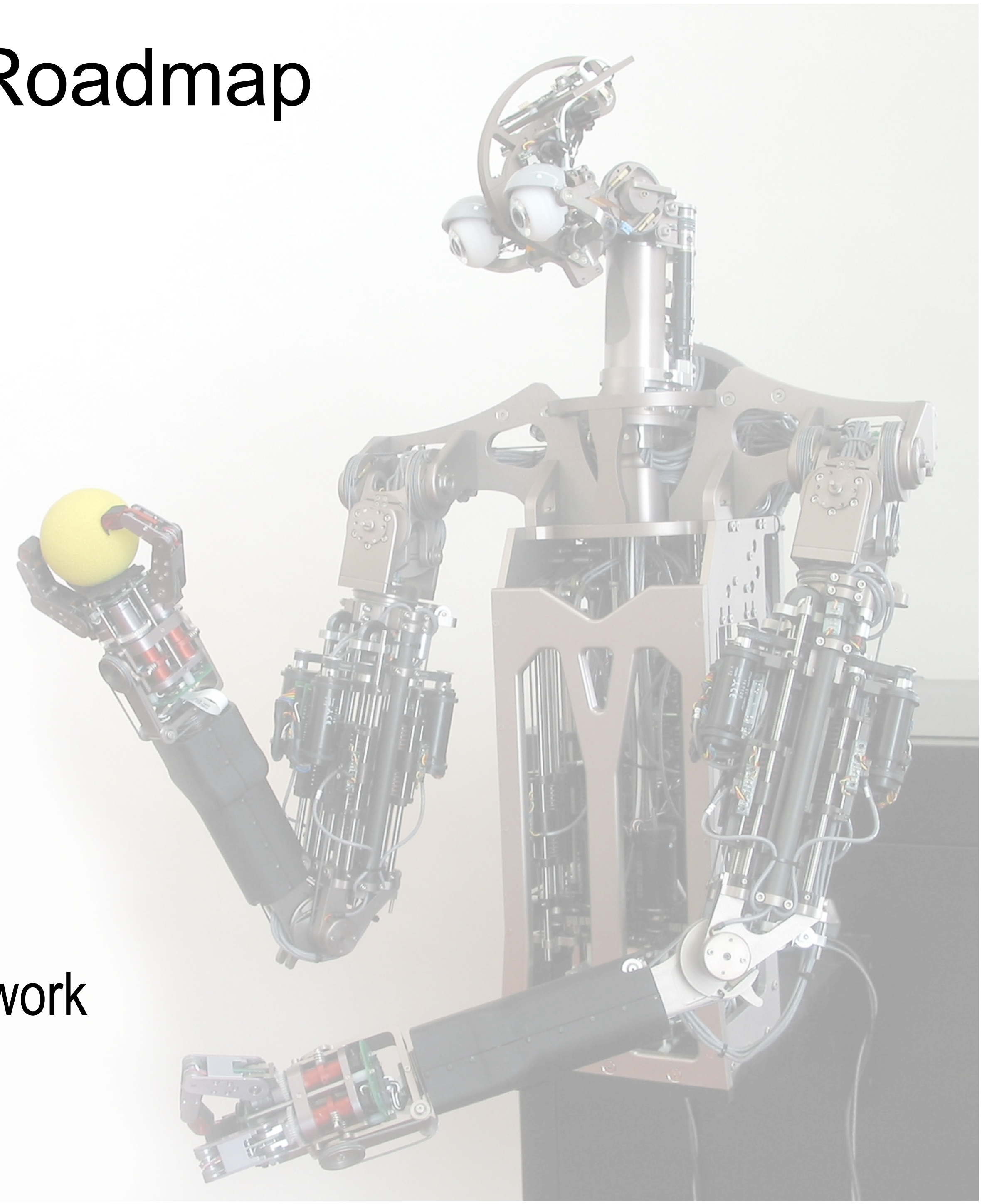
- •Approach

- •Robot design
- •Visual system
- •Control architecture

- •Working with object tips
- •Working with people
- •Manual skills

- •Helping with chores

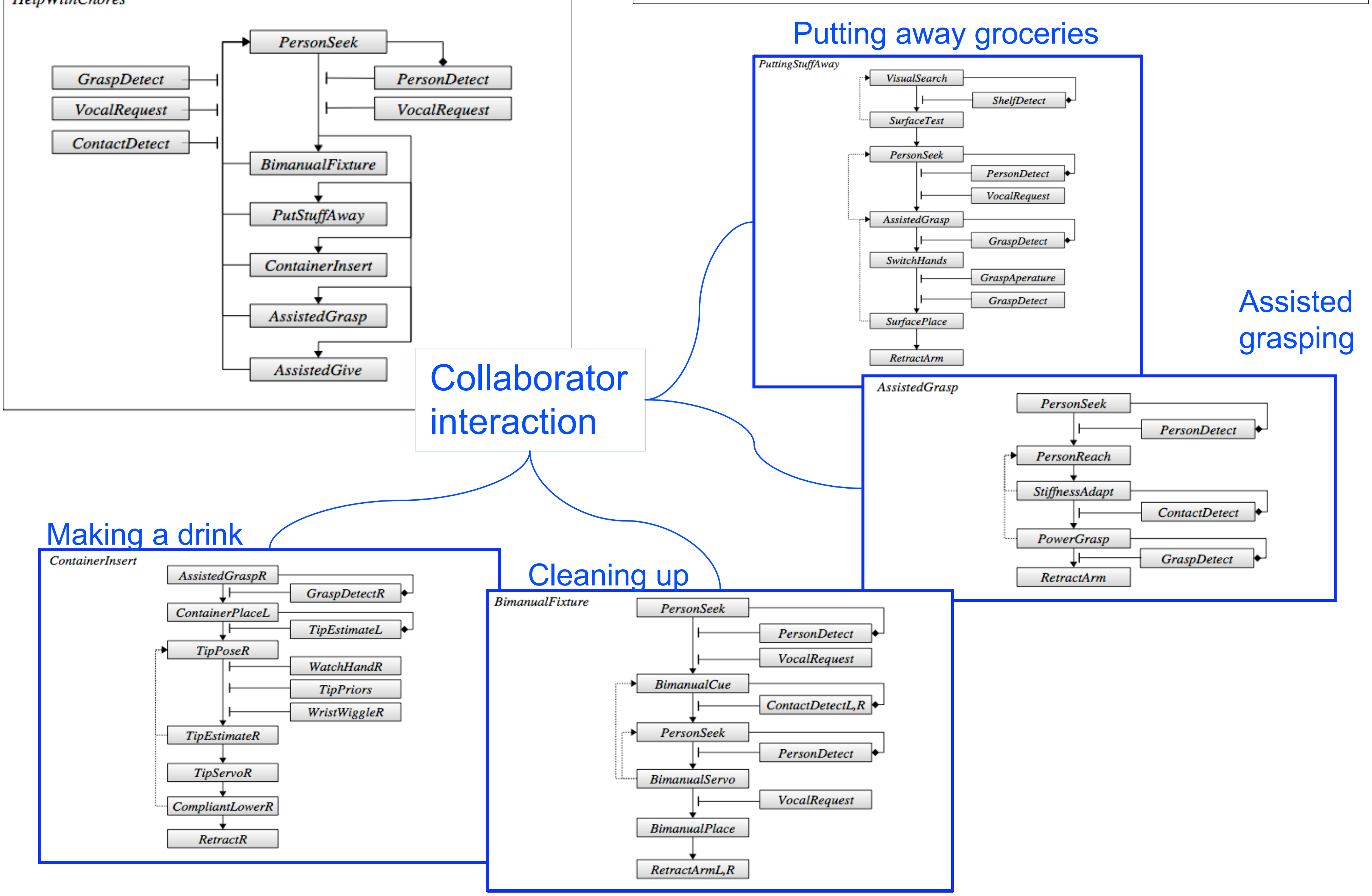
- •Conclusions and future work



