Robots Among Us: Socially Assistive Interaction

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Many thanks

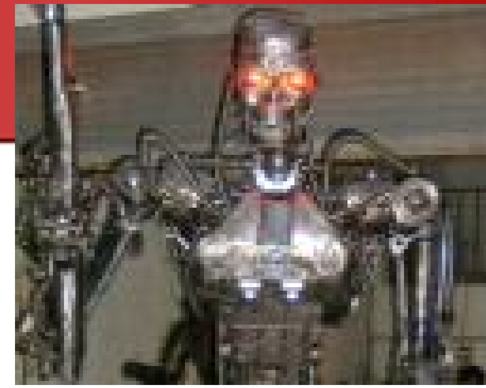
for the opportunity

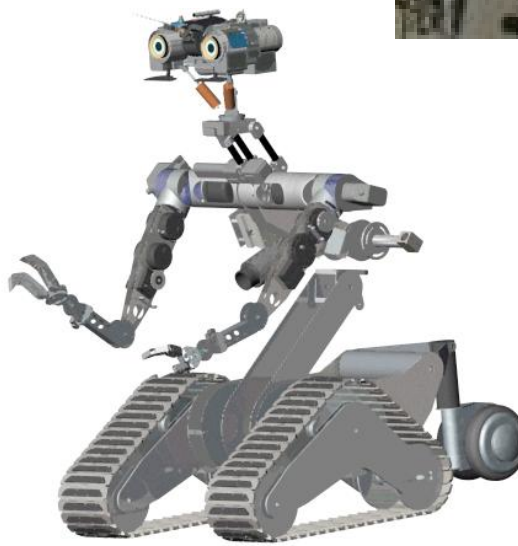
to visit FORTH and Crete and to participate in the

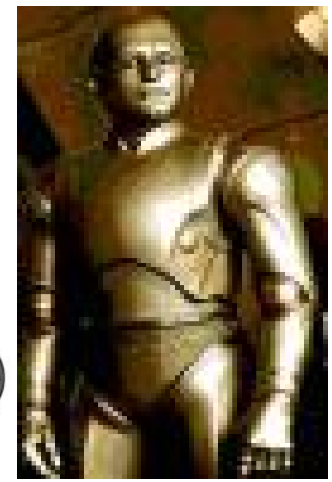
FORTH & Onassis Lectures

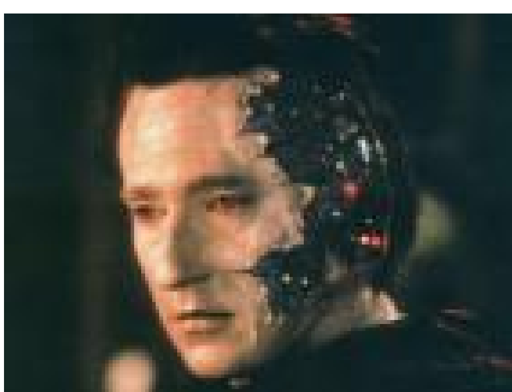
The most common symbols of a society of the future is …

Robots!





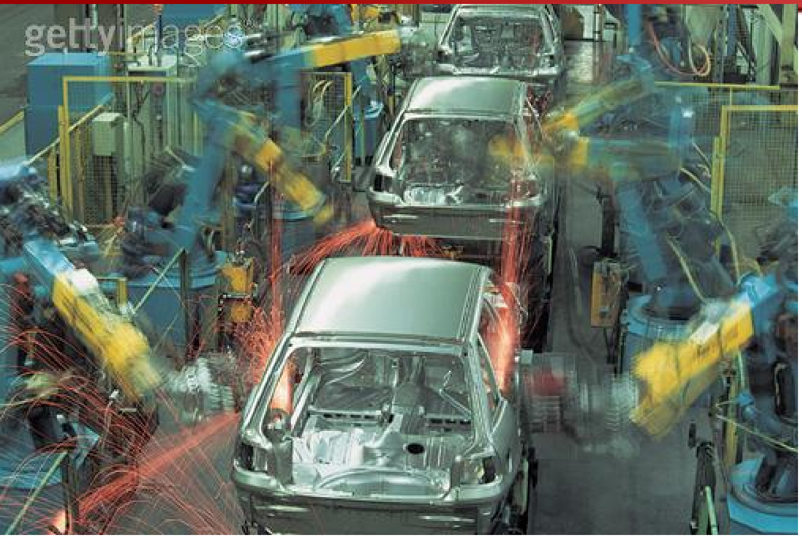




Ir

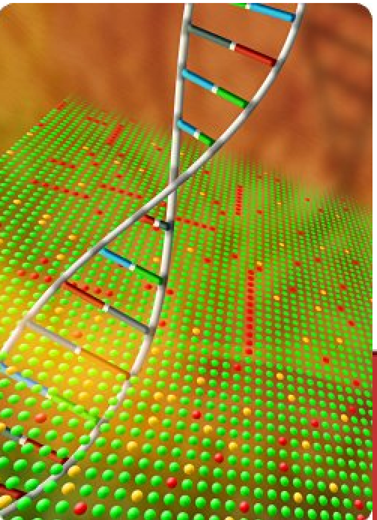
US

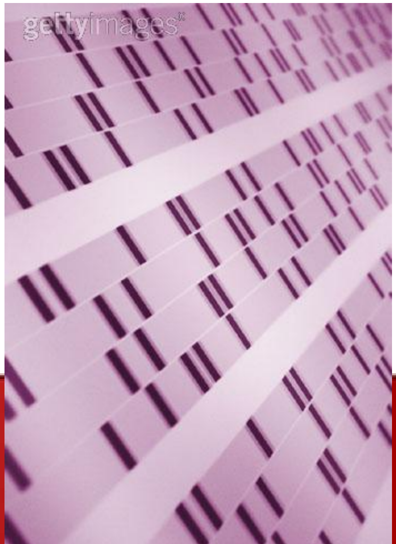
Robots True to Their Name



Auto-assembly

Genome sequencing





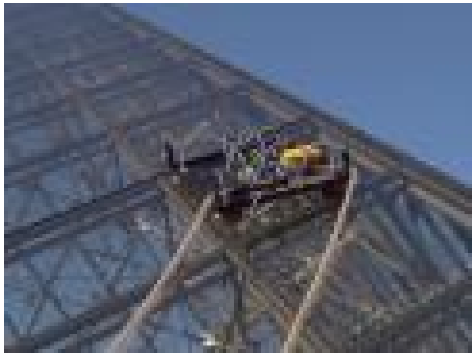
Vacuuming

Where Are the Robots?

- Large numbers used in assembly (from cars to genes) and cleaning (vacuums)
- Less pervasive but growing numbers in the military, entertainment, service
- Let’s consider some trends…

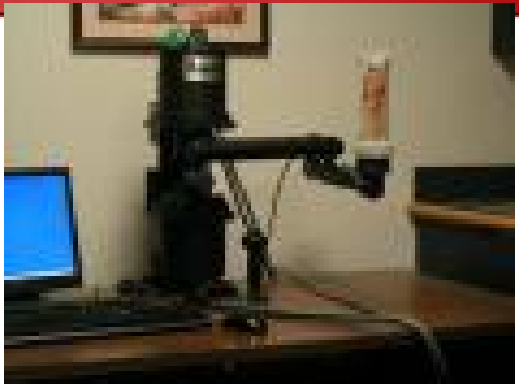
Some Service Robots

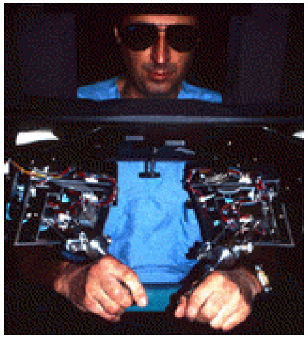
- Port automation, cargo loading
- Cleaning (floors to airplanes)
- Warehouse monitoring
- Lawn mowing
- Window washing
- … Companionship



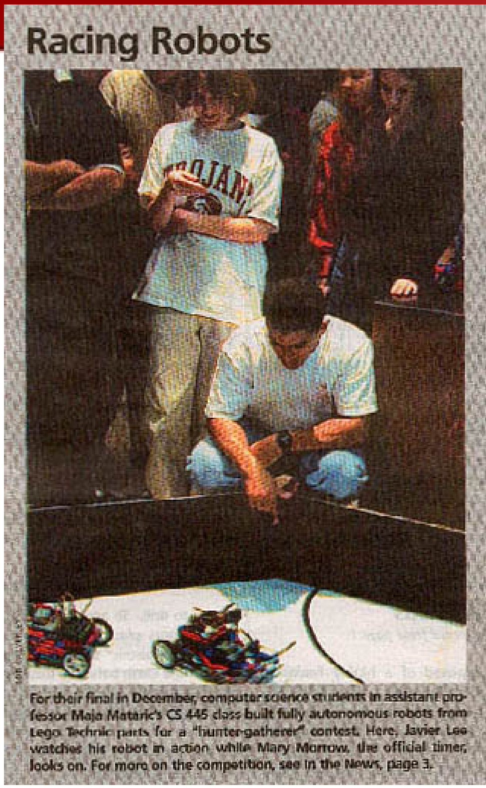
Robots in Medicine and Health

- Surgical robotics
  - Hip replacement
  - Neurosurgery
  - Cardio-thoracic surgery
  - Urology/prostate surgery
- Rehabilitation & physical therapy robots
  - Stroke
- Prosthetics
  - Limbs





Robots In Education



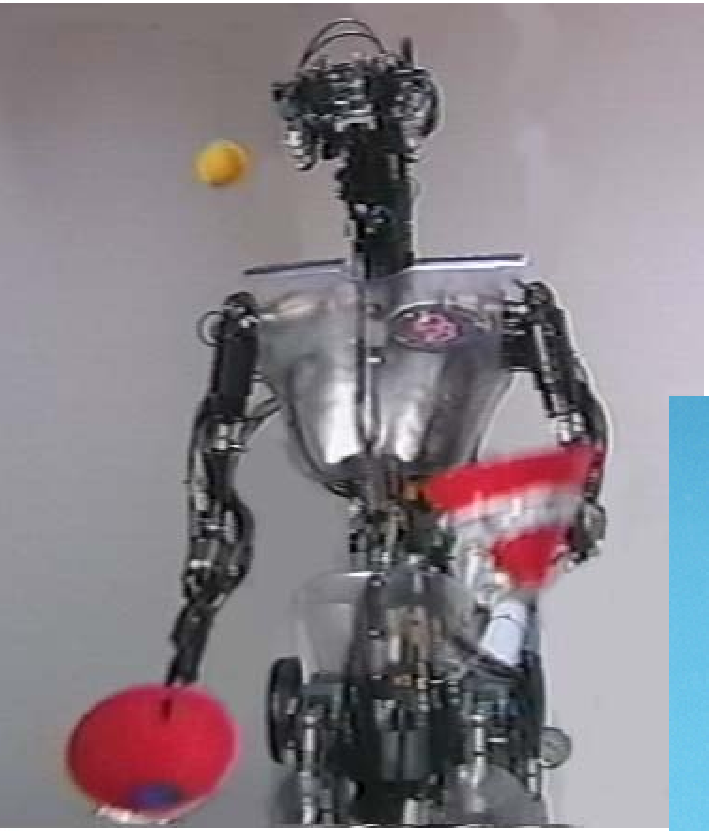
Racing Robots

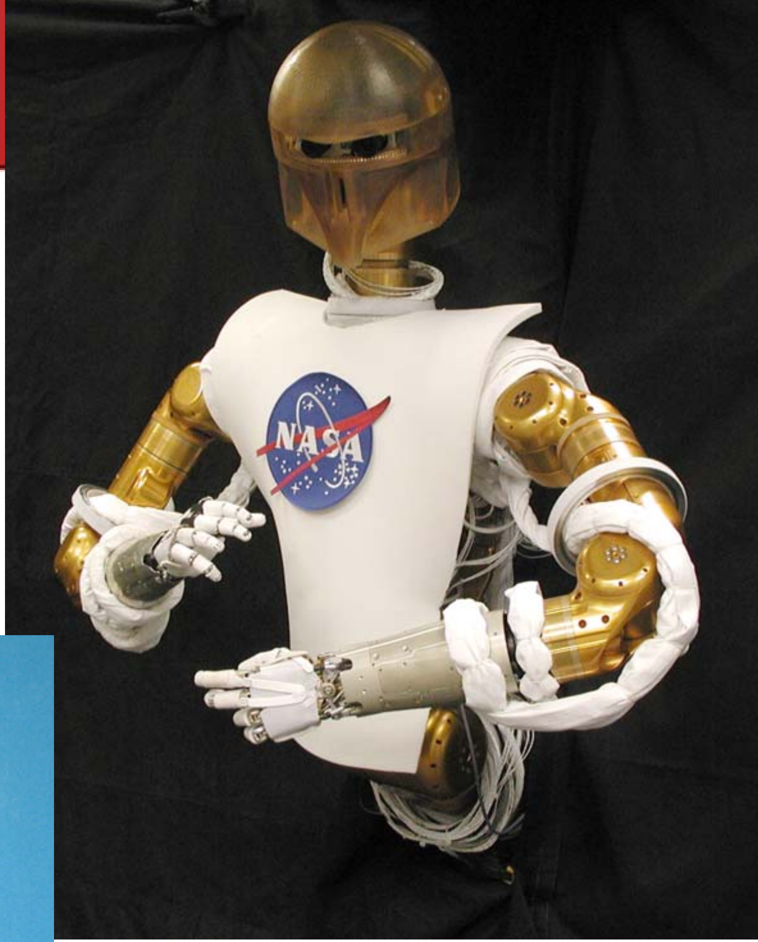
For their final in December, computer science students in assistant professor Maja Mataric's CS 445 class built fully autonomous robots from Lego Technic parts for a "hunter-gatherer" contest. Here, Javier Lee watches his robot in action while Mary Morrow, the official timer, looks on. For more on the competition, see In the News, page 3.

Proven effective as tools for:

- teaching science, technology, engineering, & math
- recruiting & retaining under-represented student groups
- K-12 → university

Humanoids





A Good Time to be a Roboticist

- *Robotics is about to enter and change our daily lives, in the next one-two decades*

- Very large investments into robotics R&D are being made both by governments and by industry to make this a reality

Why Now?

- Enabling economics and demographics: large markets/user populations can benefit

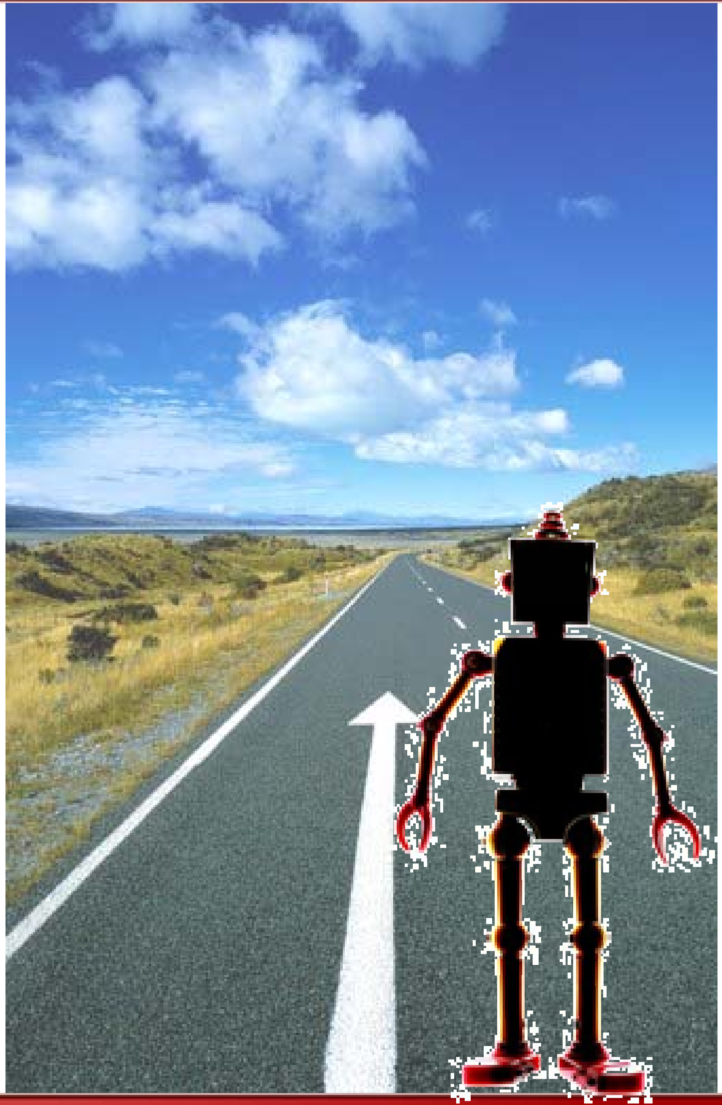
- Enabling technologies:
  - Sensing: off-the-shelf vision, lasers, motion capture
  - Communications: ubiquitous
  - Computation: Moore's Law still with us
  - Affordable robot hardware (e.g., iRobot)

A Prediction (not by an Oracle)

- Specialized niche products will succeed first (e.g., intelligent vacuum cleaners, toys, tele-presence, partially autonomous vehicles, semi-intelligent appliances, etc.)

- This will pave the way (through manufacturing and maintenance channels and social/public acceptance of the technology) for more sophisticated, costly, general-purpose systems (e.g., humanoids)

What Should be the Future of Robotics?



Enduring Societal Challenges

Regaining function & retaining independence

1 in 5 children is overweight

1M Parkinson's patients,

50,000 new/year

750,000 strokes/year in US alone

Guidance & protection

thousands perish in natural and man-made disasters

Elderly at highest risk from injury and assault

Individualized development, learning and training

6.6M special ed students

3.5M children with ADHD

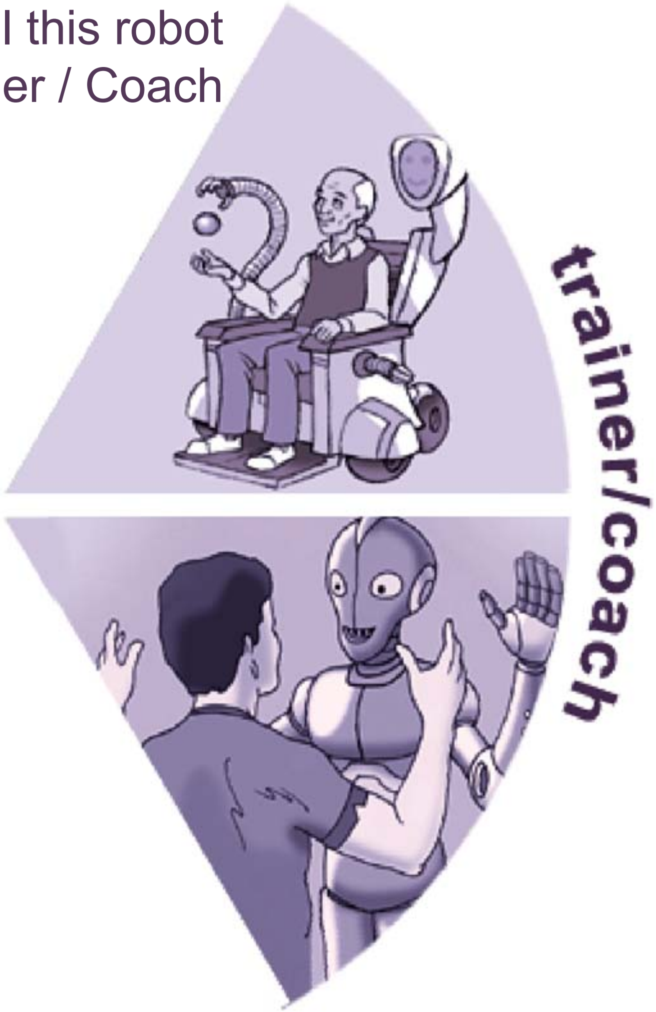
6.2 to 7.5M people with mental retardation

Addressing Enduring Societal Challenges

An opportunity for
human-centered technology
to address
large-scale societal challenges
and improve human quality of life

Imagine a robot …

We call this robot Trainer / Coach



… that can assist a physical therapist

… that is enjoyable to interact with

… that minimizes embarrassment

… that is tirelessly devoted 24-7

… that can get doctor or nurse help whenever needed

… that helps numerous people regain their independence

Imagine robots…

We call these robots
Shepherds / Guides

… that assist people as part of a team

… that serve as eyes and ears

… that are easy to command and interact with

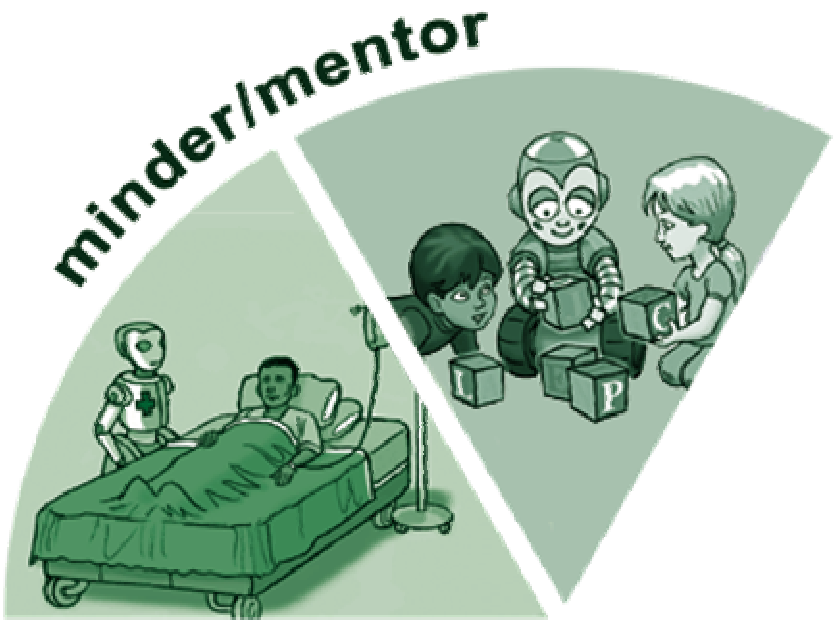
… that are unobtrusive

… that are available 24-7 at an unsafe location

… that increase the number of lives saved and protected

Imagine a robot …

We call this robot
Minder / Mentor



… that can help to identify early signs of autism and other developmental disorders

