How Machines Learn: From Robot Soccer to Autonomous Traffic

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Research Question

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- Autonomous agents
- Multiagent systems
- **Machine learning**
- **Robotics**

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Autonomous Bidding, Cognitive Systems,
Robot Soccer, **Traffic management**

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  - Way of selecting actions that gets you the most reward

How did you do it?

How did you do it?

- What is your policy?
- What does the world look like?

Formalizing What Just Happened

Knowns:

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- **Q-learning**: provably converges to the **optimal policy**
  - Proof: **contraction mappings** and **fixed point theorem**

A harder problem

- You had 3 actions and saw one of 10 colors

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- What if you had to control 12 joints . . .

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- What if you had to control 12 joints . . .
- . . . and saw something like this 30 times per second?

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Several Different Leagues

RoboCup Soccer

Small-sized League

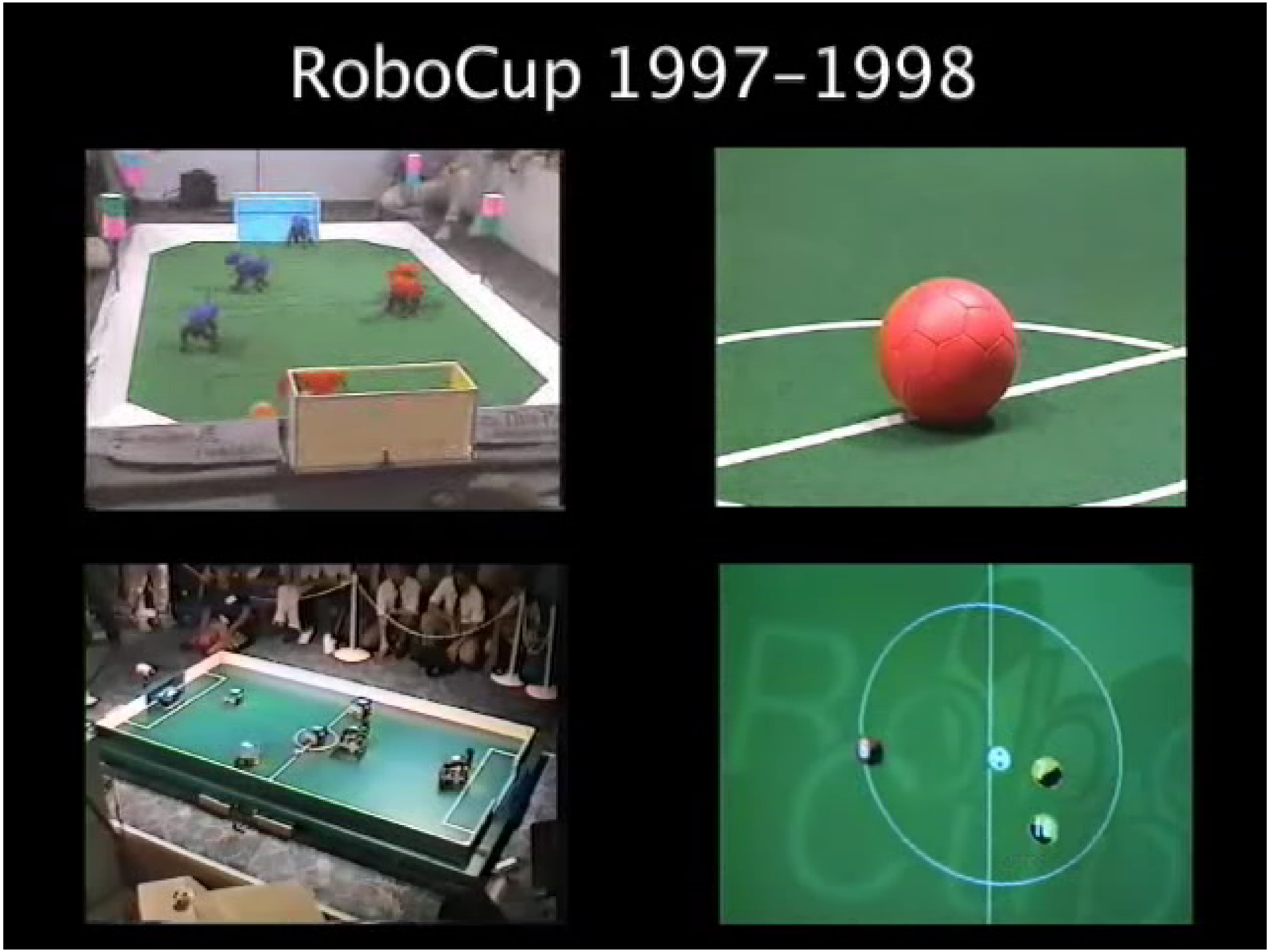
Middle-sized League

Legged Robot League

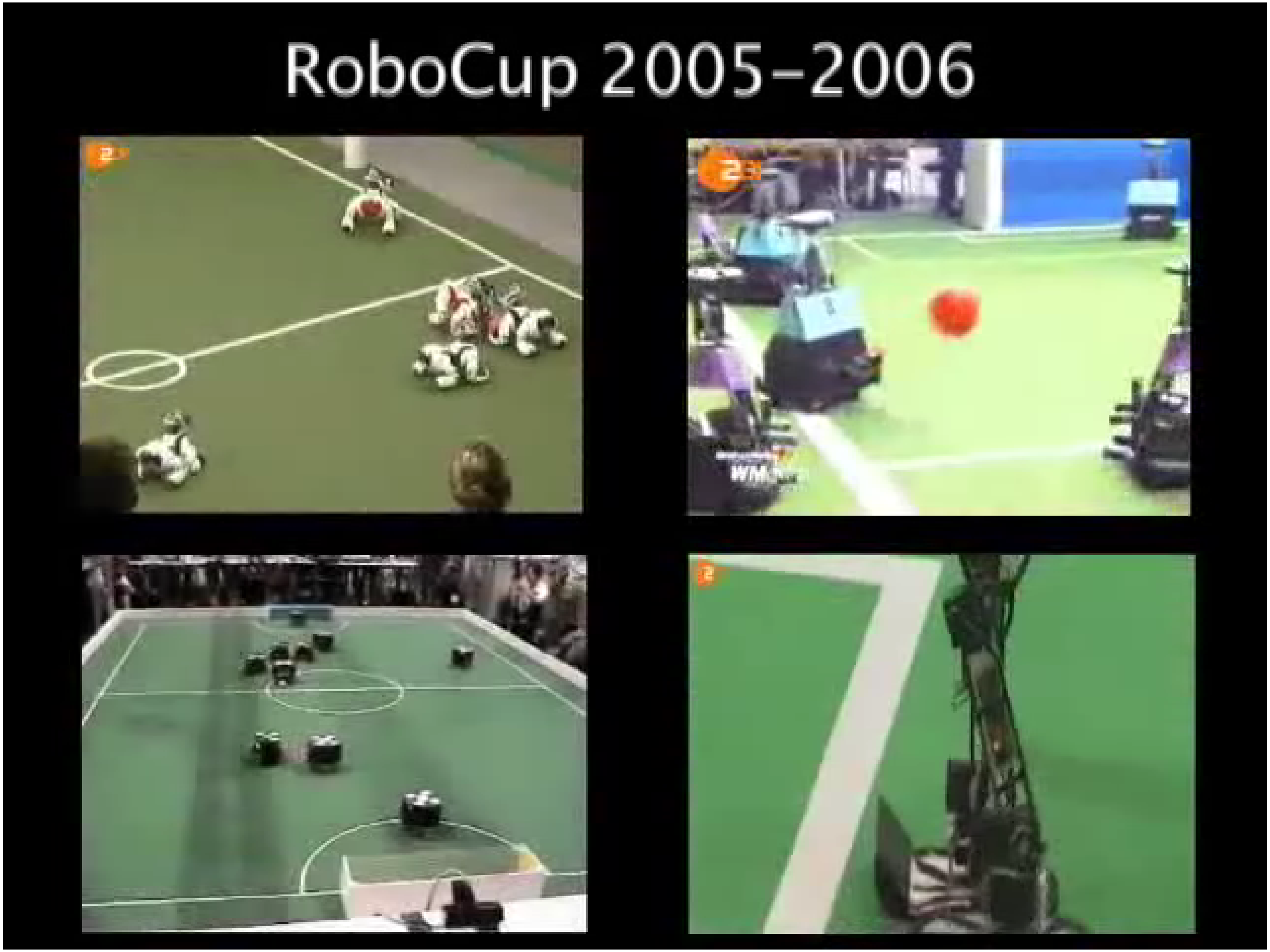
Simulation League

Humanoid League

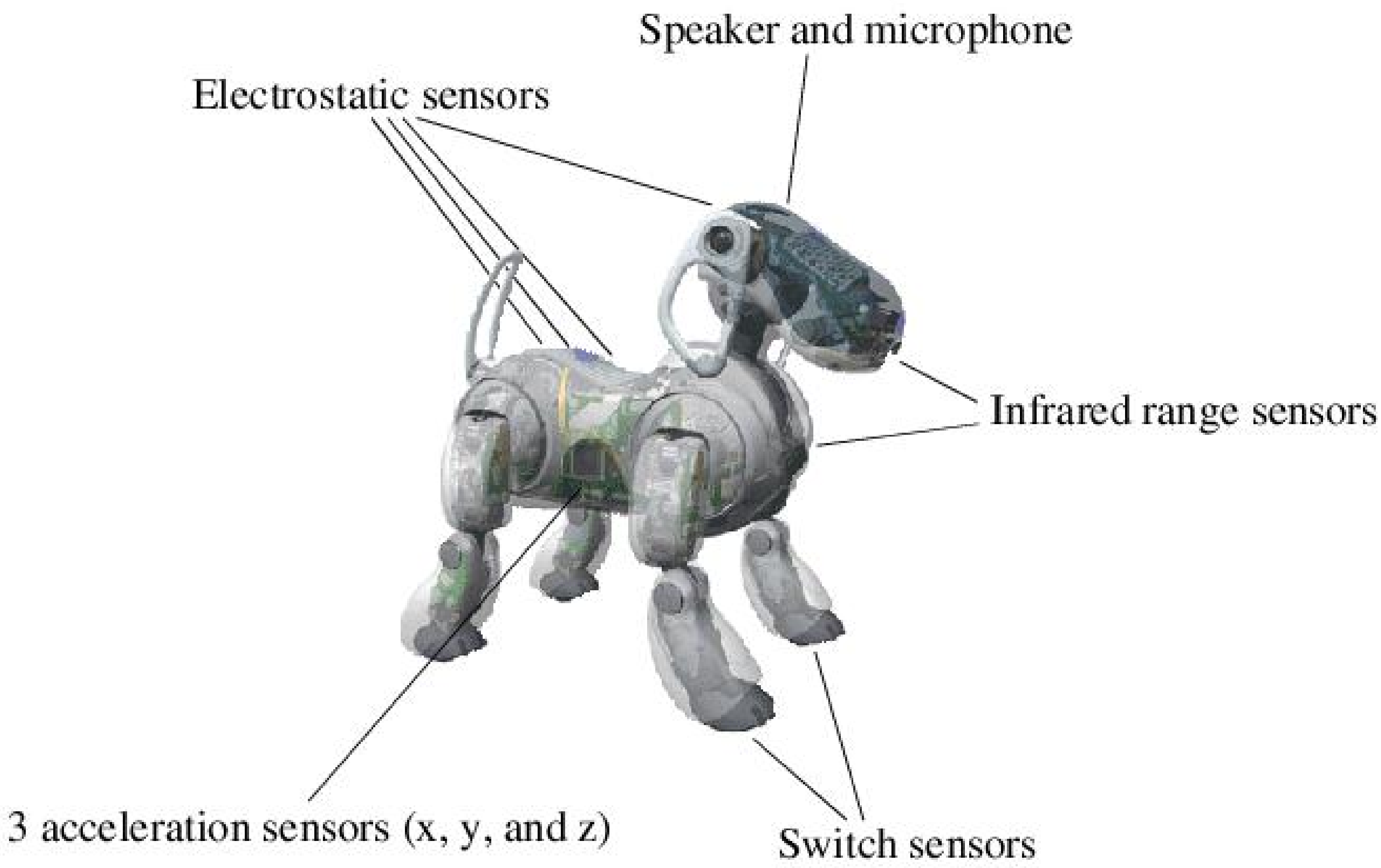
The Early Years



A Decade Later



Sony Aibo (ERS-210A, ERS-7)