Helping with chores

Helping with chores

Collaborator composes task plan

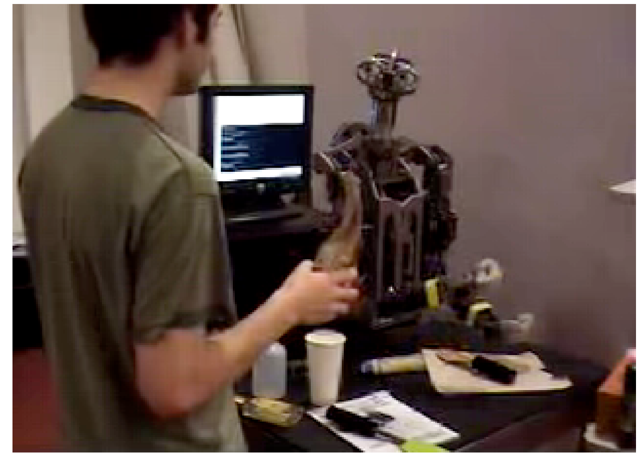


Putting away groceries

"Domo, shelf"

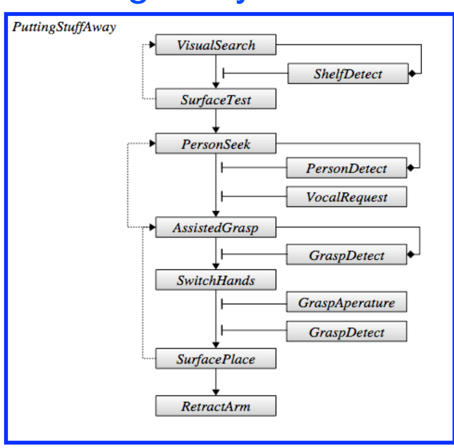
"Domo, take"

1. Find a flat surface
2. Verify it is reachable
3. Take item from person