… that can provide continuous support to patients & caregivers

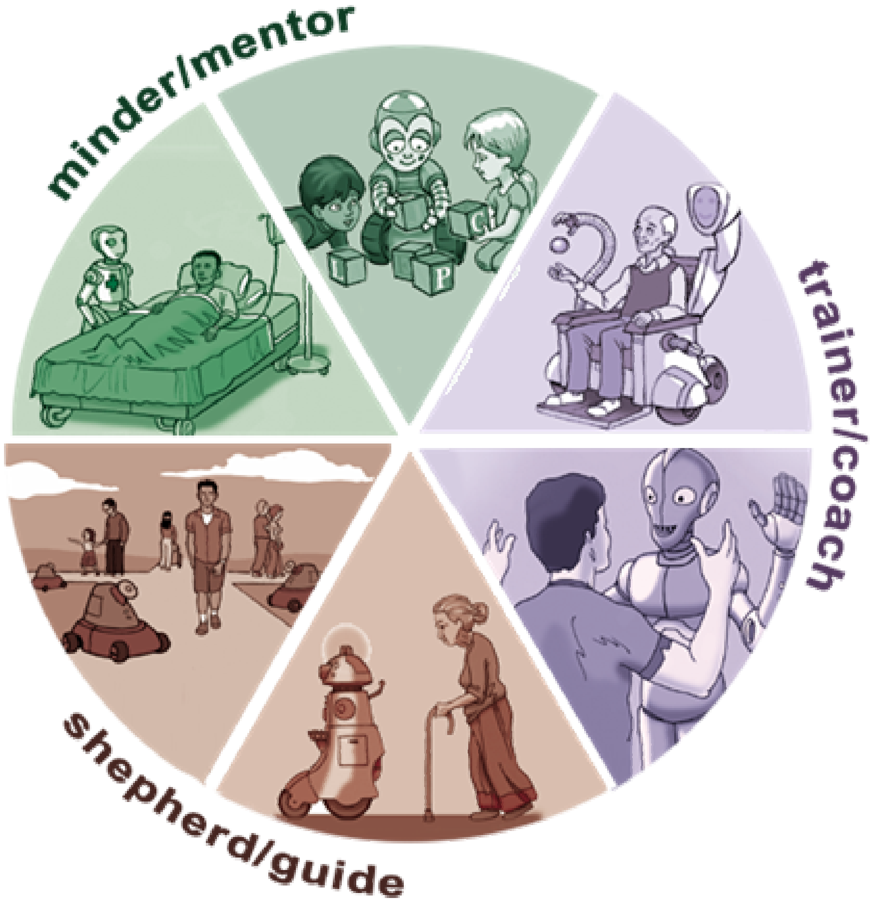
… that is individually customizable

… that provides continuous motivation for therapies

… that helps numerous people lead happier lives

Human-centered robotics technology

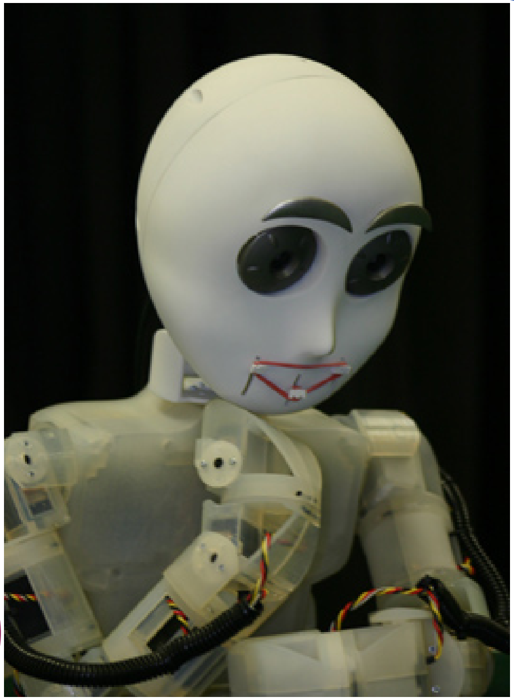
working with people
to help address
societal needs



Robot Capabilities → Research Challenges

Monitor and interpret human activity

Respond quickly, safely, and adaptively



Engage and motivate

Adapt to the user's changing needs

Interact with caregiver medical/teaching/ responder staff

Achieve assistive goals

Multidisciplinary Research Endeavor

Inherently multidisciplinary, demanding a deeper understanding of people, society and technology

Changing the Role of Machines in Society

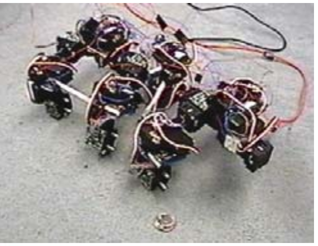
Safety, ethics, and social issues must be addressed alongside the research and technology development

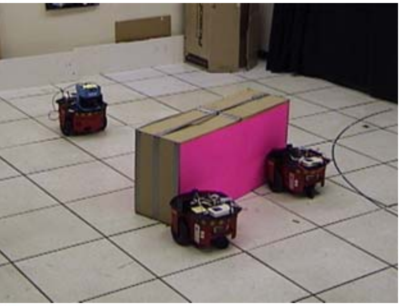
Outline

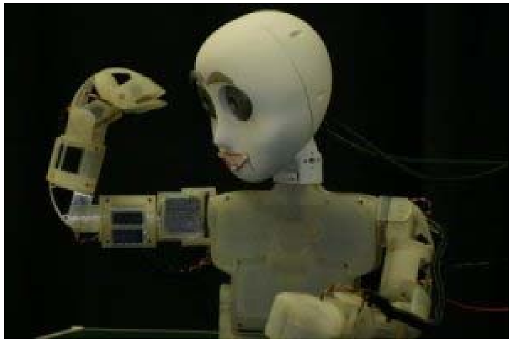
- Overview & goals
- Action
  - Behavior primitives: derivation, classification, and learning
- Interaction
  - Multi-robot coordination
  - Imitation
  - Embodied communication for HRI
- Engagement
  - Improved performance from engagement and motivation
  - The role of personality

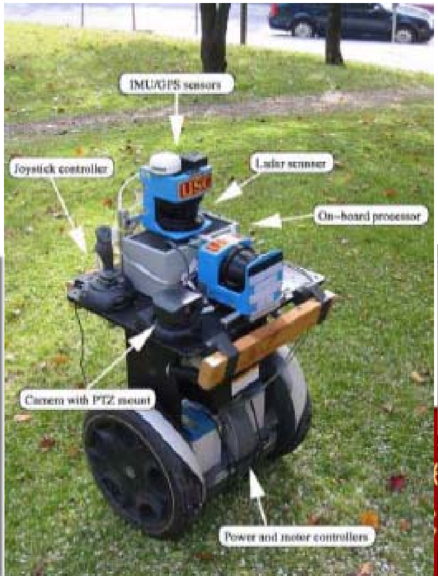
USC Robotics Research Areas

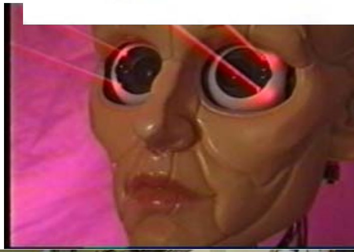
- Assistive robotics
- Humanoids
- Sensor-actuator networks
- Multi-robot systems and robot teams
- Self-reconfigurable robotics
- Nano-robotics











Specific Goals

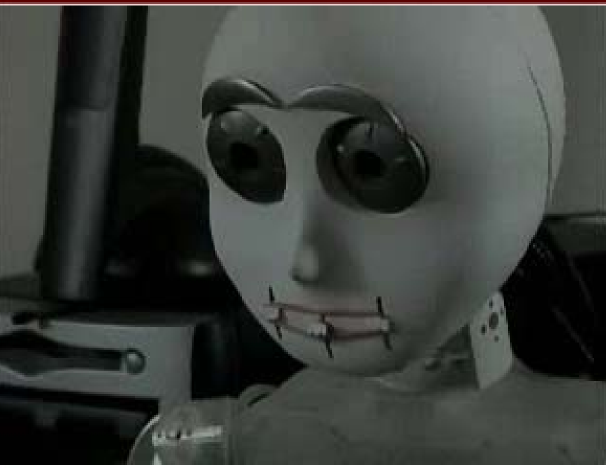
1. Understand people better: Use robotics to gain insights into human behavior and human-robot interaction
2. Help people: Develop technology to effectively assist people

(Robots do not replace people, they work with people)

Diagnosing and Treatment of Developmental & Social Disorders

- Scientific goals: gaining a better understanding of (growing) cognitive and social disorders
- Autism and ADHD particularly amenable to robotics-based intervention
- Robots starting to be used for
  - Diagnosis: augmenting human ability
  - Treatment: socialization & education

Some of Our Socially Assistive Robots



Special education

Arm
rehabilitation
exercises

Cardiac recovery

Walking and running

NIH stroke
rehabilitation
study

Outline

- Overview & goals
- Action
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- Interaction
  - Multi-robot coordination
  - Imitation
  - Embodied communication for HRI
- Engagement
  - Improved performance through engagement and motivation
  - The role of personality

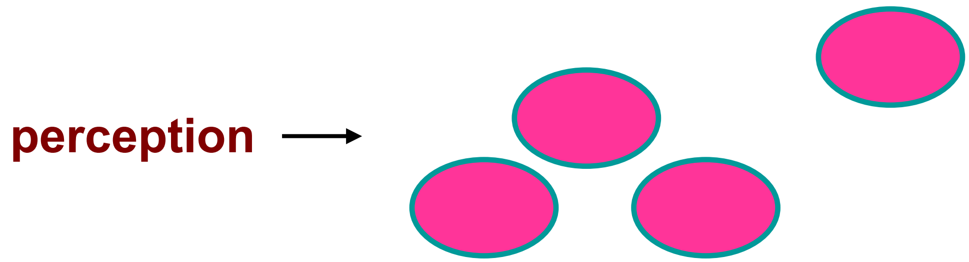
Tackling Complexity

- Activity generation: Real-time robot control in dynamic human-populated environments is an open problem
- Activity understanding: activity is hard to perceive, interpret, and respond to appropriately and quickly
- *We aim to reduce the dimensionality of these inter-related problems by deriving a tractable "vocabulary" of prototypical activities (for the robot and human) at each relevant level of abstraction (individual, team, crowd)*

→ *Unified model: a generative vocabulary of activities is the substrate for control, activity understanding, and learning*

Activity Generation

- The robot is endowed with a set of primitive behaviors (pre-programmed or learned); these constitute the *generative behavior vocabulary*, the substrate for control

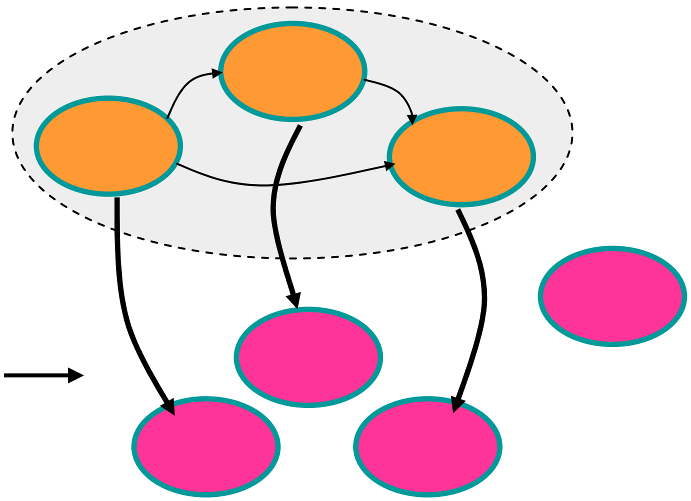


Activity Generation

- The robot is endowed with a set of primitive behaviors (pre-programmed or learned); these constitute the *generative behavior vocabulary,* the substrate for control
- The primitives are composable through sequencing and/or superposition to generate higher-level activities

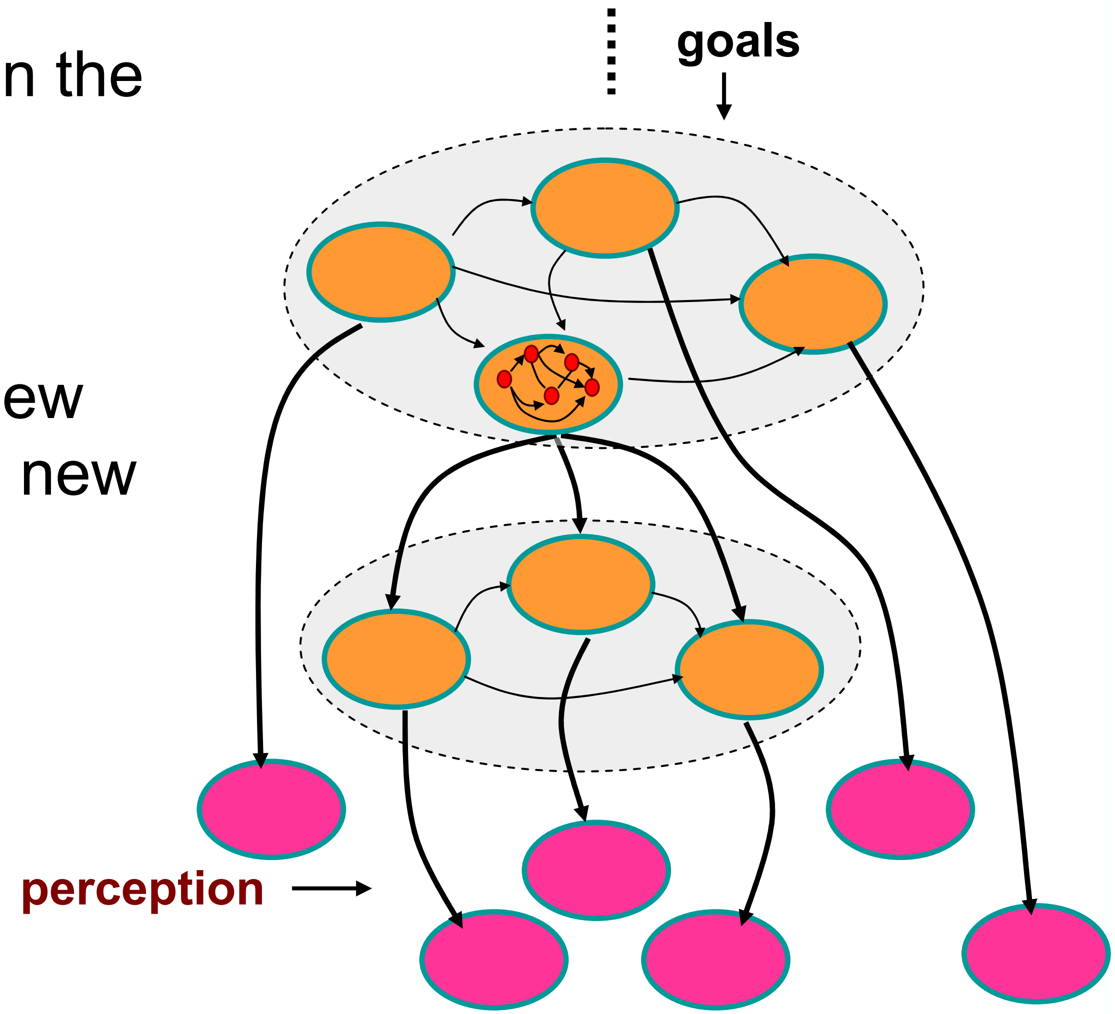
→ Inspiration comes from neuroscience of motor control

perception →



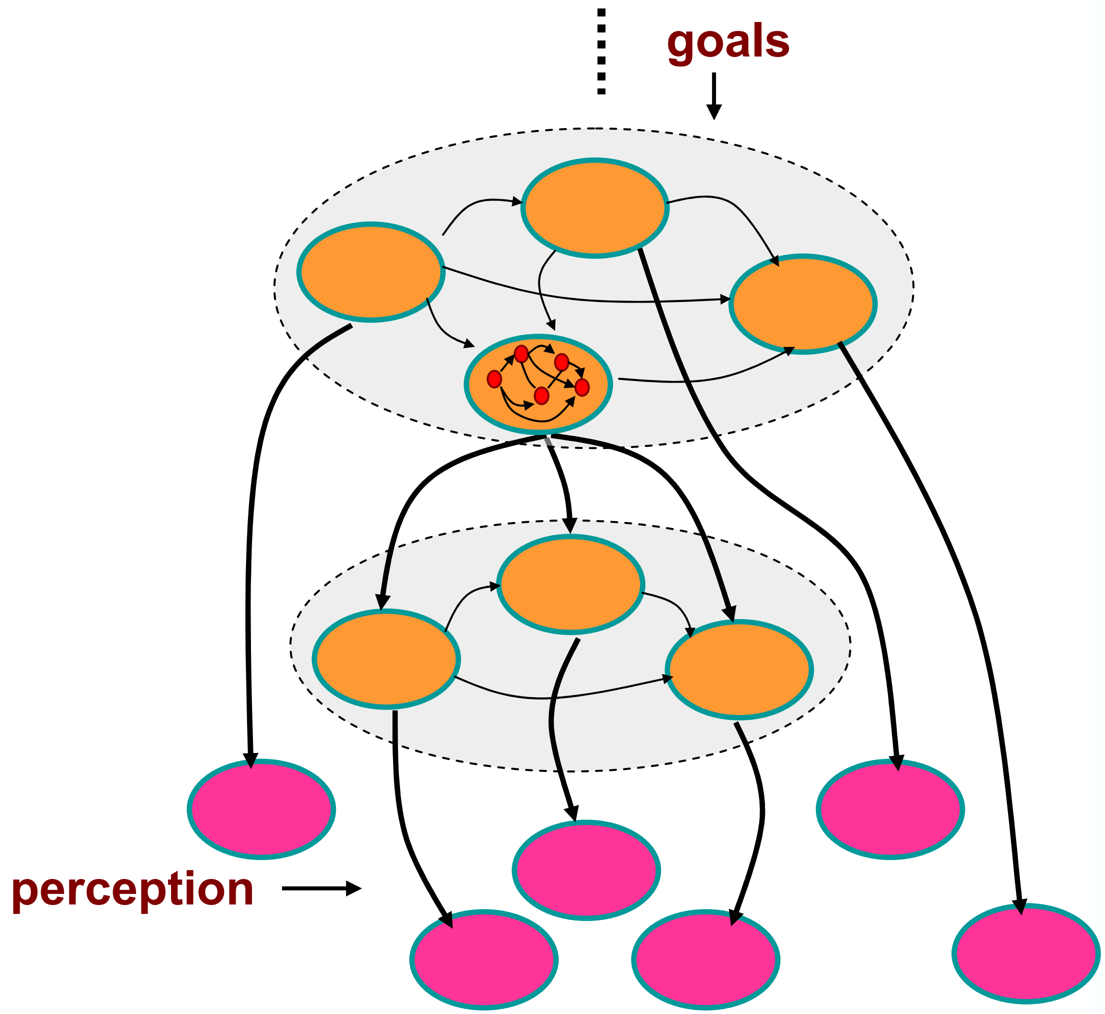
Activity Generation

- Planning is conducted in the reduced space of the vocabulary
- Learning expands the vocabulary by adding new behavior primitives and new compositions



Activity Understanding

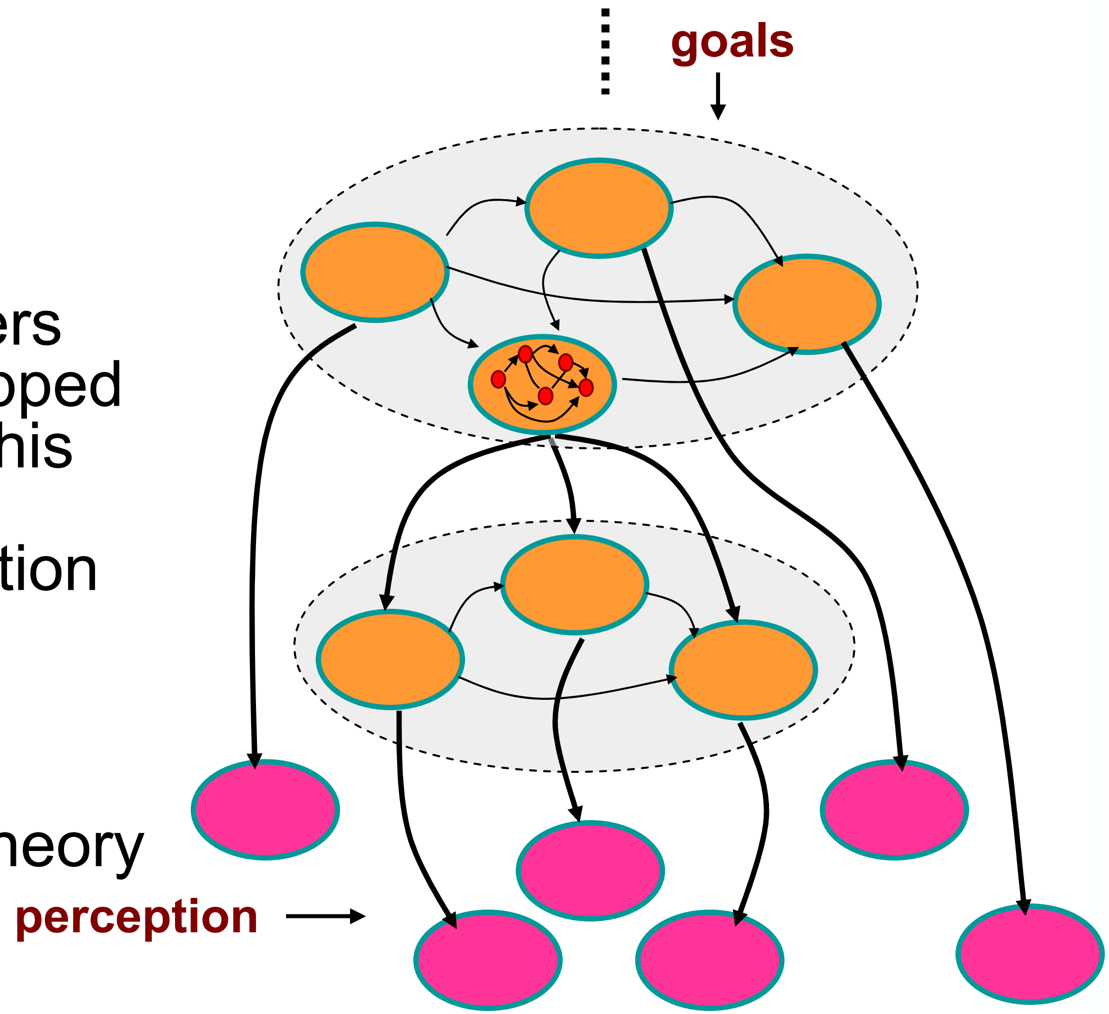
- The same behavior vocabulary is also the substrate for activity understanding



Activity Understanding

- The same behavior vocabulary is also the substrate for activity understanding
- Observed activity of others (people or robots) is mapped onto and classified into this vocabulary, allowing interpretation and prediction

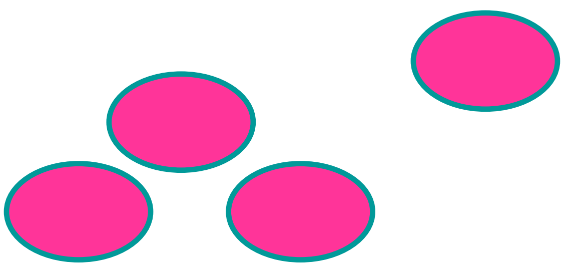
→ Inspiration comes from neuroscience of mirror neurons and the motor theory of perception



Activity Generation

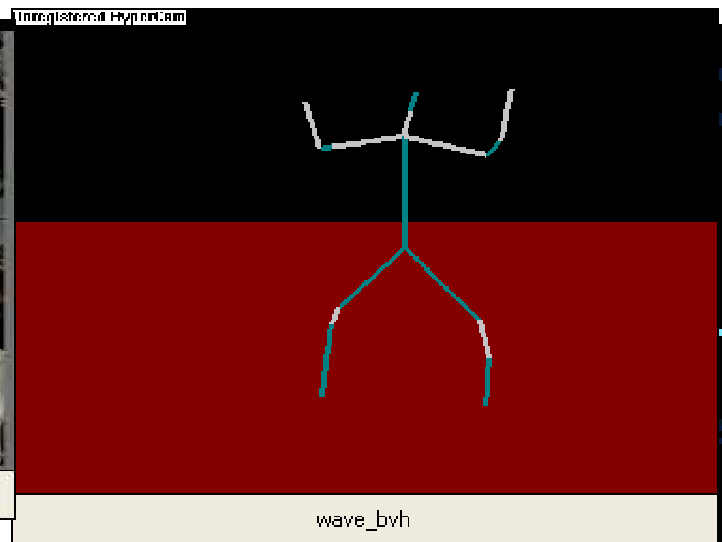
- The robot is endowed with a set of primitive behaviors (pre-programmed or learned); these constitute the *generative behavior vocabulary,* the substrate for control

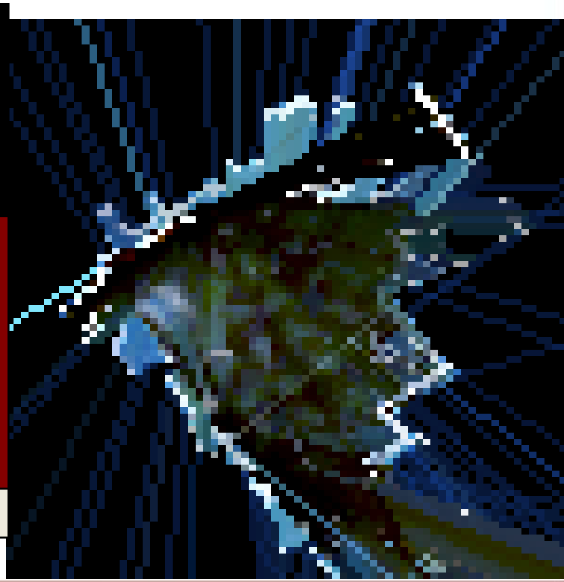
- Where do the primitives come from? What are the right ones? How many should there be?