4. Switch item to closest hand
5. Place item on shelf

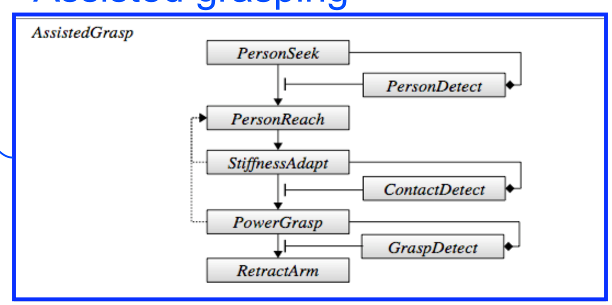


Collaborator interaction

Putting away



Assisted grasping



Making a drink

"Domo, insert"

"Domo, give it"

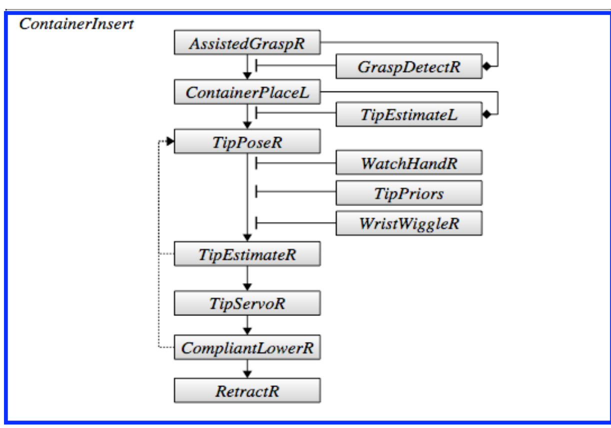
"Domo, insert"

"Domo, shelf"