Learning Behaviors From Data

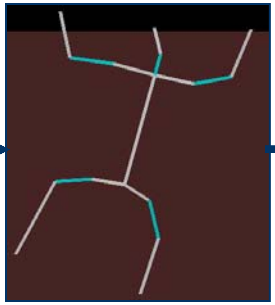
- A data-driven approach: learn primitive behaviors, and derived their controllers, directly from captured activity data
  - 3D human kinematic data
  - 2D individual and group trajectories





Deriving Behavior Vocabularies

- Goal: automatically derive a vocabulary of parameterized behaviors from natural human motion data
- Input: kinematic motion, joint angle time-series
- Process:
  - motion segmentation
  - grouping of exemplars through dimension reduction and clustering
  - generalizing behaviors into forward models



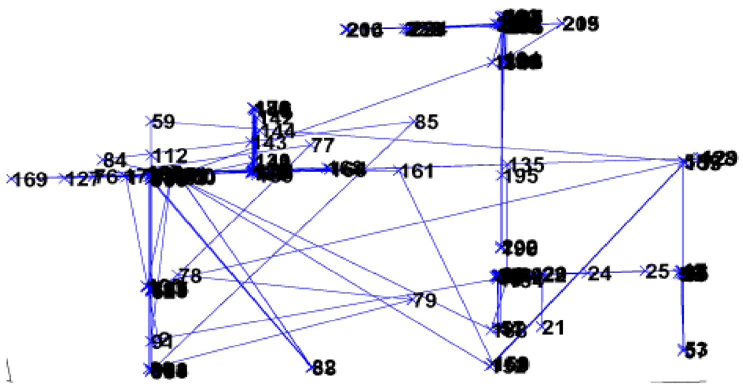
Natural Human Performance

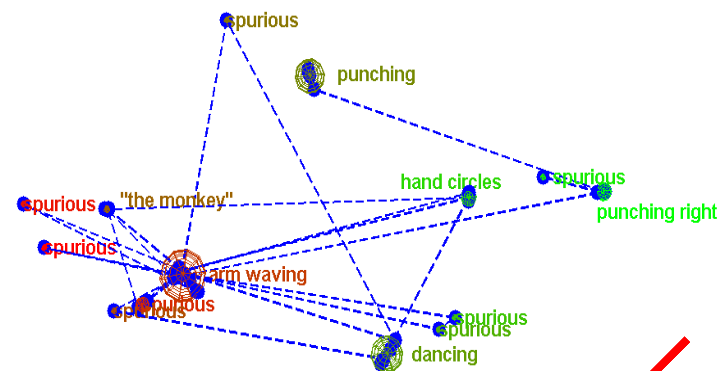
Motion Capture

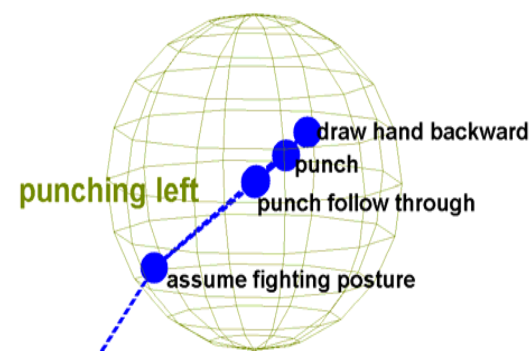
Vocabulary for a Robot

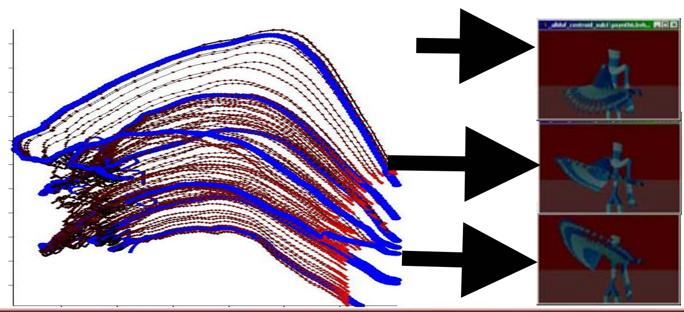
Behavior Derivation Overview

- Take 3D data, apply non-linear dimension reduction and clustering to get primitives (e.g., punch), iteratively re-apply to get meta-level behaviors (e.g., swing, punch, pull back), interpolate for forward models



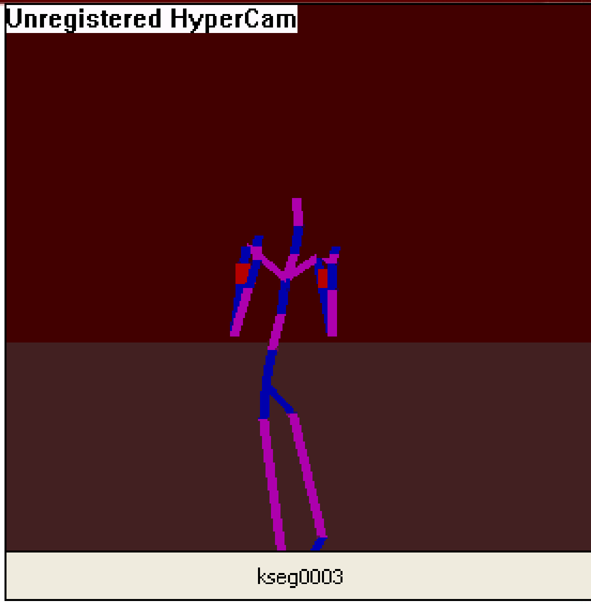




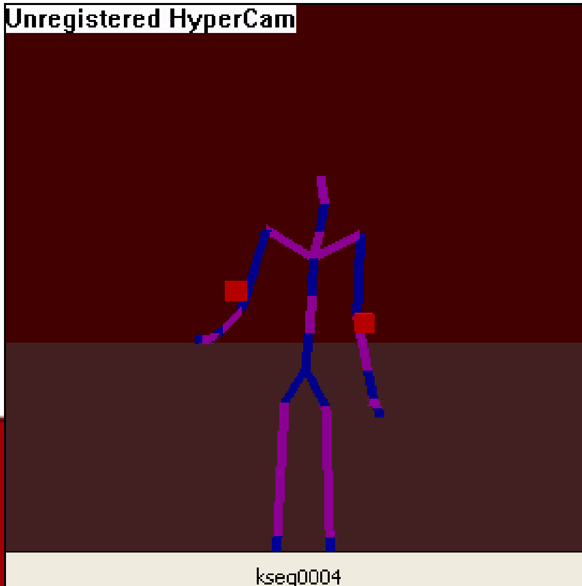


A Few Details

- Segmentation
  - Kinematic centroid
- Dimensionality reduction
  - PCA insufficient
  - Isomap (global spectral dimension reduction) had to be extended to handle temporal data
- Example input size
  - ~22,000 frames at 30 Hz of 40 DOF
  - dancing, punching, arm waving, hand circles, semaphores

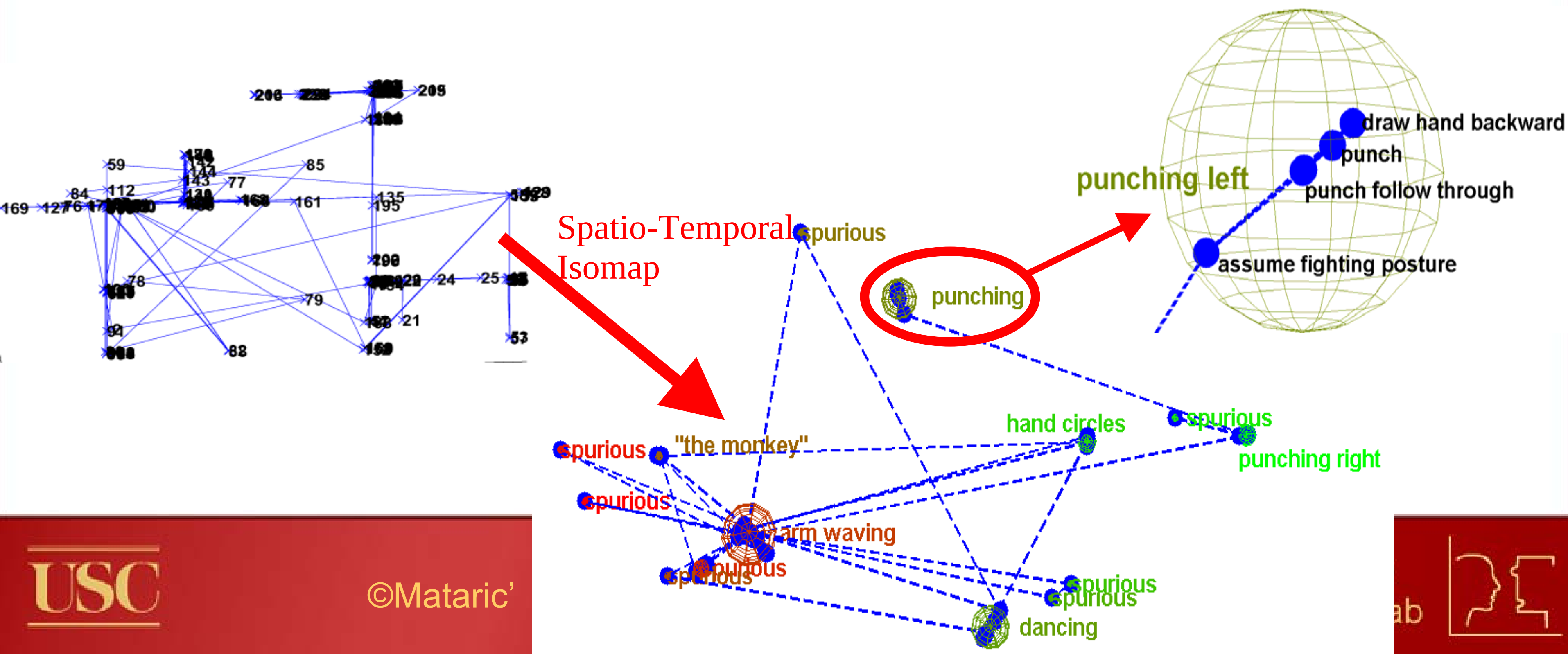


Color change indicates segment boundary



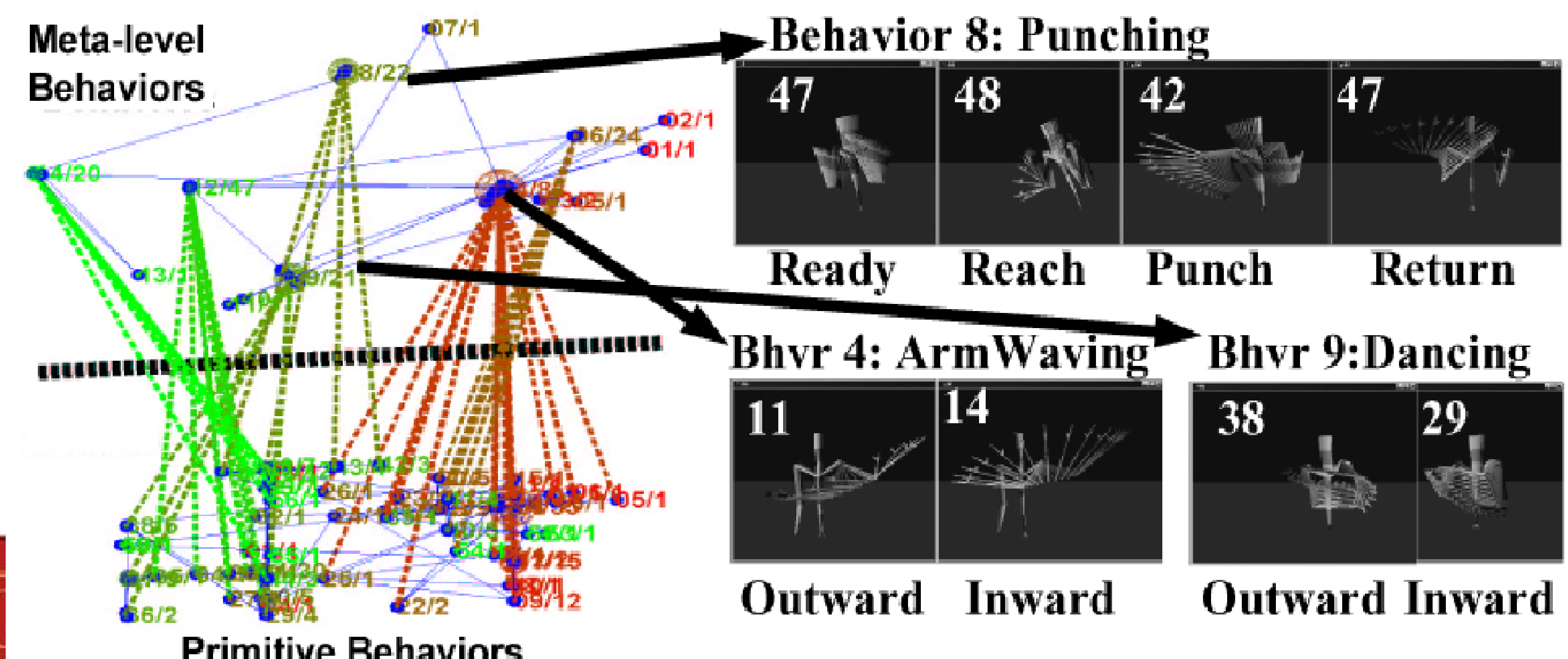
Deriving Meta-Level Behaviors

- Perform second embedding using the output of the first embedding as input
- Brings segments of subsequently performed primitives into clusterable proximity



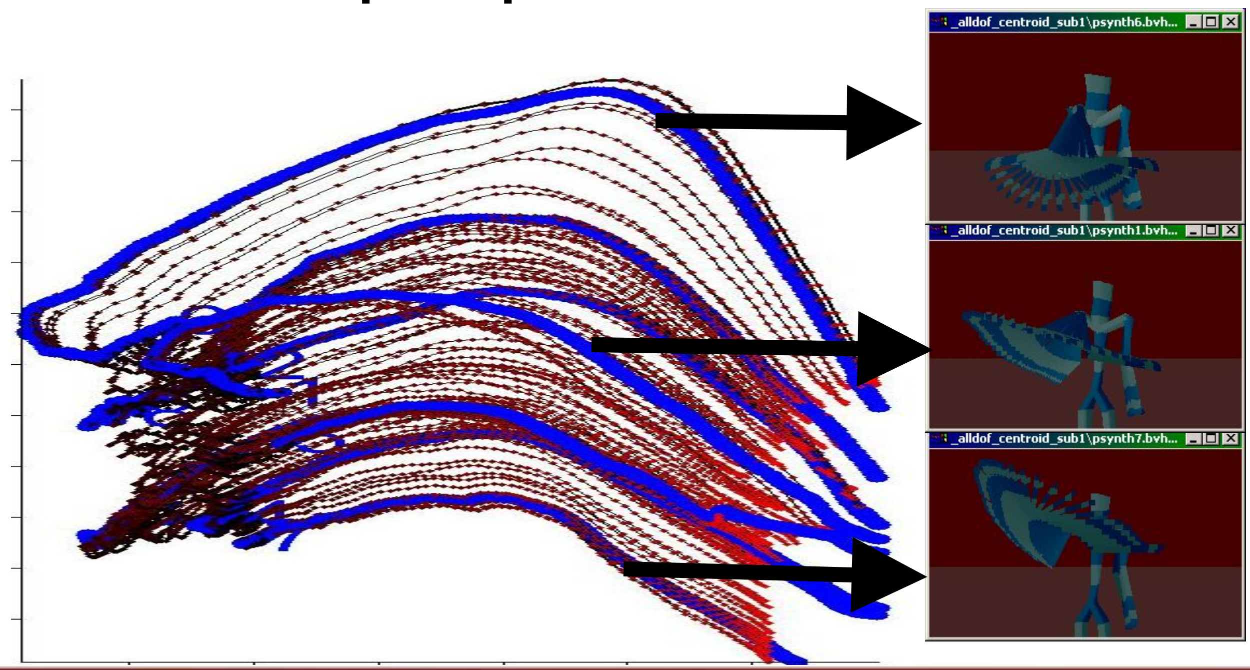
A Derived Behavior Vocabulary

- Meta-level behaviors sequentially index into primitives
- Primitives produce kinematic motion through interpolation

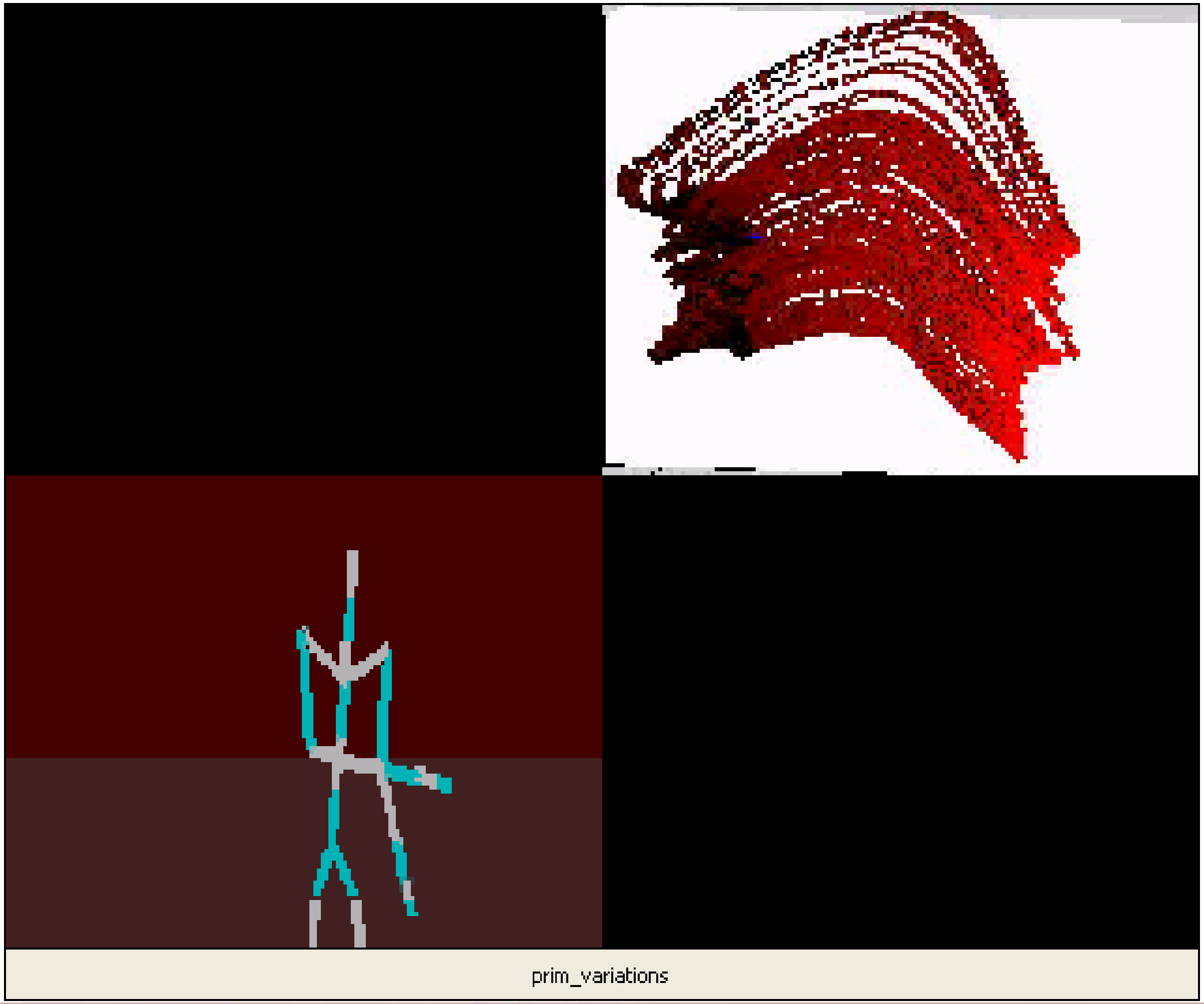


Forward Model Motion Synthesis

- Forward models allow for motion to be synthesized dynamically
- Generalize for motion not specifically represented in input performance



Forward Model Motion Synthesis



PCA-view of primitive flow field in joint angle space

Corresponding kinematic motion

Using Primitives to Classify Activity

- Primitive behaviors are sets of parametrized trajectories/exemplars
- They are used to generate movement and also to classify observed human(oid) movement
- We use a Bayesian classifier; the primitive (model) serves as the condition distribution

→ The resulting movement control and understanding are both real-time processes, performed by the robot on-line, facilitating HRI

Bayesian Primitives Classifier

- Simple Bayesian classifier:

  $$P(C|X) = P(X|C)*P(C)$$

  C is a class (behavior); *X* is an observation (joint angles)
  - P(X|C) can be determined by primitives
  - P(C) can be assumed to be uniform