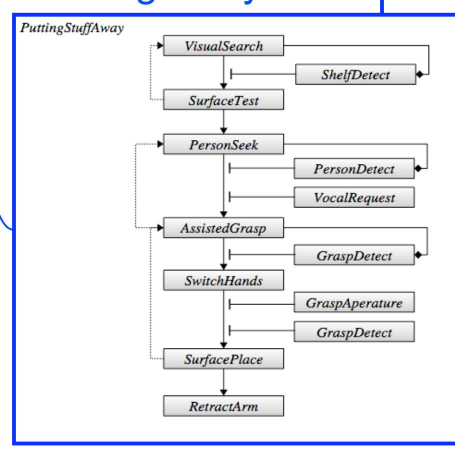
1. Take bottle from person
2. Take cup from person
3. Insert bottle tip into cup
4. Give bottle to person
5. Take spoon from person
6. Insert spoon tip into cup
7. Put cup on shelf

Collaborator interaction

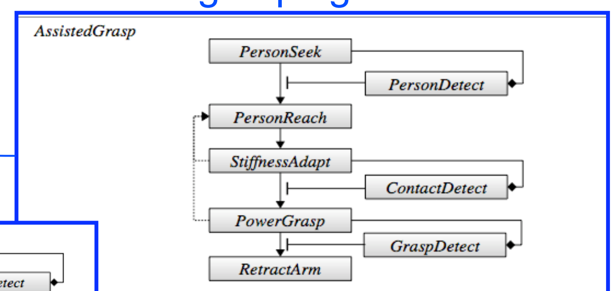
Bimanual Insertion



Putting away



Assisted grasping



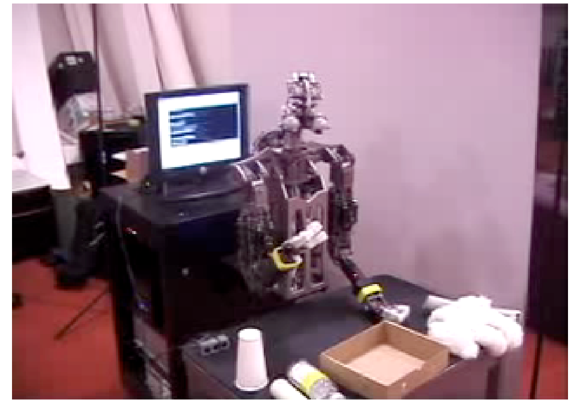
Cleaning up

"Domo, box"

1. Cue person to hand the box
2. Detect contact cue during hand-off
3. Form bimanual grasp
4. Track person as they move
5. Position box near the person as items are placed in it

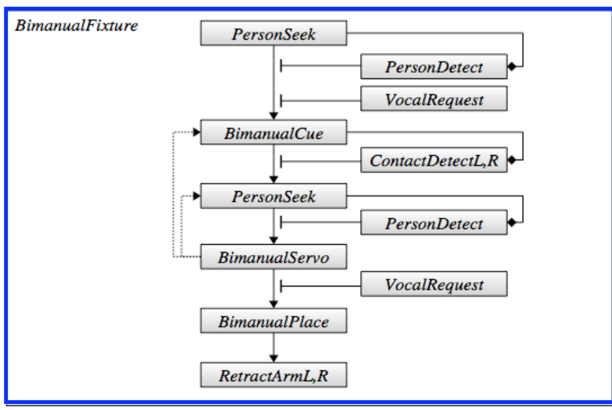
"Domo, done"

6. Lower the box onto the table

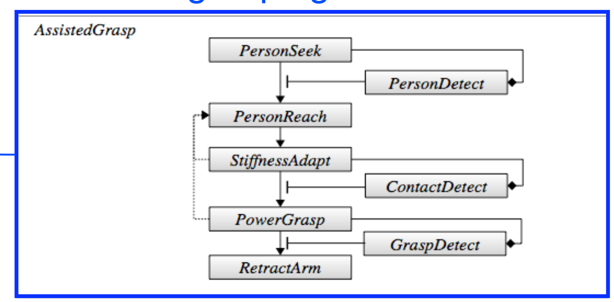


Collaborator interaction

Bimanual fixture



Assisted grasping



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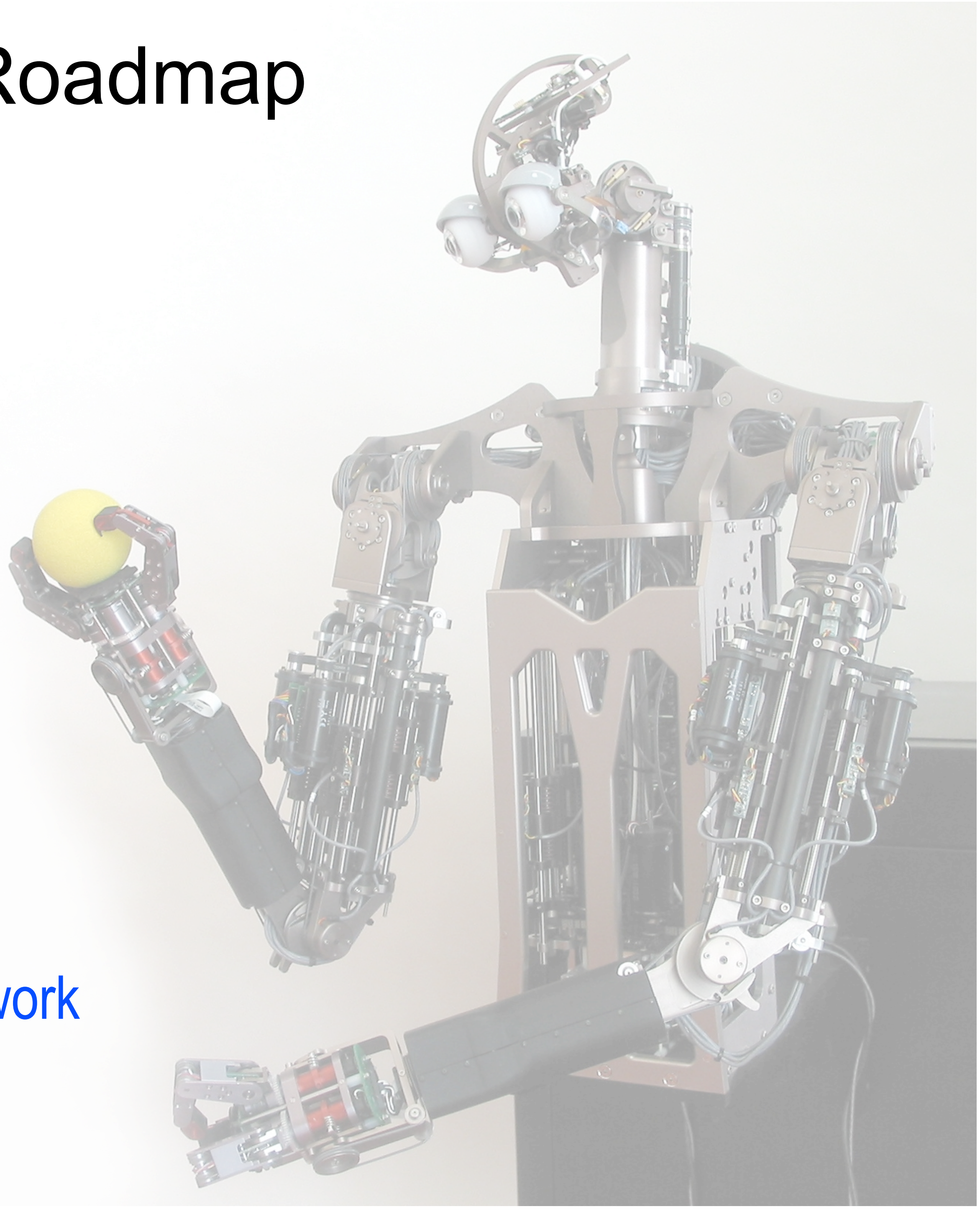


Further details…

C. Kemp, A. Edsinger, and E. Torres-Jara. ”Challenges for Manipulation in Human Environments", IEEE Robotics & Automation Magazine, To Appear, 2007.