- How is P(X|C) determined by primitives?
  - The exemplars (and valid interpolations in-between) fill a high-dimensional subspace of joint-angles over time
  - Subspace serves as a model for that behavior
    - P(X|C) determined from a “smoothed” distribution of assumable joint-angles for a given behavior
    - This gives the probability of any given value for all of the joints involved in the primitive behavior

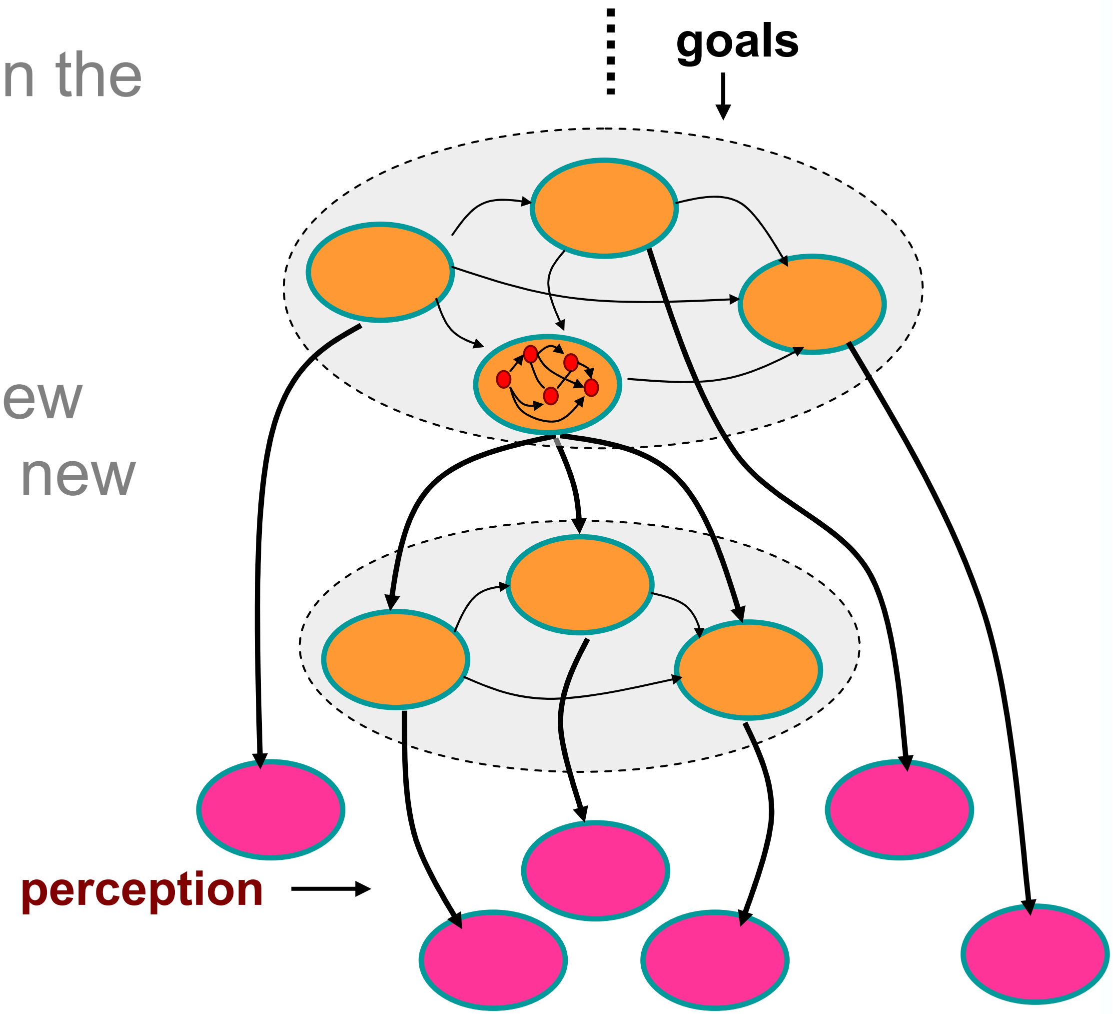
Classification Results

Dataset	Description	% error
Primitive movements	50 non-exemplar instances of primitives executed on physically simulated humanoid	3.39
Motion capture and animation data	550 movements from animation and mo-cap	0.03

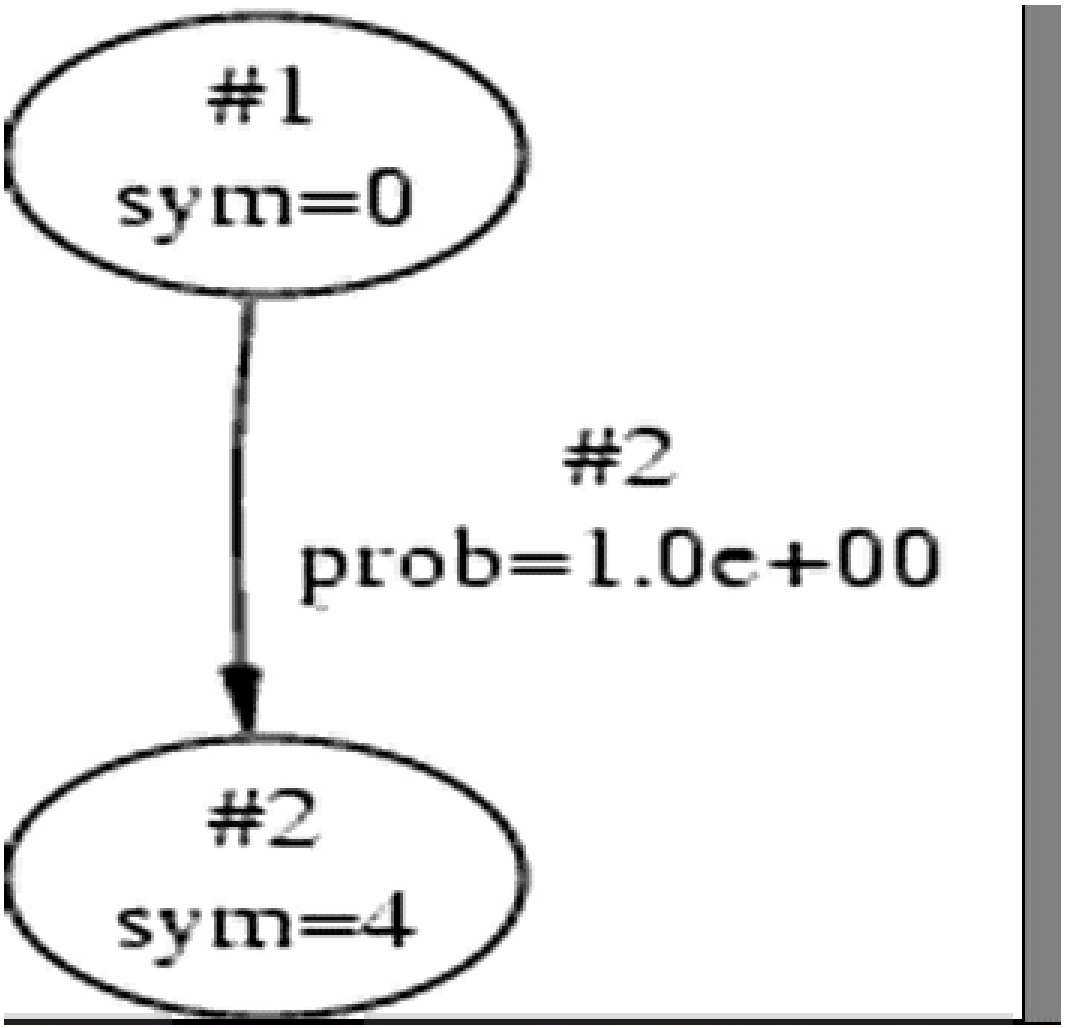
Activity Generation

- Planning is conducted in the reduced space of the vocabulary
- Learning expands the vocabulary by adding new behavior primitives and new compositions

- What can be learned?



Model Learning



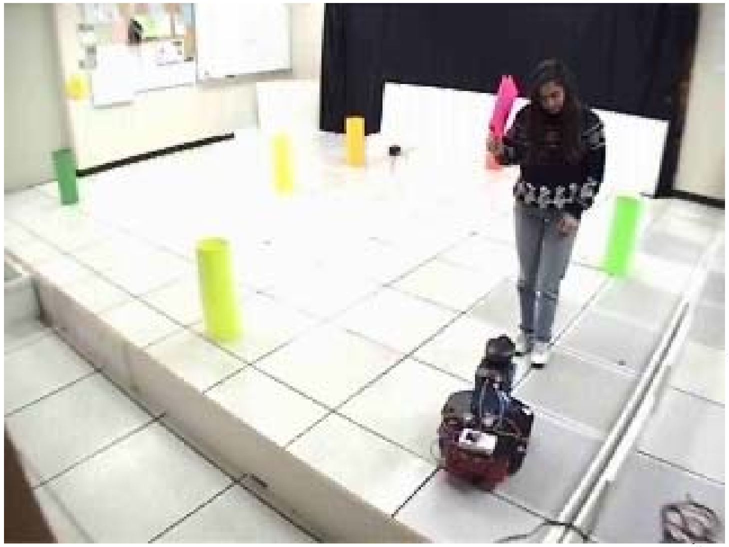
<u>Network learned from:</u>
3500 input behavior instances
≈20 minutes of on-line real-time data

[Goldberg & Matarić 2000]

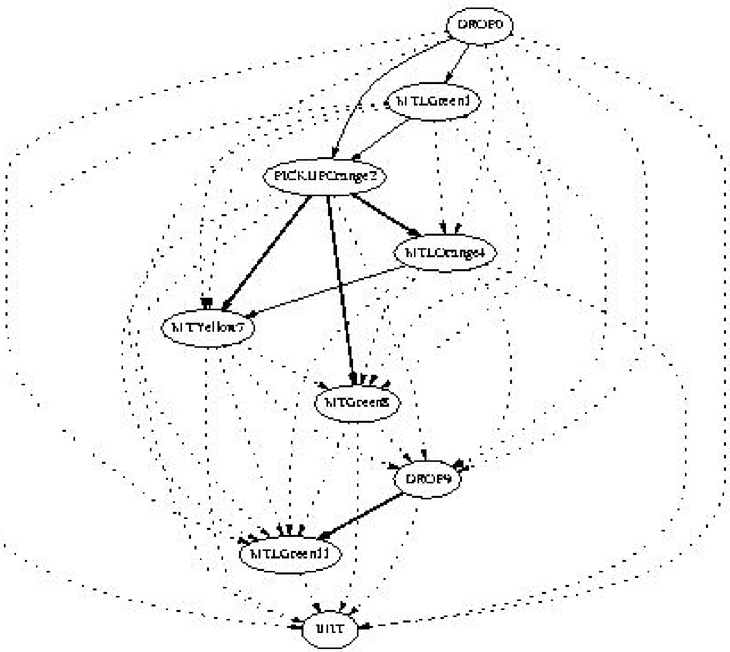
Task Learning From Demonstration

- Learning an object transport task

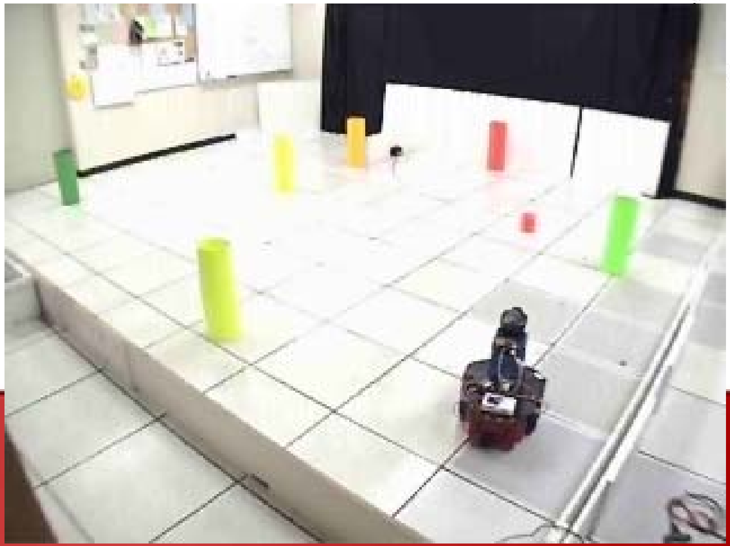
Human demonstration



Learned network:



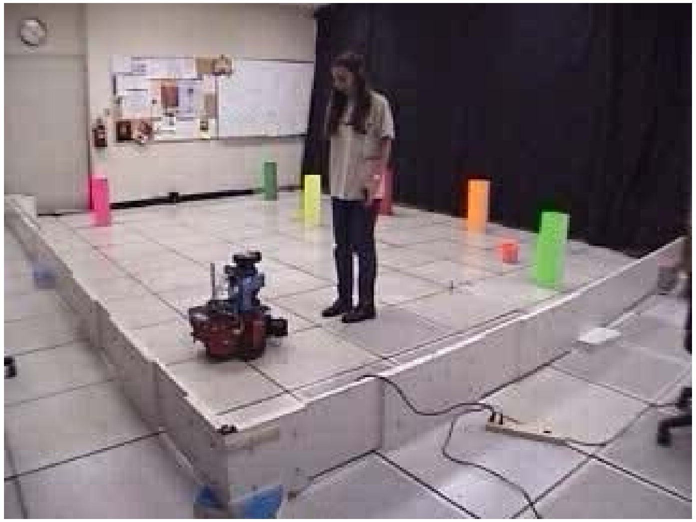
Robot execution



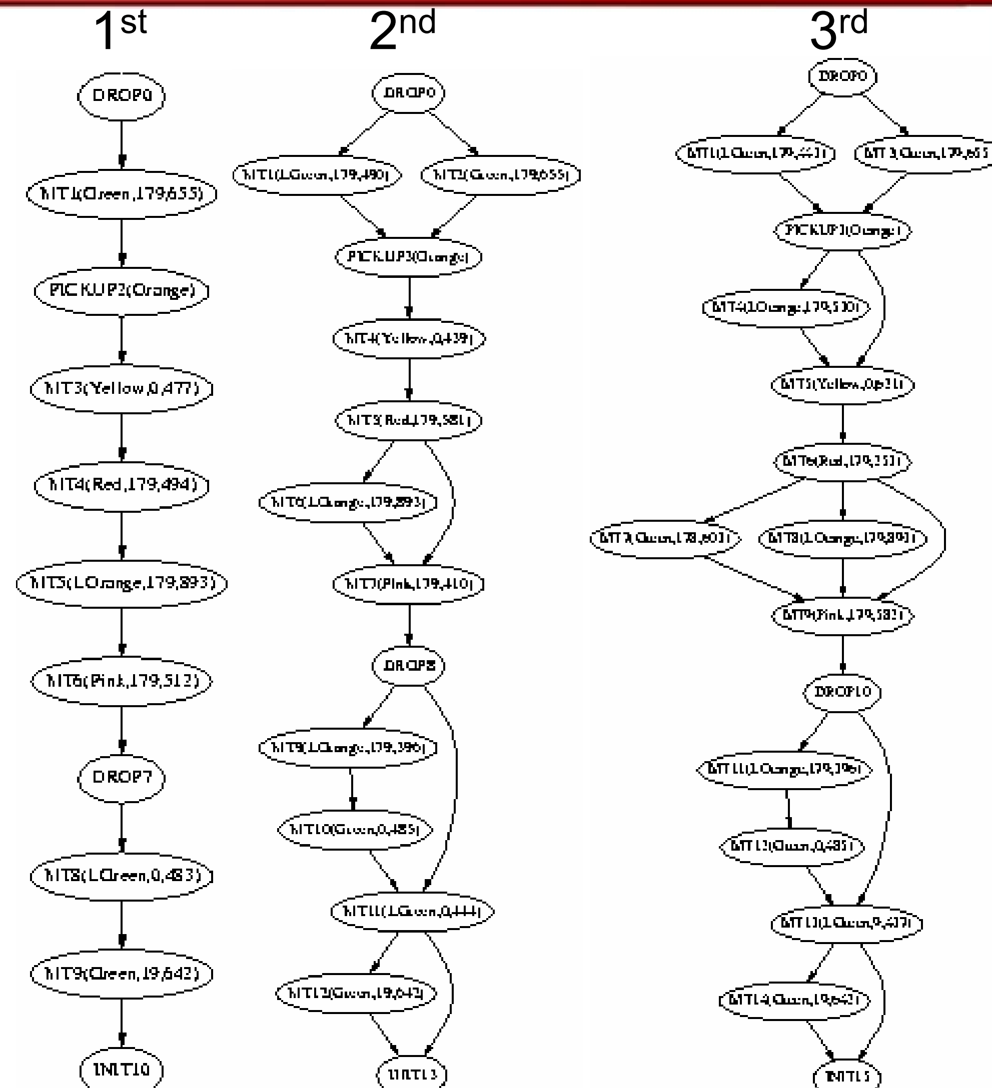
Environment can be changed at execution-time.

Task Refinement From User Interaction

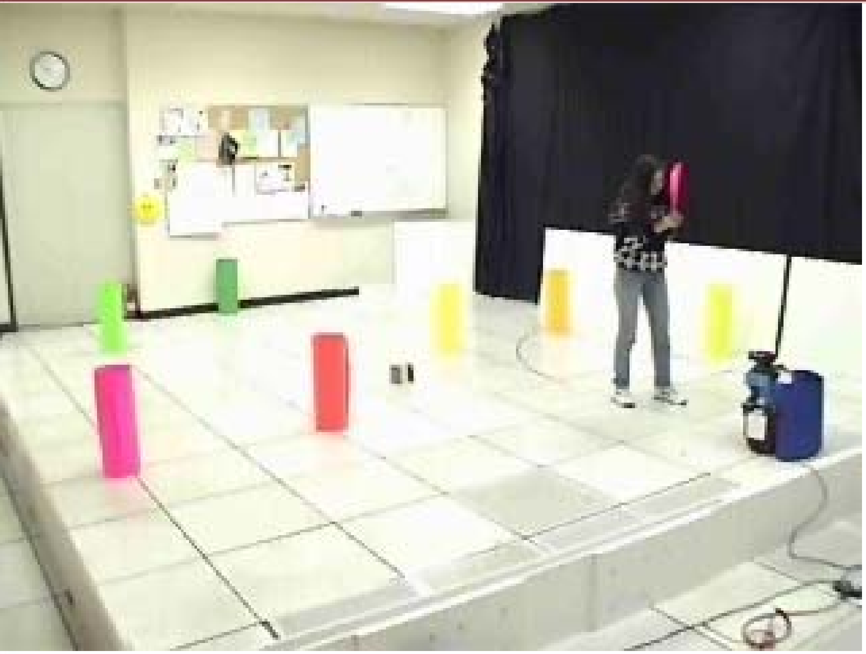
3rd human demonstration (putting through)

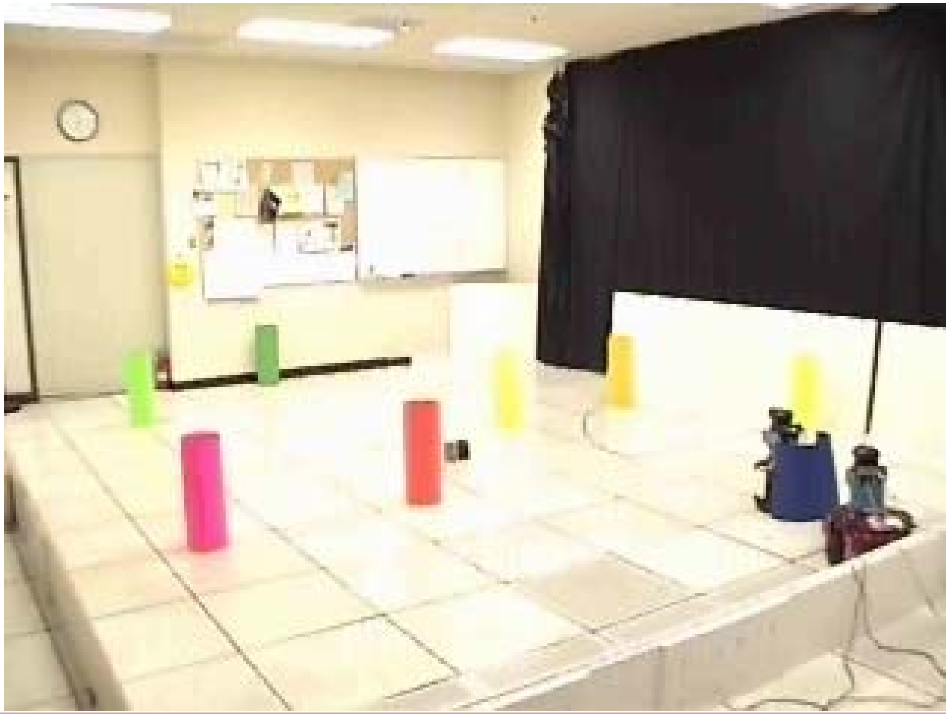


Learned task (changed environment)



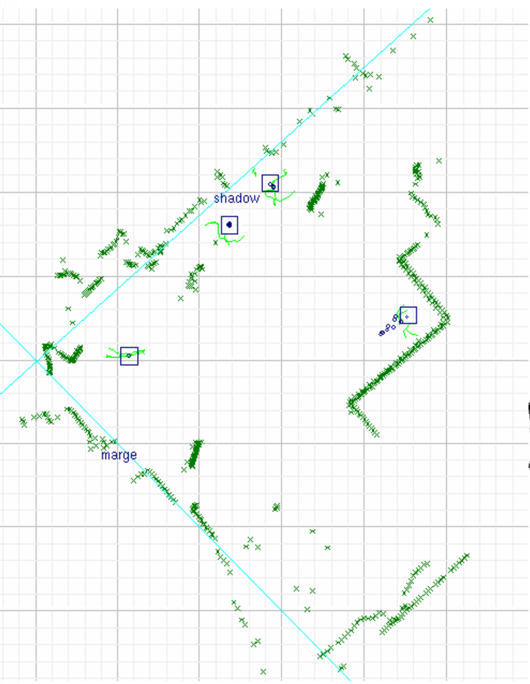
Another Benefit: Robots Teaching Other Robots

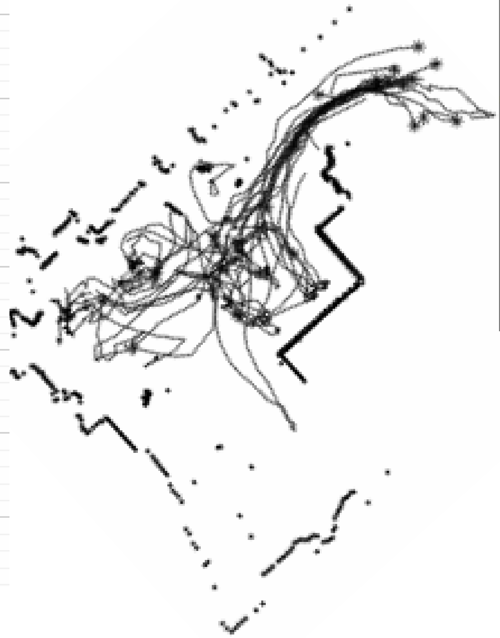


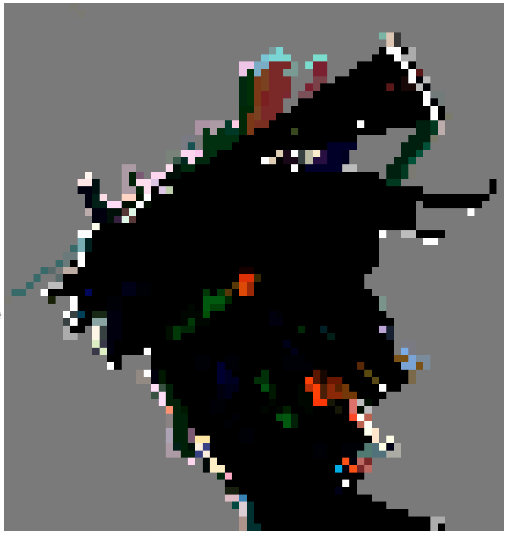


Learning Spatial & Social Primitives

- Use 2D position/trajectory (laser) data, apply proxemics, spatio-temporal occupancy grids, spatial statistics, and entropy measures (KL-divergence) to derive spatio-temporal patterns for classifying activity







Social Primitives

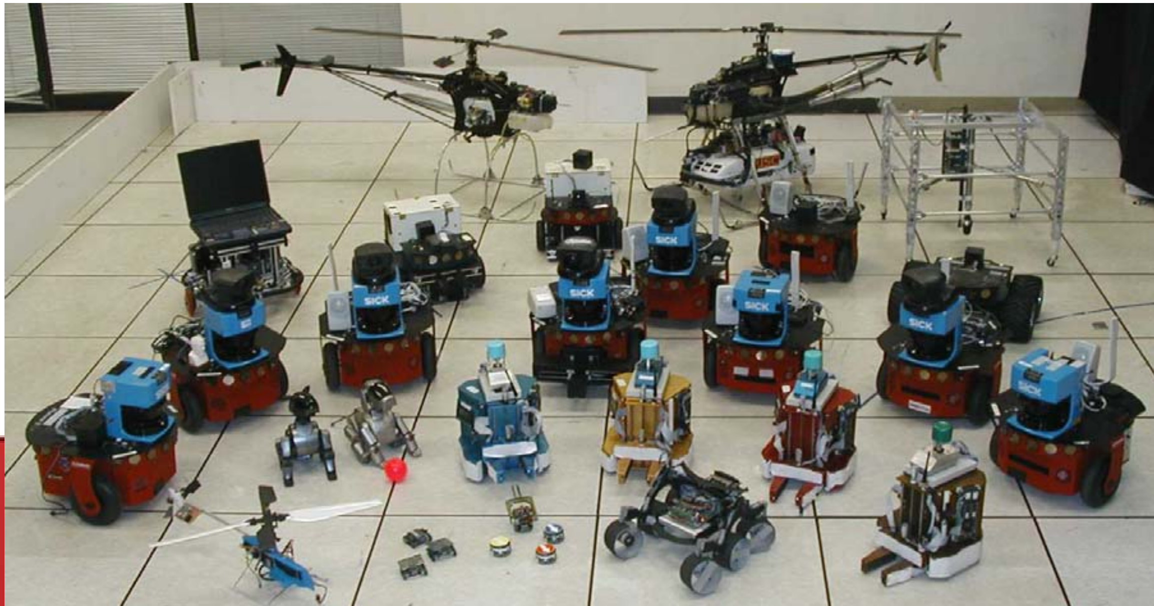
- We are working on applying the same ideas of structure from data for dyadic (one-on-one) and group interactions
- Crowds are more easily modeled; with crowd behavior the goal is to see if we can control it externally, to affect collective flow patterns dynamically with robot teams (e.g., for evacuation)

Outline

- Overview & goals
- Action
  – Behavior primitives: derivation, classification, and learning
- Interaction
  – Multi-robot coordination
  – Imitation
  – Embodied communication for HRI
- Engagement
  – Improved performance through engagement and motivation
  – The role of personality

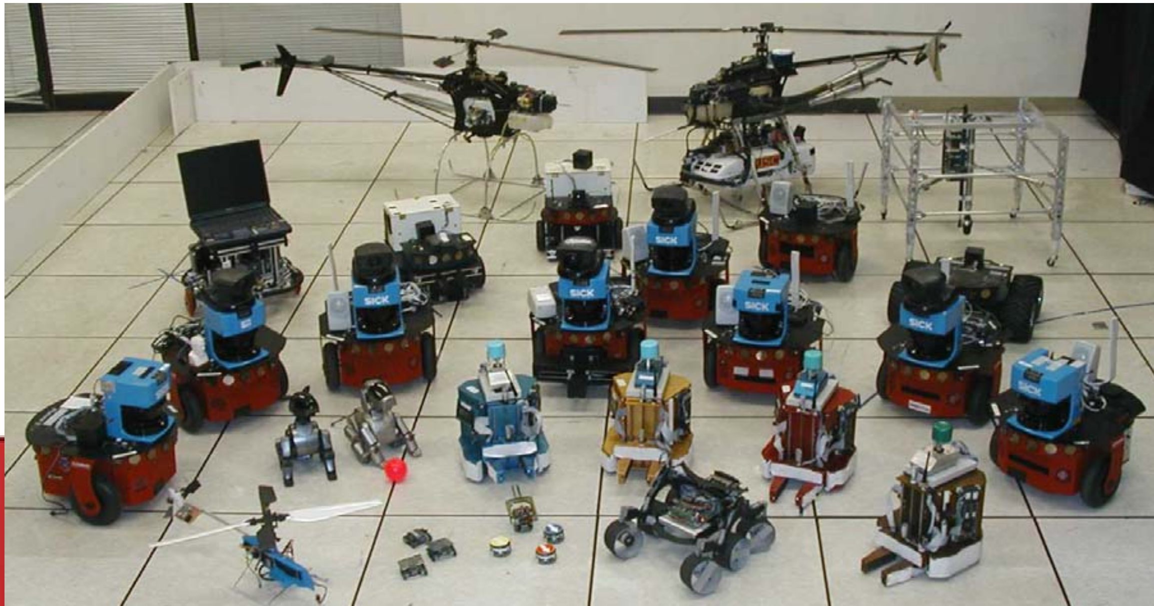
Multi-Robot Coordination

- Inter-robot interaction is a form of social behavior
- Problem: How do we control a group, team, or even swarm of robots?
- Challenges: Scalability, local v. global information and control, communication choices, robustness



Multi-Robot Coordination Projects

- Formal frameworks for explicit and swarm control
- Optimal strategies for *multi-robot task allocation* (MRTA) in the OAP context
- Methods for automated synthesis of provably correct team controllers for group and swarm tasks
- Physics-based swarm and crowd behavior modeling



MRTA as OAP

- Optimal assignment is a well-known problem, originally studied in the operations research community:

There are *n* workers, each looking for one job, and *m* available jobs, each requiring one worker. Each worker has a nonnegative skill rating for each job. The problem is to assign workers to jobs in order to maximize the overall performance.

- We can pose a RMTA problem as an OAP:

Given *n* robots, *m* single-robot tasks, and estimates of how well each robot can be expected to perform each task, assign robots to tasks so as so maximize overall expected performance.

- MRTA is a dynamic decision problem; in some cases it can be solved statically & iteratively. Online assignment involves tasks that arrive one at a time.

Utility

- Each robot must estimate the value of its actions = utility (also fitness, cost, valuation)
- Assume that each robot *R* can estimate two things regarding an available task *T*:

Q_{RT} : expected quality of execution

C_{RT} : expected cost of execution

$$U_{RT} = \begin{cases} Q_{RT} - C_{RT} & \text{if } R \text{ is capable of executing } T \text{ and} \\ & Q_{RT} > C_{RT} \\ 0 & \text{otherwise} \end{cases}$$

Optimal Assignment Algorithms

- Centralized: Hungarian method [Kuhn, 1955] and other (primal and dual) simplex methods
  - running time ~ $O(mn^2)$ (or $O(n^3)$)
- Distributed: various auction algorithms, e.g., [Gale and Shapley, 1962, Bertsekas, 1990]
  - running time proportional to bidding increment, but often tractable
- Greedy task allocation algorithms are:
  - 2-competitive for offline assignment [Avis, 1983]
  - 3-competitive for online assignment, which is optimal [Kalyanasundaram and Pruhs, 1993]

MRTA Solution Quality Insights

- Most implemented MRTA systems (soccer, box pushing, etc.) employ greedy algorithms

- Since the underlying assignment problem does not satisfy the greedy-choice property (not a matroid), they cannot produce optimal solutions.

Example: Target Tracking

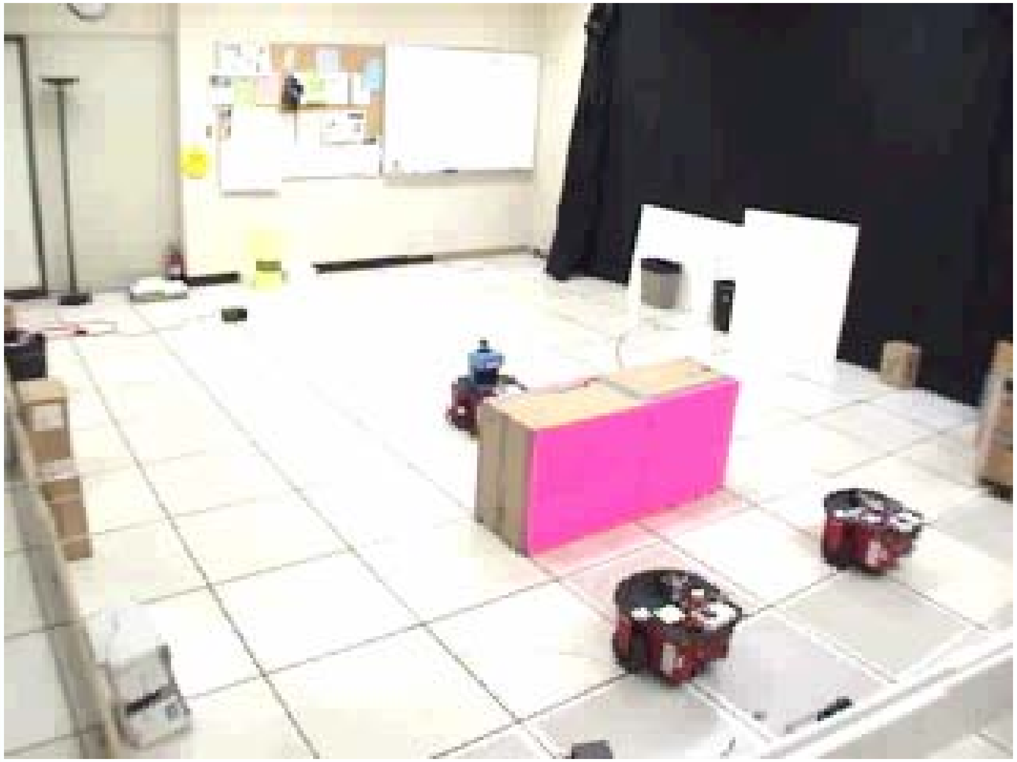
Broadcast of Local Eligibility
[Werger & Mataric 2000]

Solves the iterated assignment problem.
At each iteration:

- All tasks are considered simultaneously, with reassignment allowed
- Each robot broadcasts its utility for each task: *O(mn)*
- Each robot compares its utility for each task to that of every other robot: *O(mn)*

Example: Auction-Based Box Pushing

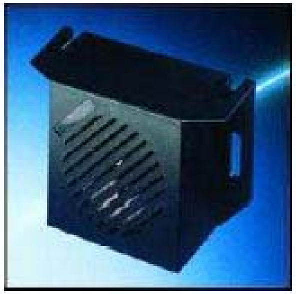
Murdoch
[Gerkey & Mataric' 2002]



Solves the online assignment problem. For each task:

- Tasks are considered sequentially, reassignment is not allowed
- Each available robot broadcasts its bid (i.e., utility): *O(n)*
- Each bidder must compute its utility for the task: *O(1)*
- The auctioneer must find the highest utility among the bidders: *O(n)*

Example: Fire Evacuation



- Scenario & assumptions:
  - Map of the environment is available
  - Locations of people not known
  - Flexible ability to accept operator input
- Goal: dynamically assign alarm-sounding robots to exits to maximize evacuation rate
- Approach: on-line multi-robot task allocation using the Hungarian algorithm to optimally assign tasks (i.e., locations to go to) to robots; operator can dynamically specify exit priorities, environment changes, etc.

Real Experimental Environment

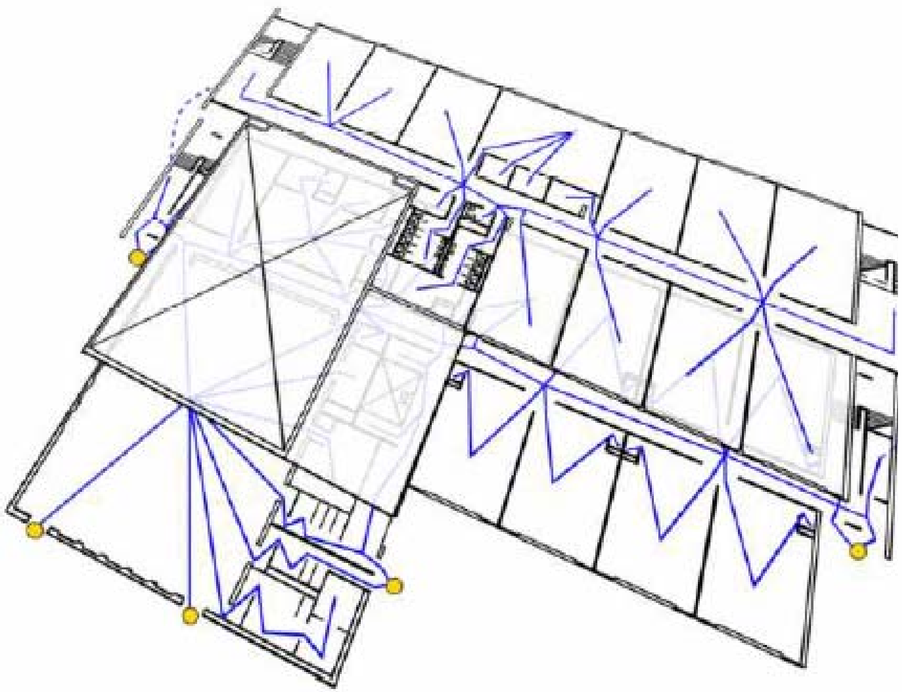


Fig. 2. The representation of a multi-fbor environment used for deployment of the beacons. The yellow dots mark the emergency exits, note the dotted line segments indicate the stairway connections in the planar topological overlay. Assignment considers where the robots are currently positioned ensuring that the distance traveled is minimized wherever possible.

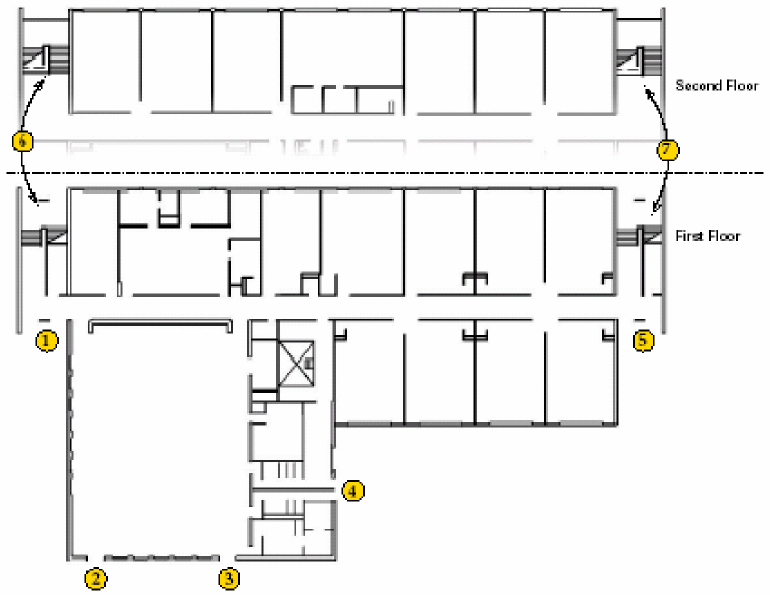


Fig. 3. The test environment with the emergency exits marked 1–5 and the connection stairways 6 and 7. The second fbor is only partially shown, but can be seen in Figure 2.

Robot Map and Controller

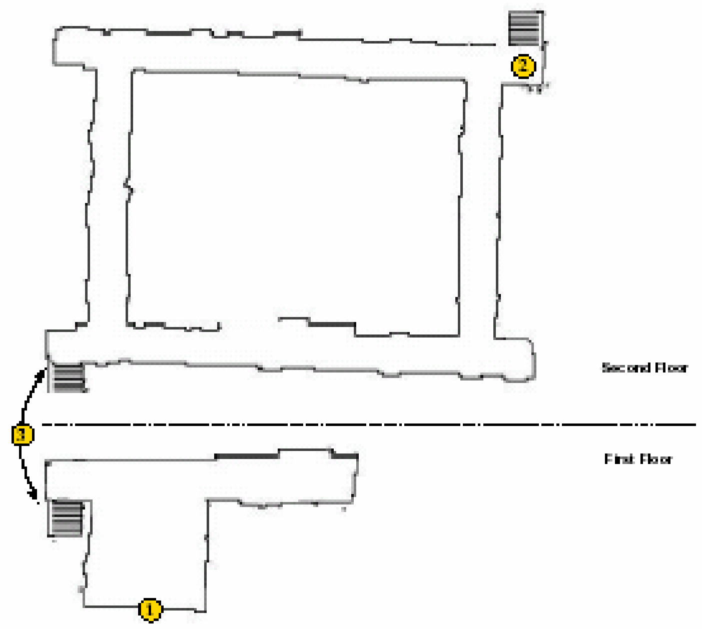
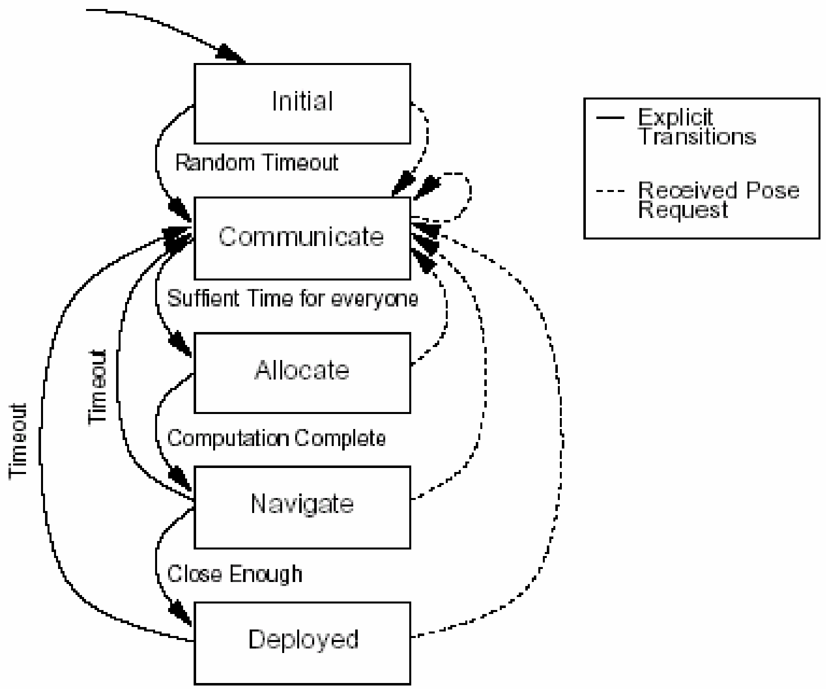


Fig. 6. The map used with physical robots. Exits marked 1, 2. The connection labeled 3 is a stairwell.