A. Edsinger and C. Kemp. "Manipulation in Human Environments", Proceedings of the IEEE/RSJ International Conference on Humanoid Robotics, 2006. Best paper award

C. Kemp and A. Edsinger. "Robot Manipulation of Human Tools: Autonomous Detection and Control of Task Relevant Features". Proceedings of the Fifth International Conference on Development and Learning, Special Session on Classifying Activities in Manual Tasks, 2006.

A. Edsinger and J. Weber. "Domo: A Force Sensing Humanoid Robot for Manipulation Research", Proceedings of the IEEE/RSJ International Conference on Humanoid Robotics, 2004

A. Edsinger. "Design of a Compliant and Force Sensing Hand for a Humanoid Robot", Proceedings of the International Conference on Intelligent Manipulation and Grasping, 2004.

R. Brooks, L. Aryananda, A. Edsinger, P. Fitzpatrick, C. Kemp, U. O'Reilly, E. Torres-Jara, P. Varshavskaya, and J. Weber. "Sensing and Manipulating Built-for-Human Environments", International Journal of Humanoid Robotics, Vol 1, No. 1, 2004.

Caveats and Extensions

- Rely on benign collaborator
- Objects within a class
- Adaptation to failure

What we do…

- Variety of everyday objects
- Variability in lighting
- Human dynamics
- Cluttered background
- No 3D object models
- No environment engineering

What we don’t do…

- Naïve collaborators
- Multiple environments
- Autonomous grasping
- Autonomous task-planning
- Differing classes of objects

Caveats and Extensions

- Task planning without models
- Dealing with arbitrary objects

What we do…

- Variety of everyday objects
- Variability in lighting
- Human dynamics
- Cluttered background
- No 3D object models
- No environment engineering

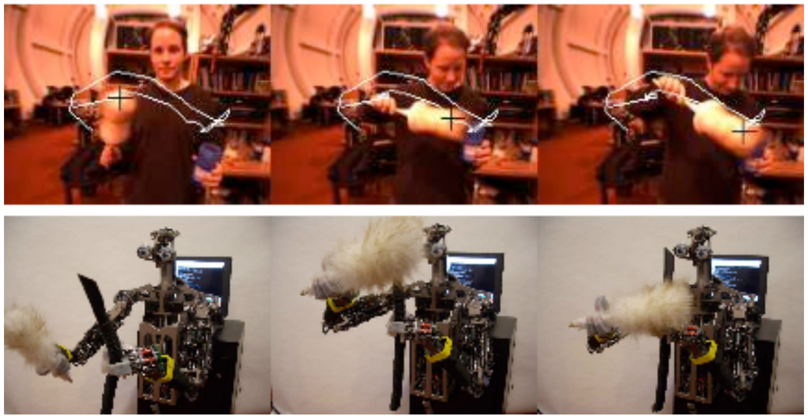
What we don't do…

- Naïve collaborators
- Multiple environments
- Autonomous grasping
- Autonomous task-planning
- Differing classes of objects

Future Work

More dynamics, more adaptation

- A suite of task relevant features
  - Tactile shape features
  - Local 3D features
  - Flat surfaces, handles
- A suite of social cues
  - Pointing
  - Force guidance
  - Gestures
- A suite of manual skills
  - Opening door
  - Stacking



Learning by demonstration
via task relevant features

Conclusions

Human environments pose unique challenges

Rather than solve impressive, dexterous tasks…

…focus on basic manual skills that account for these challenges

Lesson: People leverage structure in human environments to reduce cognitive load

…robots can do the same

Contributions

- Real robot
  - Force sensing and compliance
  - Intrinsic safety
  - Single, integrated behavior system
- Strategies for human environments
  - Let the body do the thinking
  - Cooperative manipulation
  - Task relevant features
- Accomplish useful, everyday tasks
  - Dynamics and variability
  - No object models

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