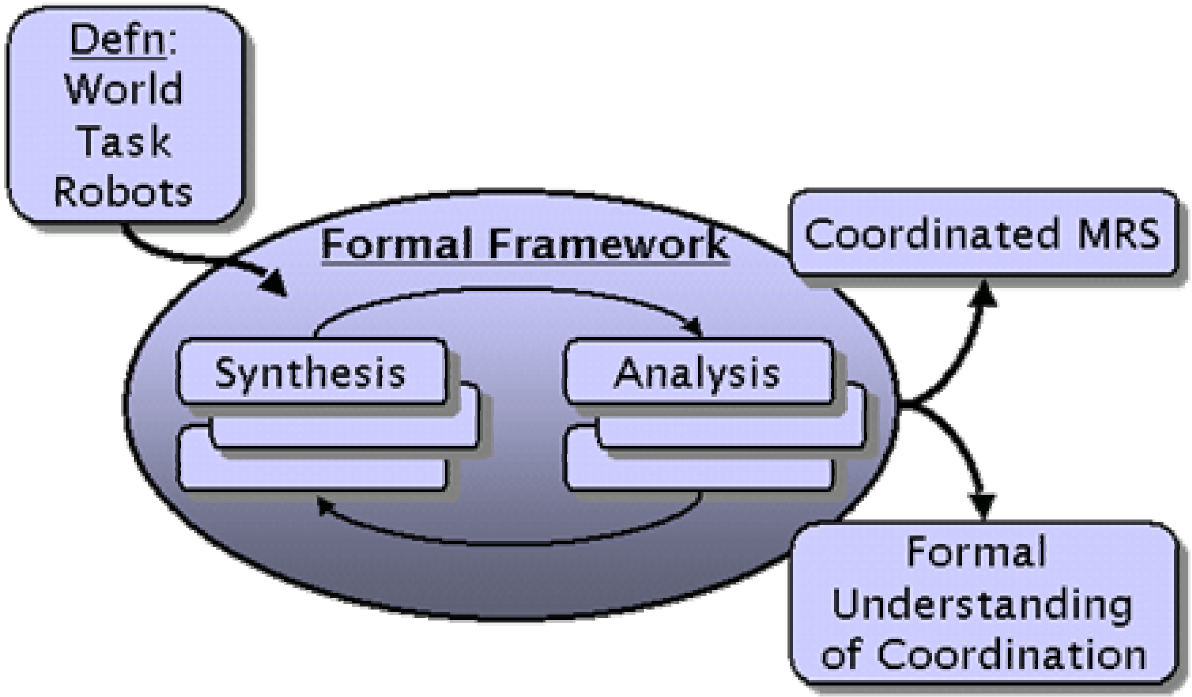


→ Optimal v. greedy performance Δ can get lost in the noise

Multi-Robot Coordination Taxonomy

- Not all MRTA problems can be treated as OAP
- Consider the following taxonomy:
  - Single-task robots v. multi-task robots (ST vs. MT)
  - Single-robot tasks v. multi-robot tasks (SR vs. MR)
  - Instantaneous v. time-extended assignment (IA vs. TA)
- Only ST-SR-IA can be treated as OAP; the rest are NP-hard and most have no known approximation algorithms
- If utilities or tasks are inter-related, things get even more complicated

Implicit Multi-Robot Coordination

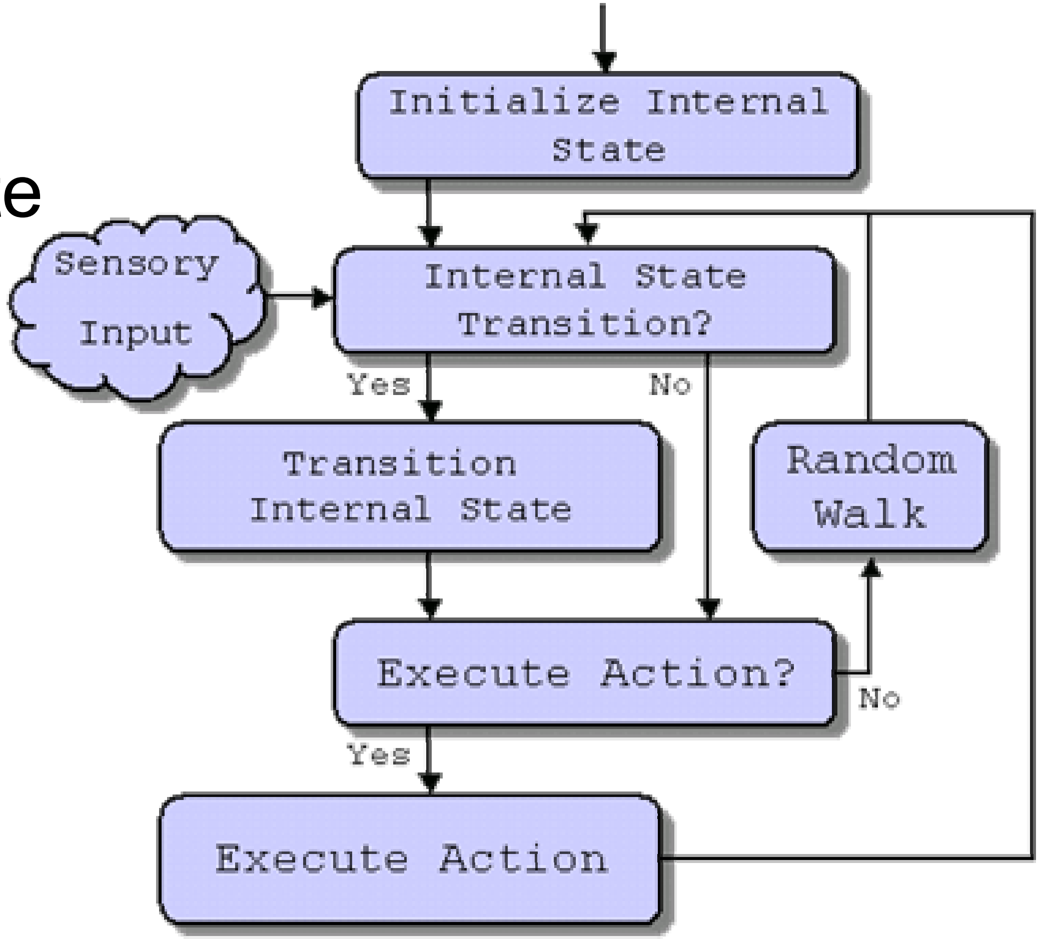


Synthesis of MRS consisting of distributed, homogeneous robots that maintain a limited amount of non-transient internal state

Analysis using a **Bayesian macroscopic MRS model** capable of quantitatively predicting task performance

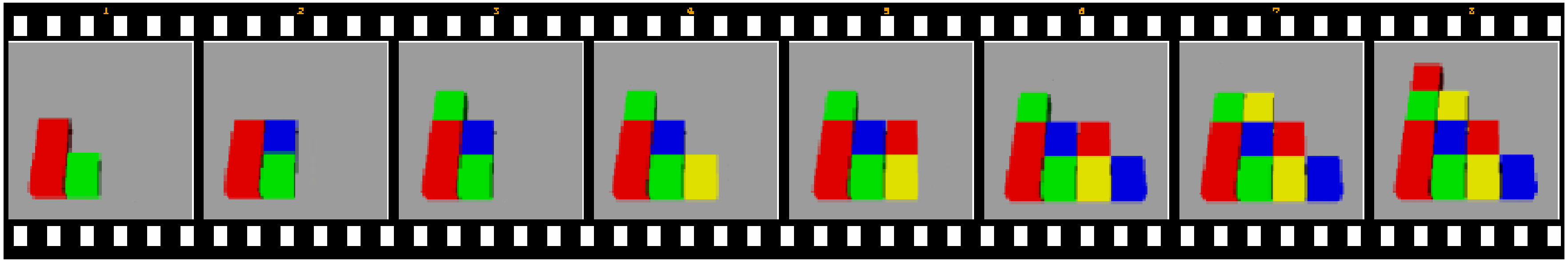
Controller Construction

- No explicit reasoning on world or task state
- To synthesize such a controller, must:
  - Define action function
  - Define internal state transition function



Construction Task Domain

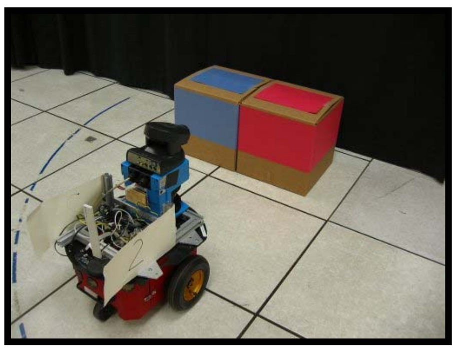
- **World State**: unique configuration of bricks
- **Task Definition**: sequential placement of colored bricks to form a given planar structure



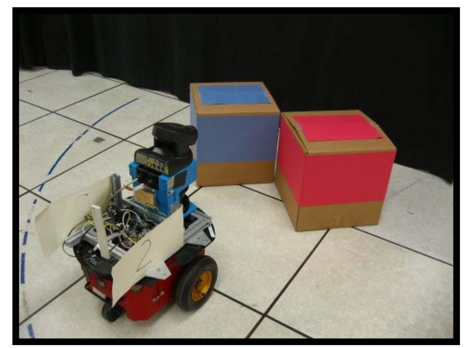
Observations in Construction

- Spatial configuration and colors of bricks within the robot's sensing range (100° FOV, 2m range)
- Two observation categories:

Flush: <Flush R B>



Corner: <Corner B R>



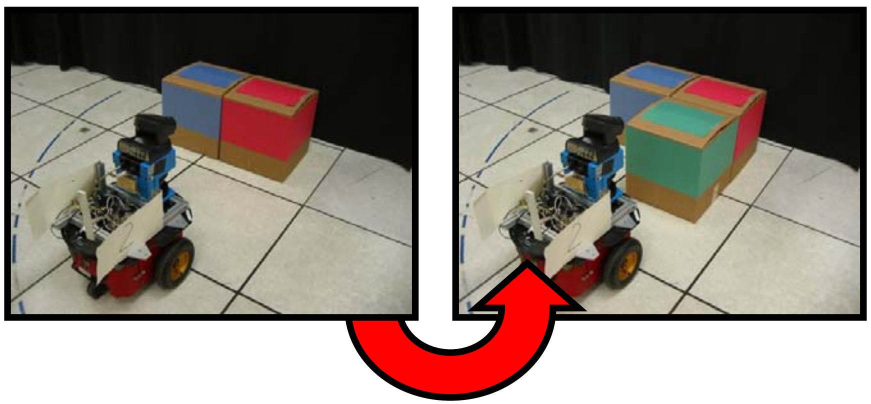
- Prob. of observing <Flush R B> given <Corner R B> = 11.5%
- Prob. of observing <Corner R B> given <Flush R B> = 1.1%%

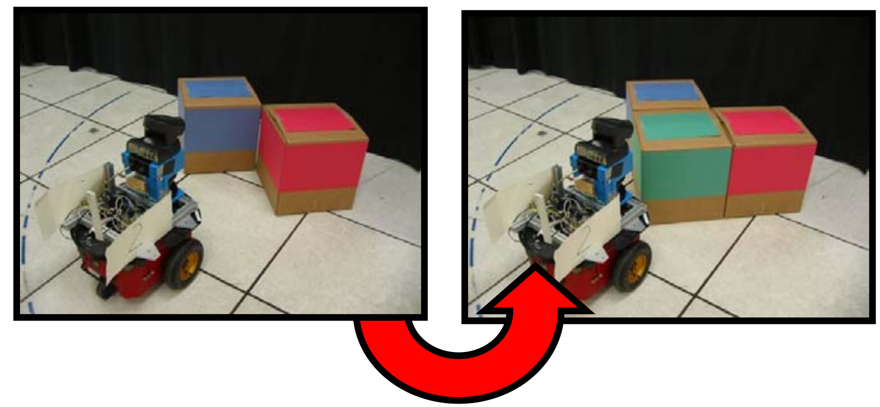
Actions in Construction

- All actions involve the placement of a single brick
- Three action categories:

Flush Right: <G Right Flush R B>
(**Flush Left**: <G Left Flush R B>)

Corner: <G CORNER R B>

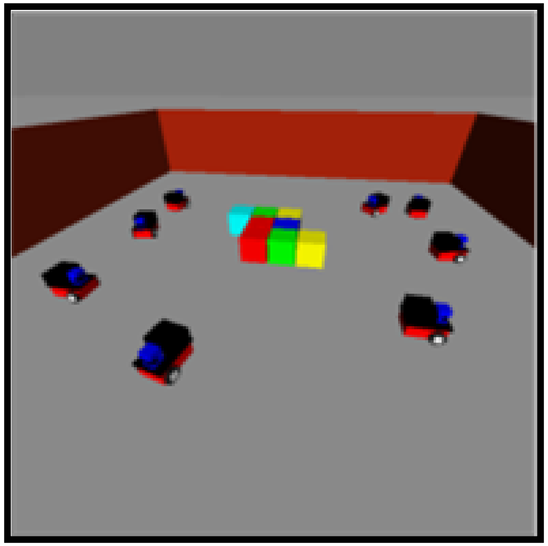


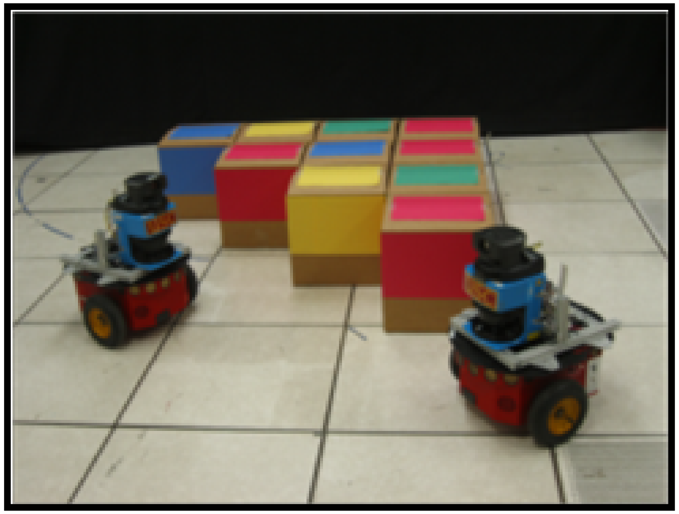


- Probability of success of Flush = 98.5% and Corner = 78.0%

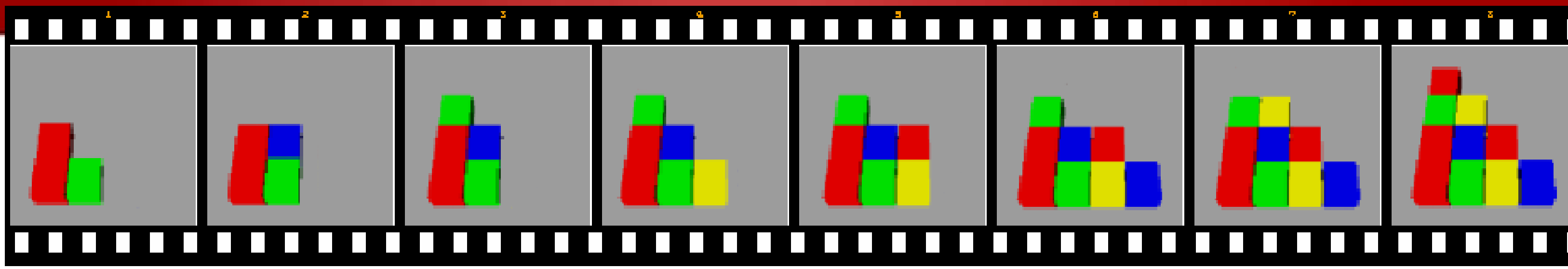
Experimental Setup

- Simulation trials
  - Gazebo, physically-realistic simulation with dynamics
  - Player
  - 8 Pioneer 2DX robots
  - 300 experimental trials for each construction task
- Real-robot demonstrations
  - Player
  - 3 Pioneer 2DX Robots
  - Laser and camera



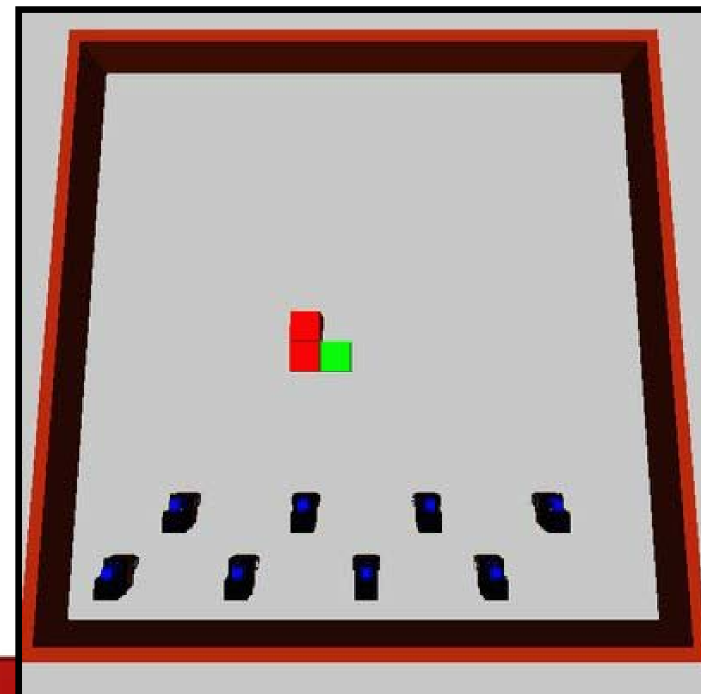


Construction Task 1: Defn. and Controller

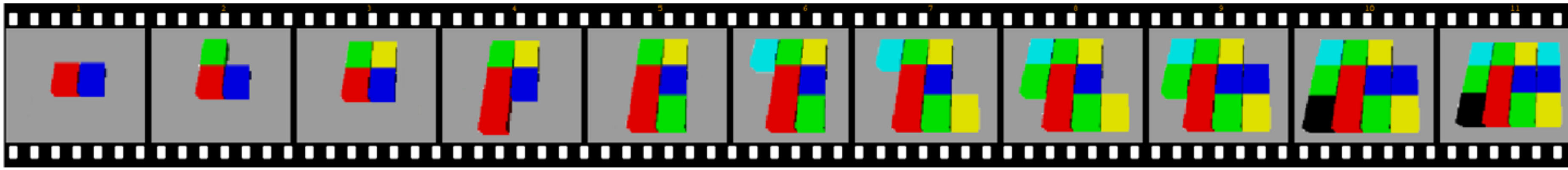


Task 1 Action Function
A(<CORNER R G>, m_0, <B CORNER R G>) = 1
A(<FLUSH R B>, m_0, <G RIGHT FLUSH R B>) = 1
A(<FLUSH B G>, m_1, <Y LEFT FLUSH B G>) = 1
A(<CORNER B Y>, m_1, <R CORNER B Y>) = 1
A(<FLUSH R Y>, m_1, <B LEFT FLUSH R Y>) = 1
A(<FLUSH B R>, m_2, <Y RIGHT FLUSH B R>) = 1
A(<FLUSH G Y>, m_2, <R RIGHT FLUSH G Y>) = 1

Task 1 Internal State Transition Function
L(m_0, <CORNER G B>, m_1) = 1
L(m_1, <CORNER R B>, m_2) = 1

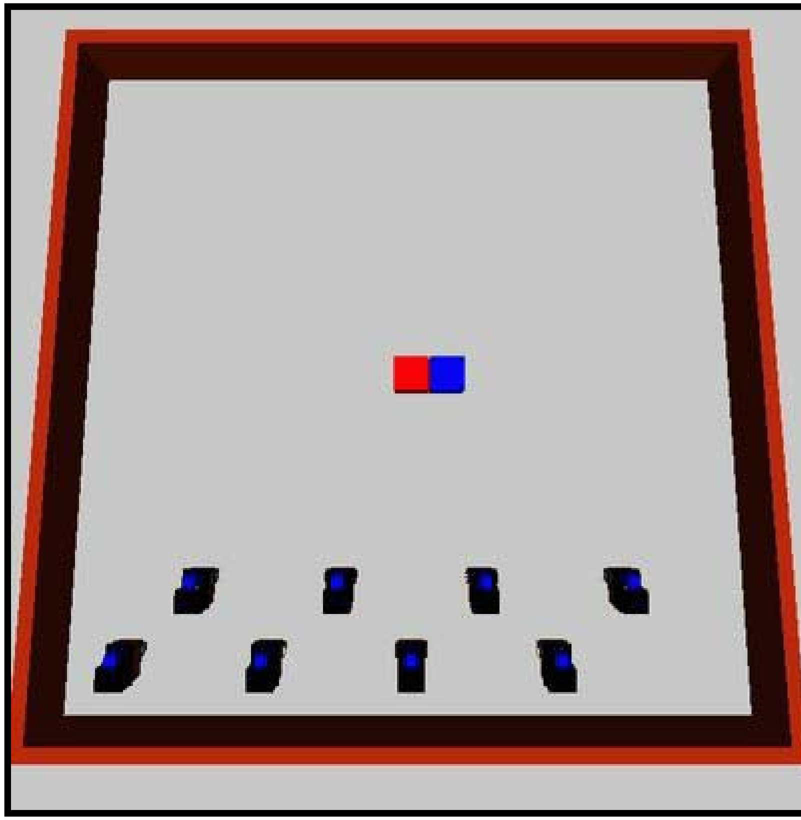


Construction Task 2: Defn. and Controller



Task 2 Action Function
A(<FLUSH R B>, m_0, <G RIGHT FLUSH R B>) = 1
A(<CORNER G B>, m_0, <Y CORNER G B>) = 1
A(<FLUSH B R>, m_1, <R LEFT FLUSH B R>) = 1
A(<CORNER B R>, m_1, <G CORNER B R>) = 1
A(<FLUSH R G>, m_2, <C LEFT FLUSH R G>) = 1
A(<FLUSH B G>, m_3, <Y LEFT FLUSH B G>) = 1
A(<CORNER R C>, m_4, <G CORNER R C>) = 1
A(<FLUSH Y B>, m_5, <B LEFT FLUSH Y B>) = 1
A(<CORNER R G>, m_6, <Bl CORNER R G>) = 1
A(<CORNER Y B>, m_7, <C CORNER Y B>) = 1

Task 2 Internal State Transition Function
L(m_0, <FLUSH G Y>, m_1) = 1
L(m_1, <FLUSH G R>, m_2) = 1
L(m_2, <CORNER R C>, m_3) = 1
L(m_3, <CORNER B Y>, m_4) = 1
L(m_4, <FLUSH G C>, m_5) = 1
L(m_5, <CORNER Y B>, m_6) = 1
L(m_6, <FLUSH Bl G>, m_7) = 1



Macroscopic Model

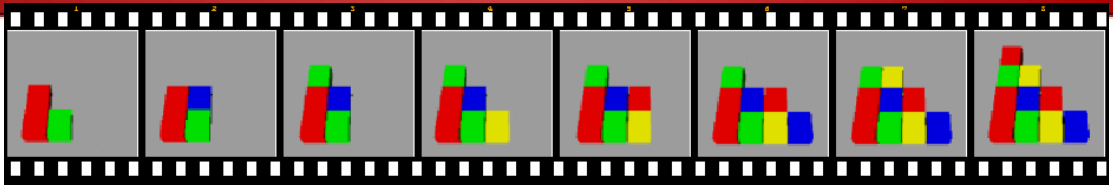
- Probability of internal state value given task state

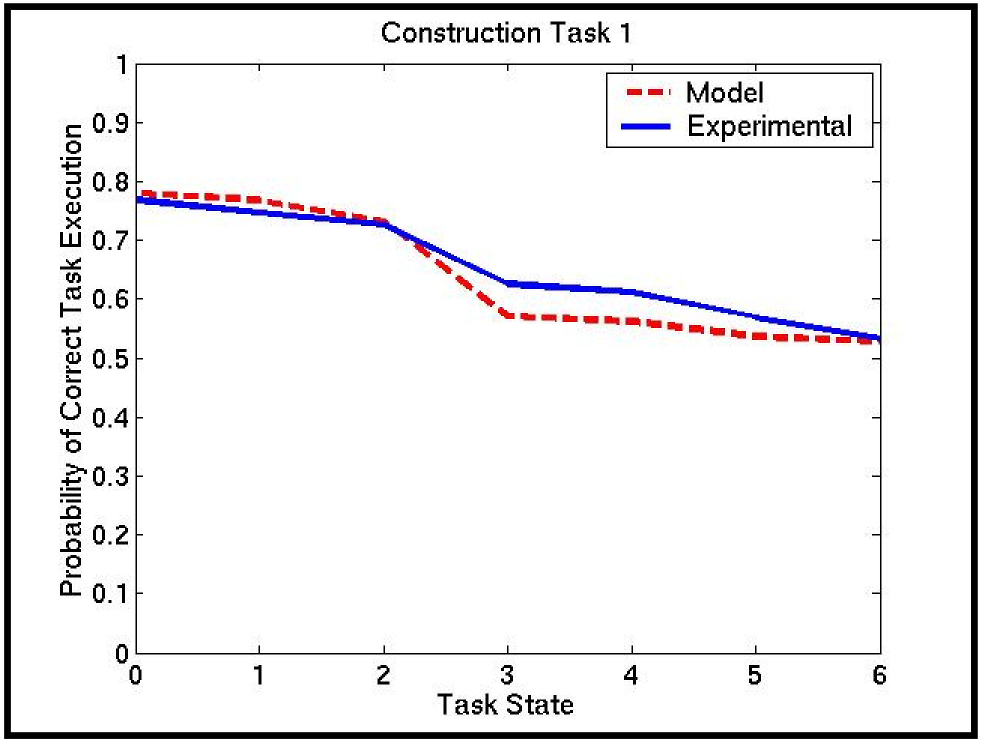
$$Pr(m_j|s_i) = 1 - ((1 - Pr(m_{j-1}|s_i)(1 - \prod_{\forall x}(1 - O(s_i, x) \cdot L(m_{j-1}, x, m_j))))(1 - Pr(m_j|s_{i-1})(1 - Pr(m_{j+1}|s_{i-1}))))$$

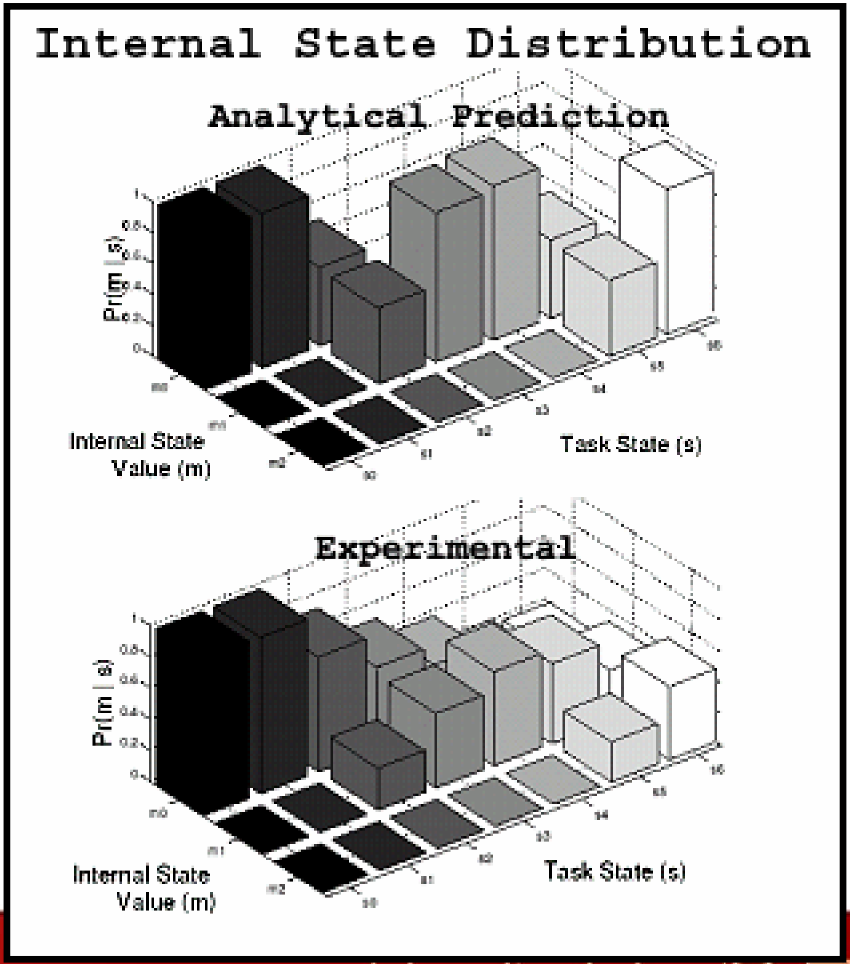
- Probability of correct task execution

$$Pr(CTE) = \prod_{\forall s_i} \sum_{\forall m \forall x \forall a} (1 - Pr(m|s_i)O(s_i, x)A(x, m, a) \cdot (1 - (P(s_i, x, a, s_{i+1}) + P(s_i, x, a, s_i))))$$

Construction Task 1: Analysis



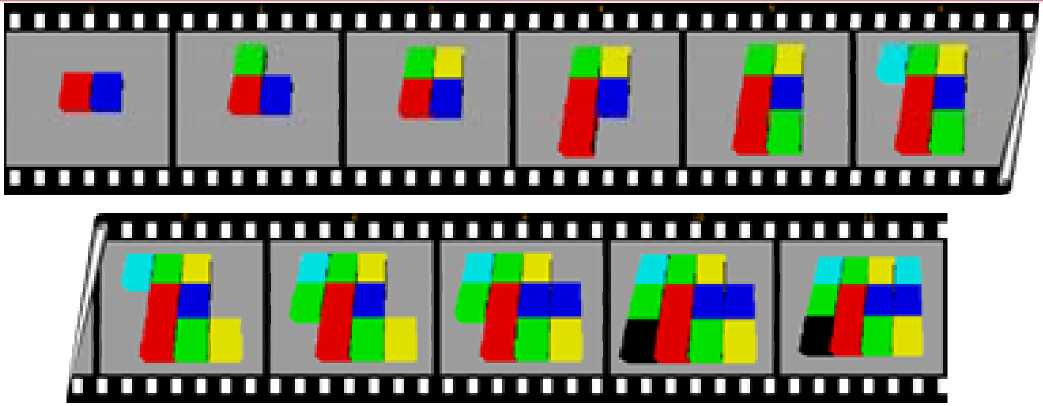


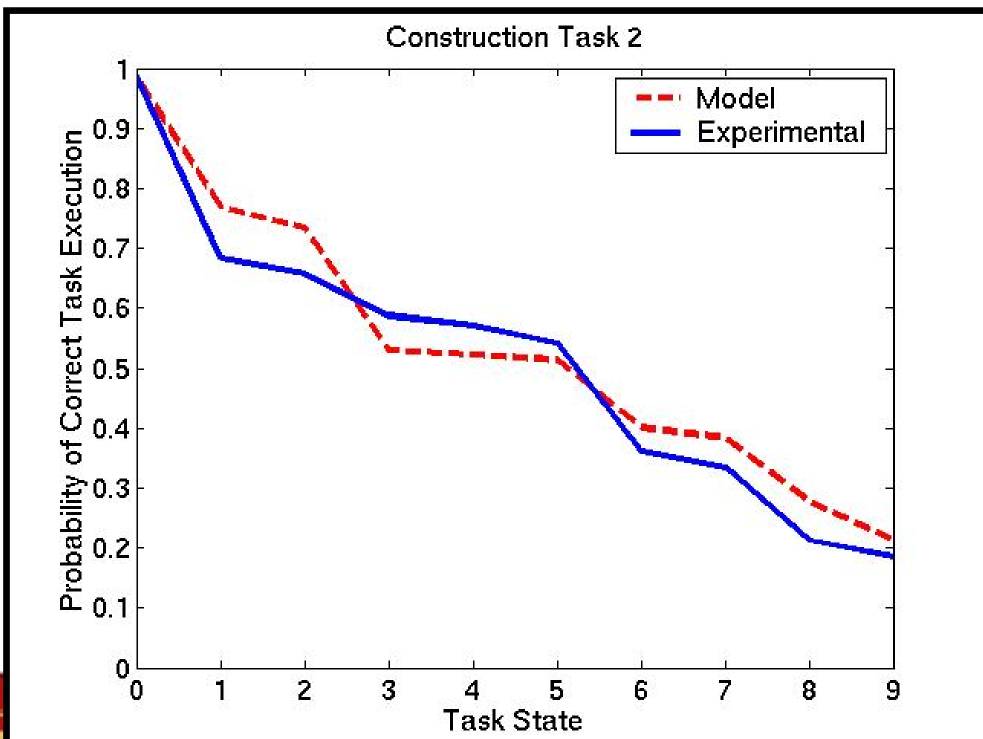


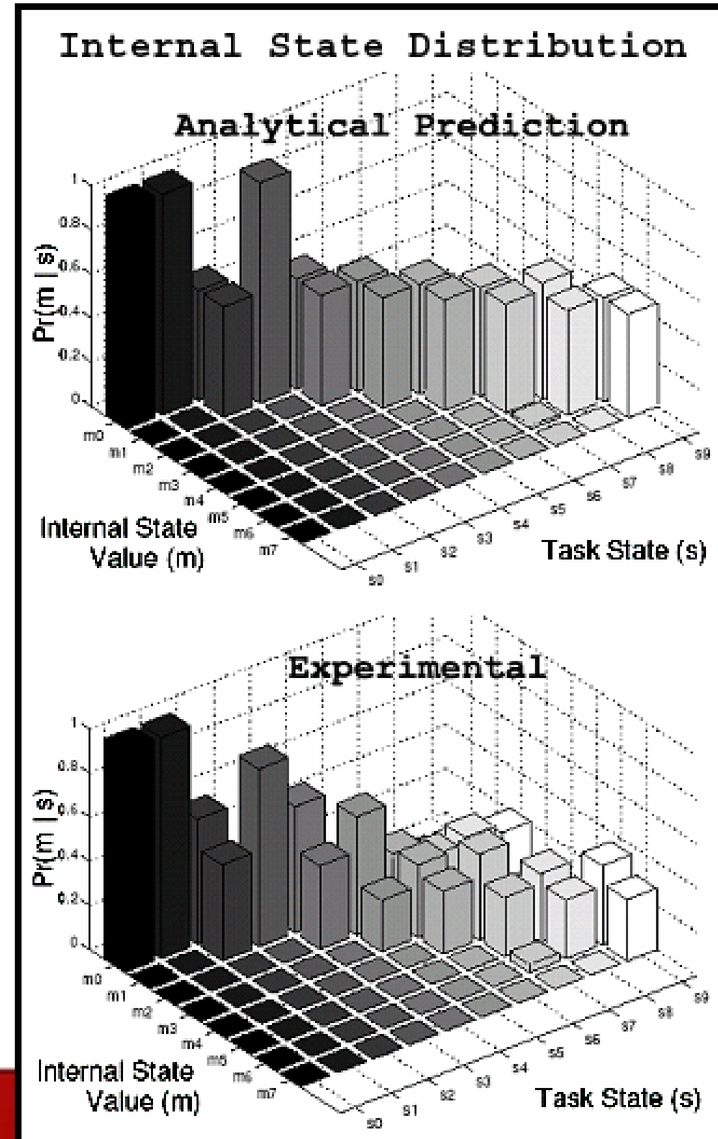
Data from 300 simulation trials

Construction Task 2: Analysis

Data from 300 simulation trials







Outline

- Overview & goals
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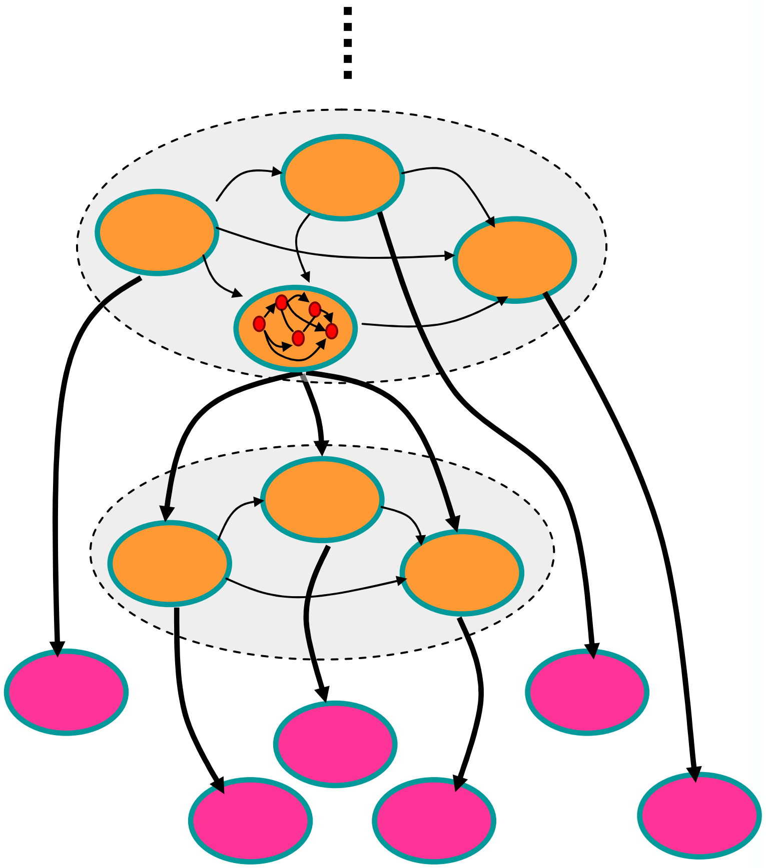
  - Imitation
  - Embodied communication for HRI
- Engagement
  - Improved performance through engagement and motivation
  - The role of personality

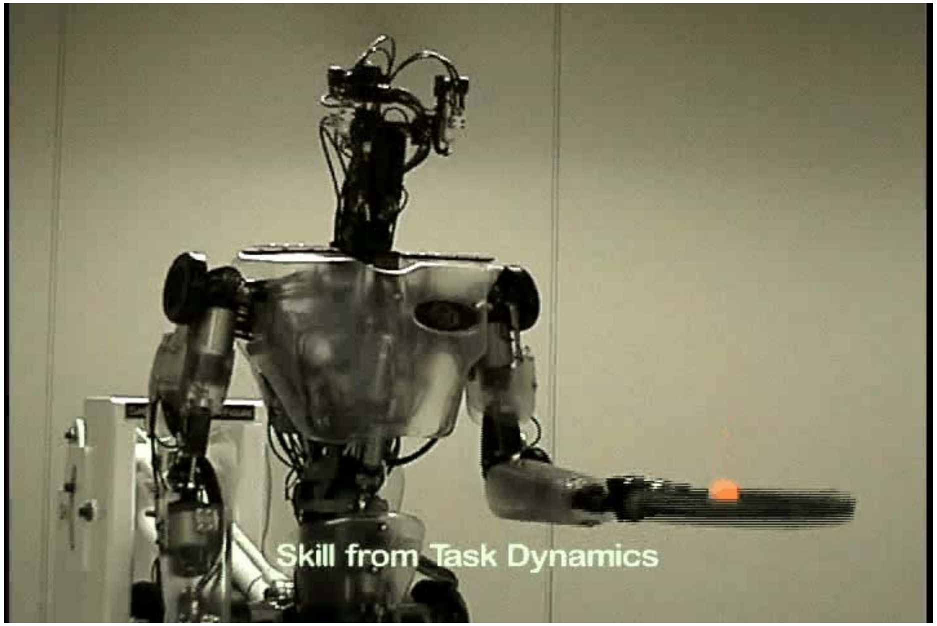
Imitation as a Tool for HRI

- Approach: The robot uses the underlying set of behavior primitives as models for classifying observed activity, imitating it, and learning new behaviors to expand its repertoire

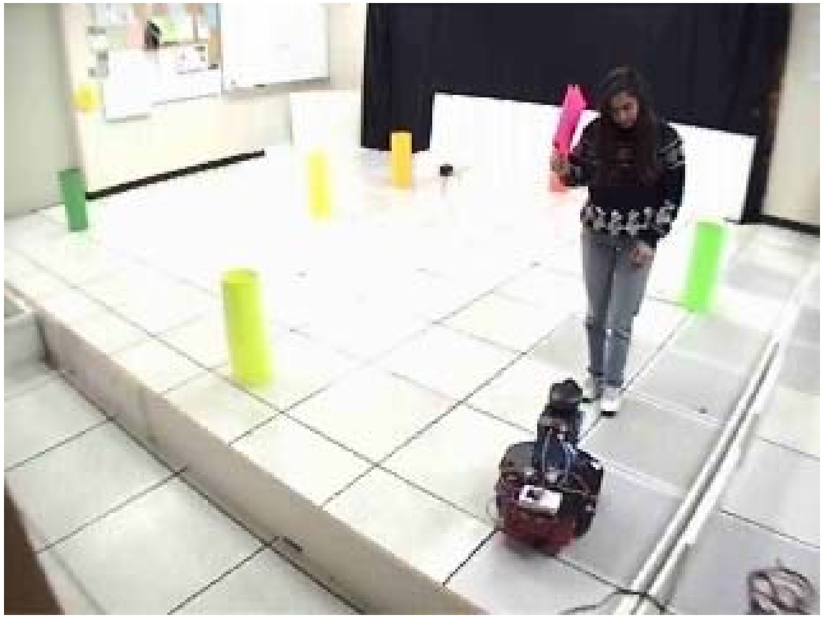
- The ability to imitate becomes a social tools for learning, interaction, and engagement



Robots That Learn Skills and Tasks From Demonstration

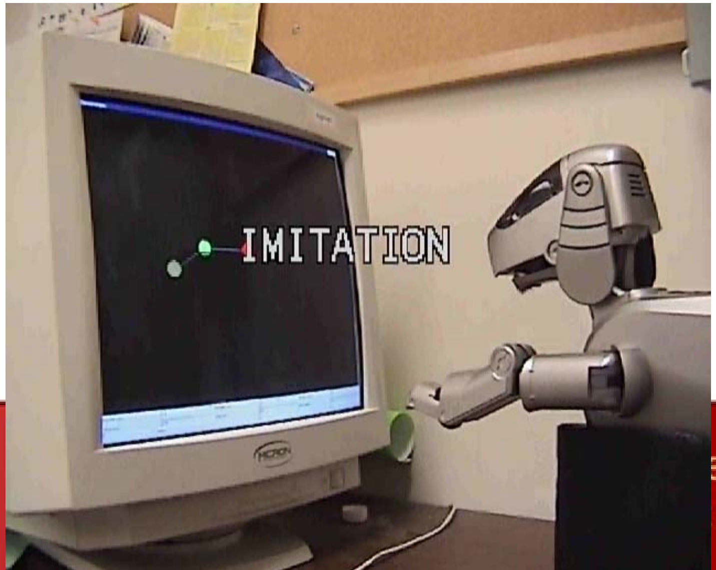


Skill learning from demonstration
Schaal

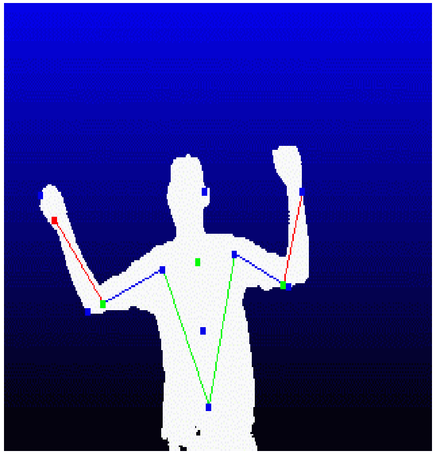


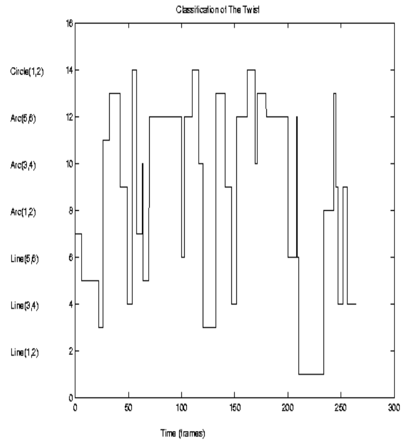
Task learning
Nicolescu & Matarić

Instantaneous imitation
Matarić

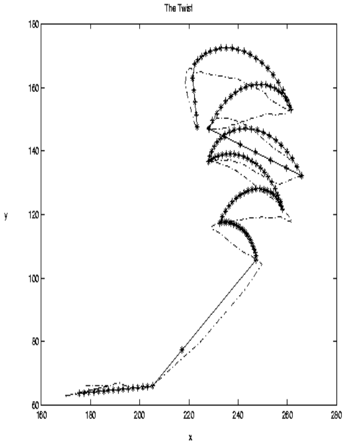


Overview of the Imitation System

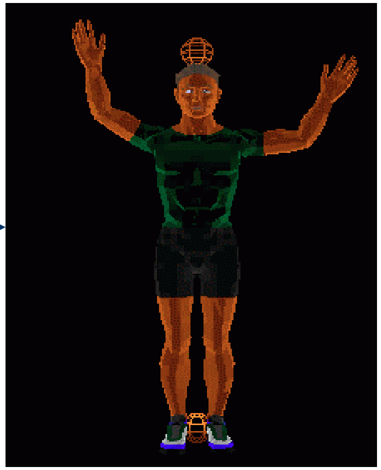




Encoded into primitive set



Endpoint trajectory



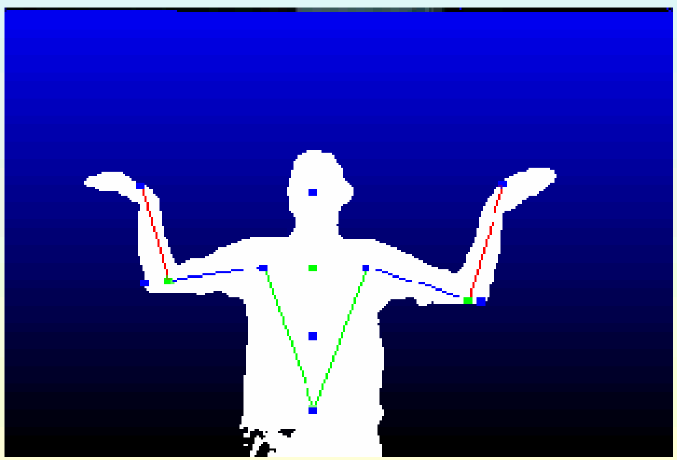
20-DOF dynamic humanoid simulation

Vision-based feature tracking

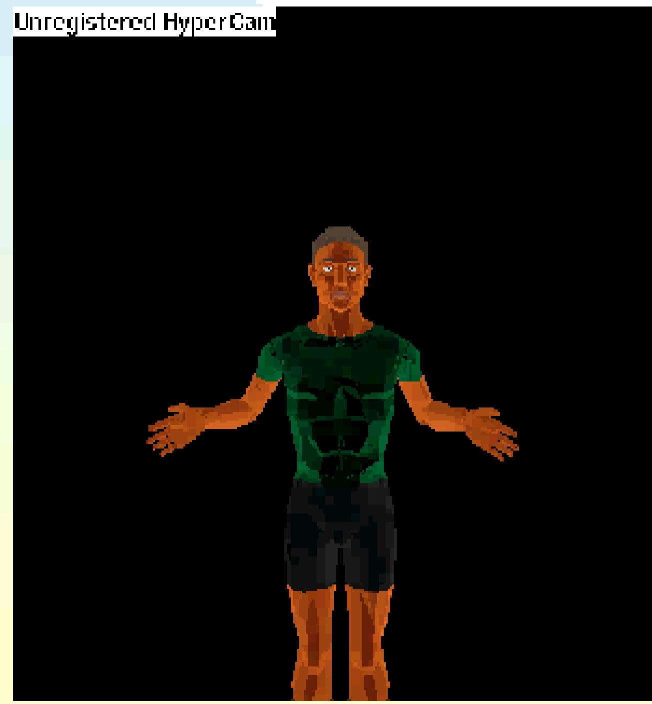
NASA Robonaut

Human-Humanoid Instantaneous Imitation

Throwing



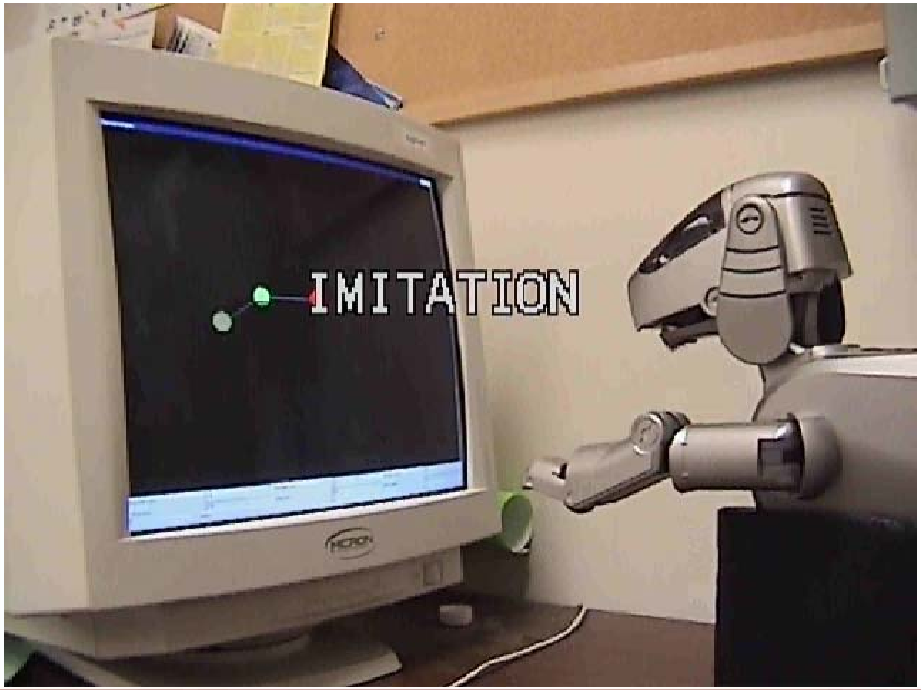
Jenkins, Mataric, Weber



Computer-Aibo Instantaneous Imitation

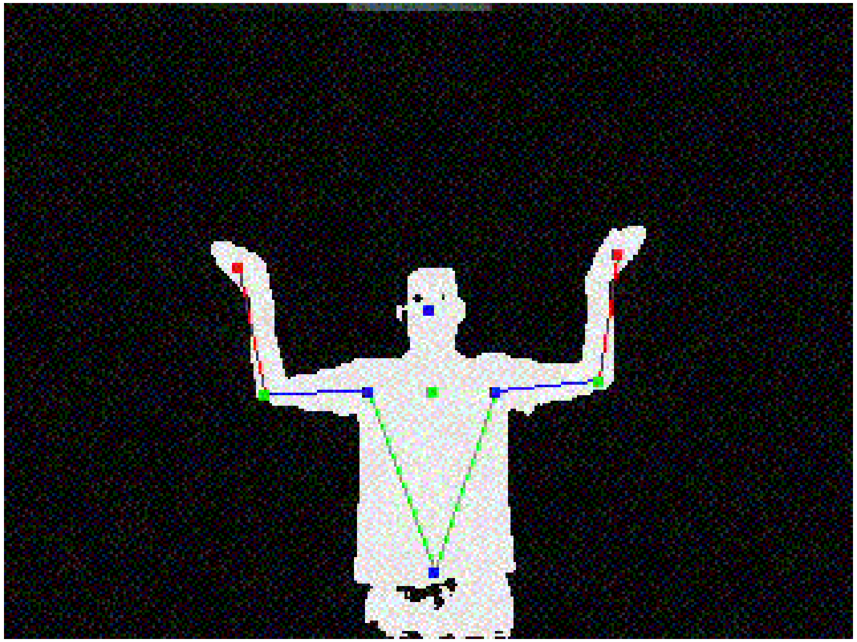
- Imitation using via-point primitives alone
- Instantaneous imitation, but jerky

- Imitation using oscillatory primitives
- Delayed imitation/phase lagged but smooth



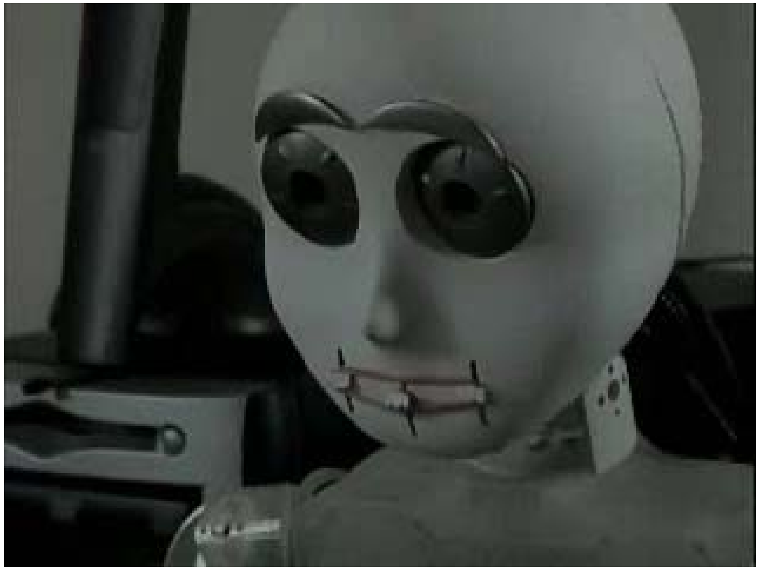
Human-Aibo Instantaneous Imitation

- Sony Aibo imitating a human; handling kinematic and joint limit mismatch
- Developed a metric of imitation quality



Leveraging Embodiment

- <u>A fact:</u> it is inherently human to automatically ascribe intentionality, goals, and feelings to physically embodied, moving entities
- <u>The hook:</u> we can't help it, so can we use it effectively?
- <u>The approach:</u> use the robot's embodiment as the main tool for action, interaction, and engagement
- <u>The test:</u> achieve measurable progress in the given problem domain.



- We focus on the social cues in posture and movement: proxemics, the amount of gesturing, mirroring, timing, and sequenced patterned activity.
- Imitation is a form of embodied interaction, establishing a “physical dialogue” between two socially interacting entities

Example of Simple Embodied Communication

- Robot uses its behaviors both to perform the task and to convey its intentions & the need for help (i.e., by trying and failing in front of the user)

inaccessible object

blocked gate

Embodied Assistive Communication

Our recent study [Gockley & Matarić HRI 05] used a rehabilitation task to test how exercise performance (measured with time-on-task) is affected by having a robot around, and how the robot's embodied communication (no speech, only proximity and amount of movement) impacted performance.

Embodied Assistive Communication

Subjects: 12, gender mixed, university-educated

Task: repetitive open-ended moving of pencils from one bit to another, a button to push when wanting to stop

Design: each participant saw 3 conditions in random order

1. **Control: no robot**
2. Aggressive robot: robot got close (personal space) and wiggled around to indicate encouragement
3. Passive robot: robot kept a distance and moved little

Robot's perception: real-time portable IMU-based motion capture worn by the subject, laser for proximity detection

Robot's movement: tied to the participant's, time-delayed mimicry

Data: questionnaires, video, motion capture

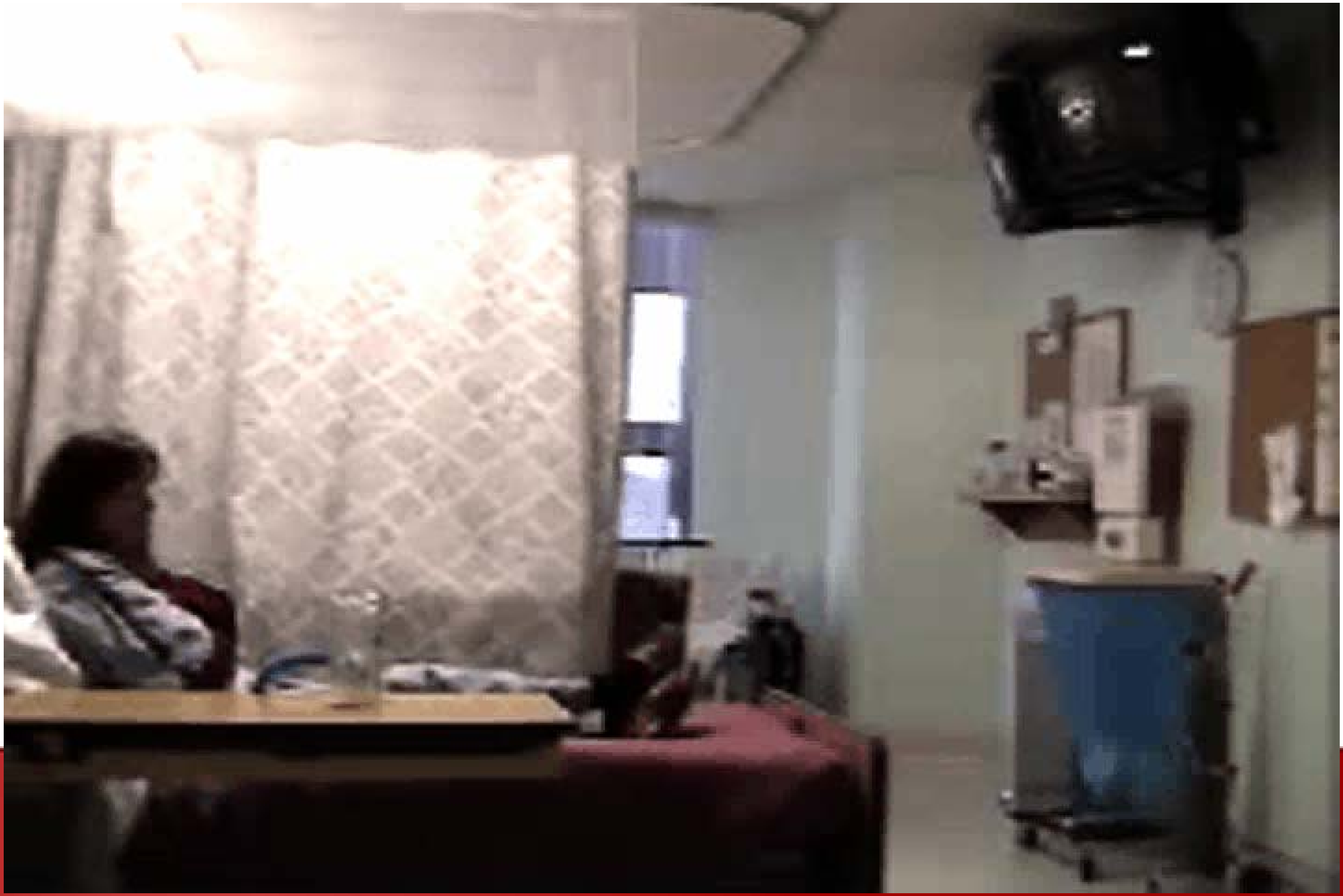
Main result: participants performed better (time-on-task was longer) when prompted by robot and all reported enjoying it more

Walking Coach & Companion

Some applications lend themselves to linguistic interaction more than others

Robot-Assisted Cardiac Surgery Convalescence

Patients readily performed spirometry exercises when prompted by the robot and reported enjoying the robot. [Kyong & Mataric ICORR 05]



Outline

- Overview & goals
- Action
  - Behavior primitives, derivation, and classification
- Interaction
  - Multi-robot coordination
  - Imitation
  - Embodied communication
- Engagement
  - Improved performance through engagement and motivation
  - The role of personality

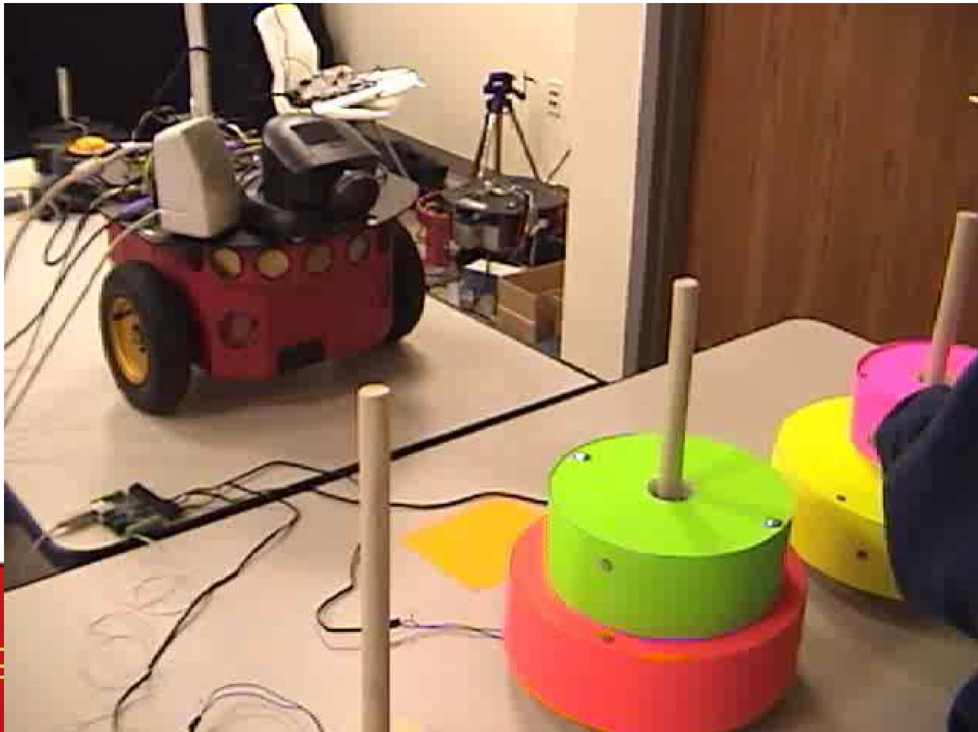
Goals & Challenges

- Goals:
  - Why a robot? Experimental confirmation of the role of robot embodiment
  - Will the effects last? Sustained task performance through engagement and motivation
  - Will it work for everyone? Insight into user differences and preferences toward personalizing robot behavior
- Philosophy:
  - Emphasis on the behavior of the robot, not its form
  - Emphasis on believability, not realism
  - Extensive testing with diverse user populations

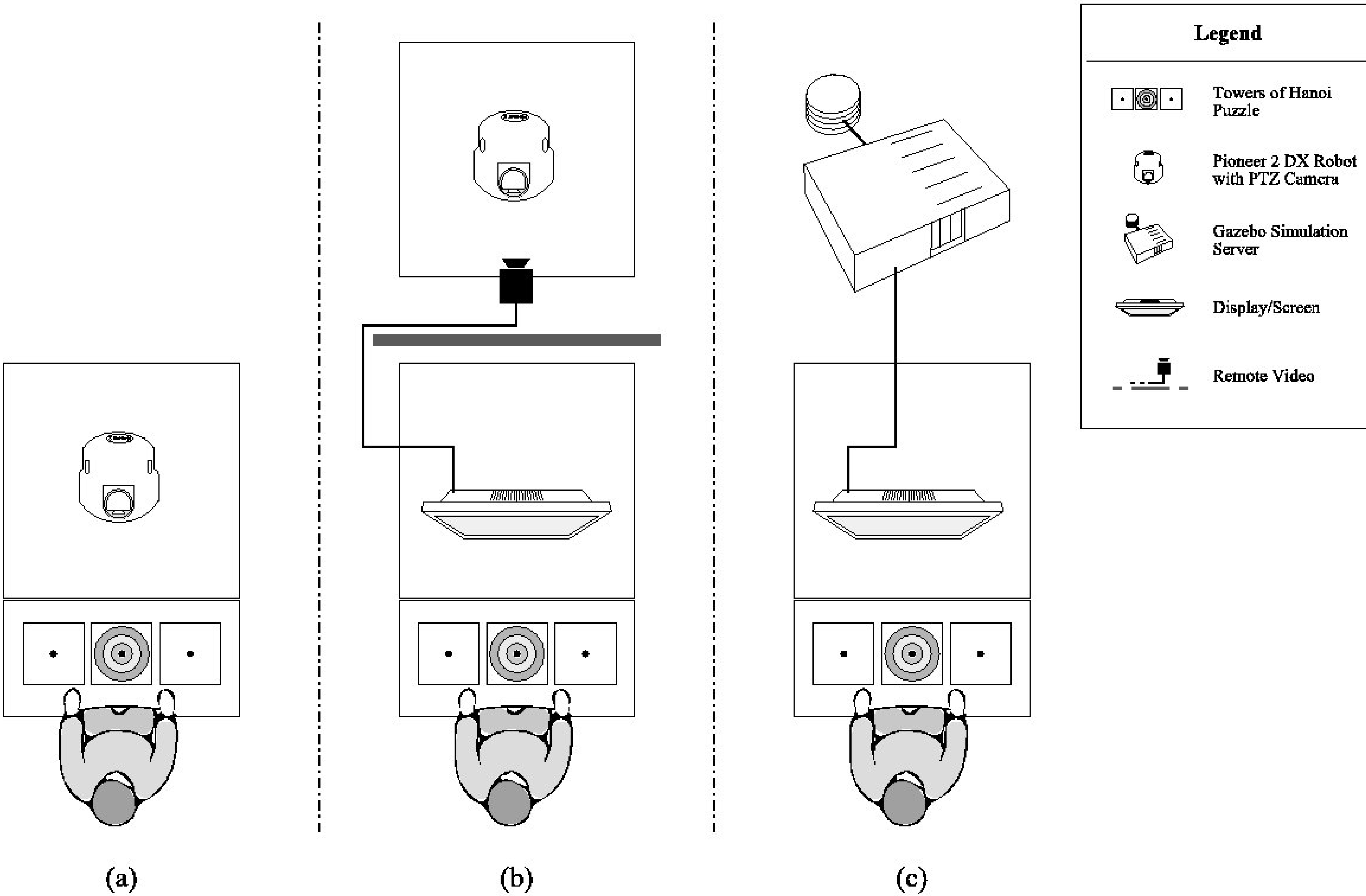
Tower of Hanoi Exercise

- Ongoing experiment validating the robot's embodiment and interaction style
- Task: Tower of Hanoi (variable difficulty), open-ended
- Interaction: Exercise "coach" provides verbal and movement feedback
- Performance measures:
  - Time-on-task
  - Correctness
  - Speed
- Robot: Hanoi Jane

Types of Feedback

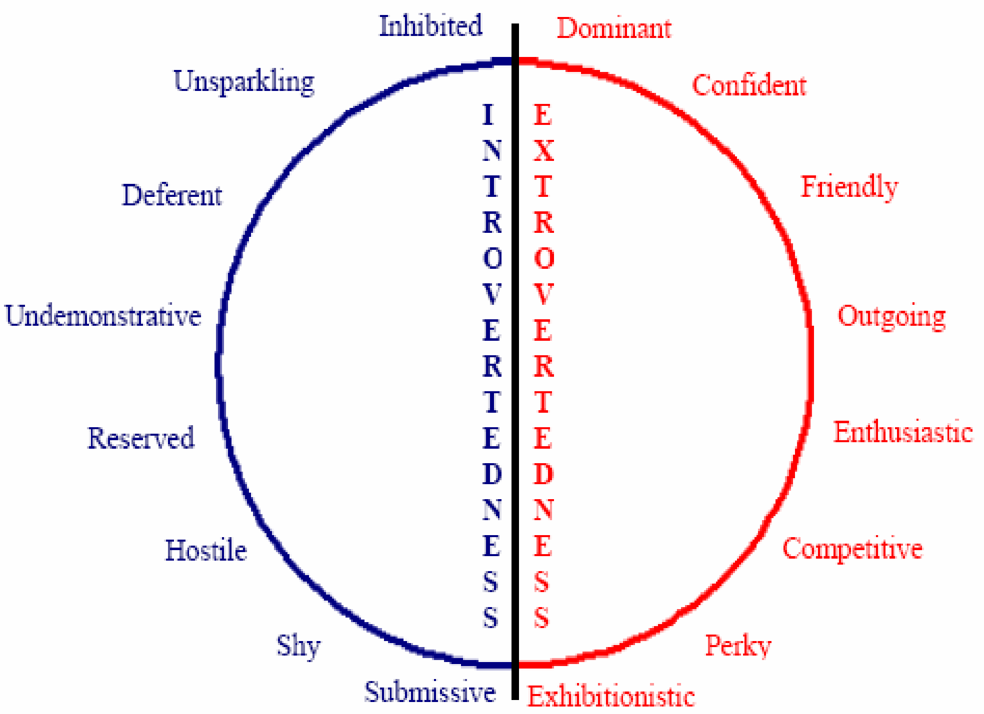


Testing the Role of Embodiment



Is User Personality Important?

- Human personality is critical in human-human interactions
- Personality plays a key role in stroke recovery
- → Personality will play a key role in human-robot interaction
  - User personality
  - Robot personality
- How to study this scientifically and use it to inform robot design?



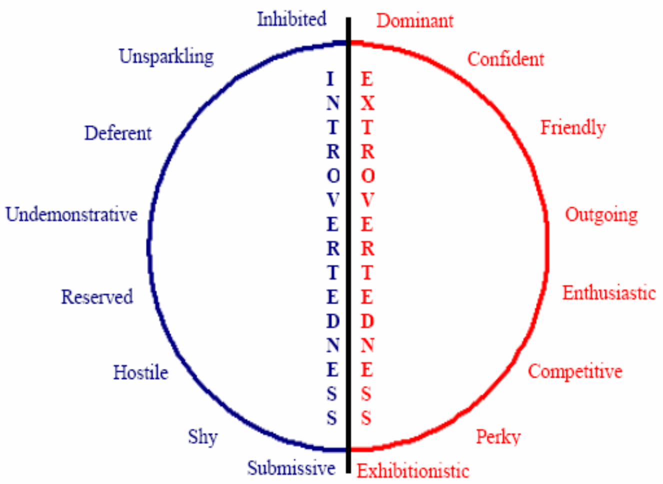
Robot-User Personality Matching

- Obtain personality data (Big 5, Myers-Briggs, Eysenk, etc.)
- Test different user-robot personality matches
- Adaptively tune the robot's expression of personality through the use of:
  - personal space
  - gestures
  - tone of voice
  - linguistic style

Robot-User Personality Matching

- Tasks: magazine shelving, moving pencils, and painting
- Pilot results:
  - Personality matched subjects performed longer on the task
  - Extraverted personalities preferred extraverted robot behavior
  - Introverted personalities reported on difference in preference (but performance varied as per above)

[Tapus&Mataric ISER 06]



A Study with Stroke Patients

- 6 high-function stroke patients, 2 women, all middle-aged, deficits on different sides of the body
- Interaction modalities:
  - Sound (beeps in response to patient movement)
  - Speech (pre-recorded male and female voices)
  - Physical movement of mobile robot

[Eriksson, Mataric, & Winsten ICORR 06]
[Mataric, Eriksson, Feil-Seifer, & Winsten JNER 06]

Stroke Patient Interaction

move_p1_human_ppt

Stroke Patient Interaction

book_p2_fx_ppt

3 hours and still going…

Insights and Results

- All reported to have enjoyed the robot
- Large personality differences in mode and amount of human-robot interaction and engagement
- Major disparity between compliance/adherence and engagement (!!)
- All preferred pre-recorded to synthesized speech
- All preferred South African accented male pre-recorded speech (different from HCI results!)

Approaches to Embodied Engagement

– Mirroring/mimicking the user (mood, amount of movement, the movement itself)
– Turn-taking games
– Commanding/controlling the robot through movement
– Encouragement and praise expression through movement & sound
– Teaching (the user or the robot) by imitation

A Testimonial

Another Testimonial

Summary

Confluence of scientific and technological opportunity + large-scale social need →
unique opportunity to shape human-centered robotics

Parting words

- More information, papers, videos, and specific contributors to the research:

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  Email: mataric@usc.edu

Thank you!