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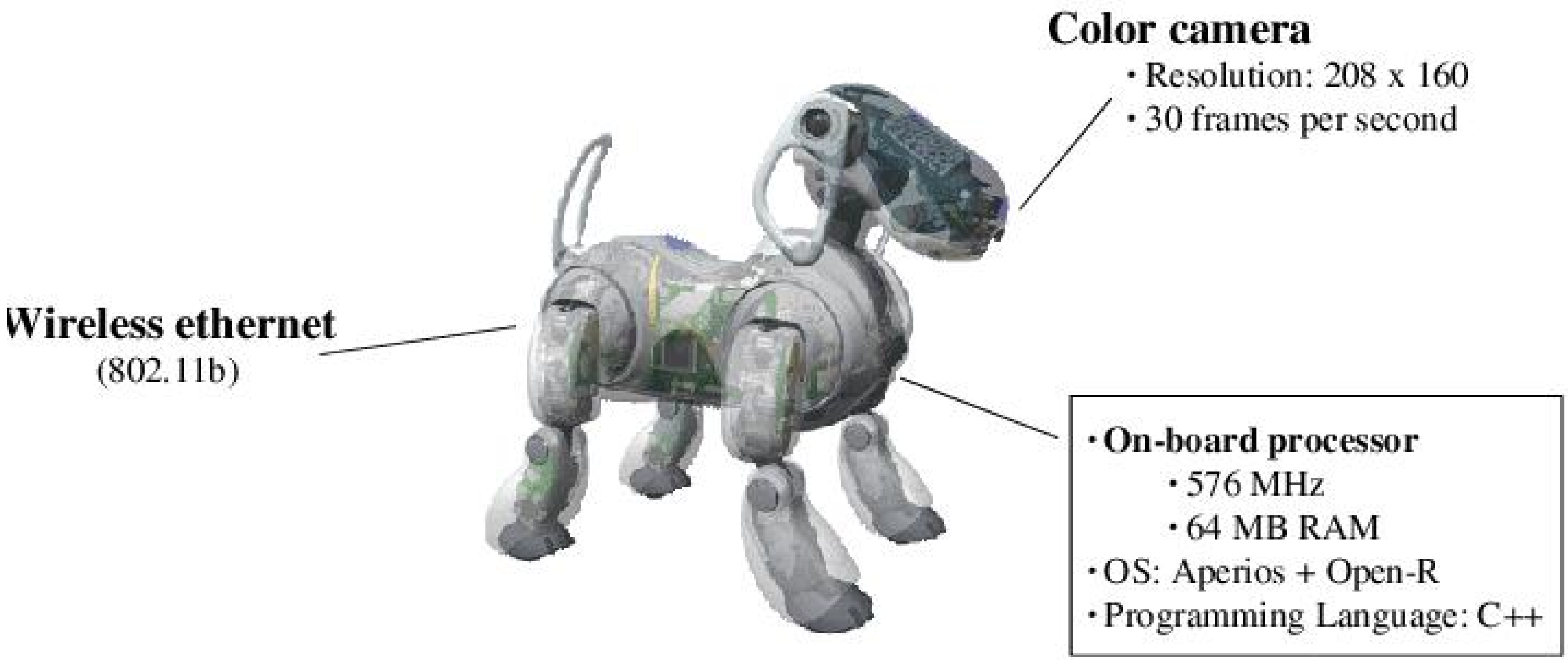
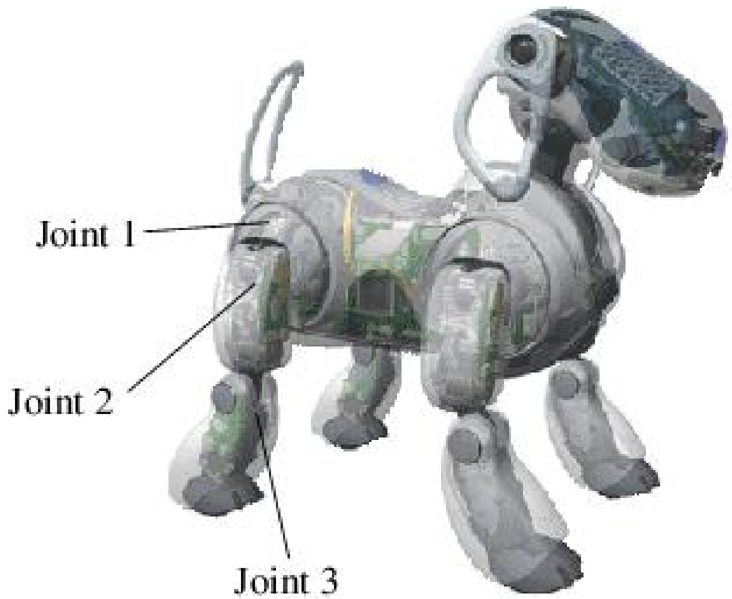


Sony Aibo (ERS-210A, ERS-7)

20 degrees of freedom



- head: 3 neck, 2 ears, 1 mouth
- **4 legs: 3 joints each**
- tail: 2 DOF

Creating a team — Subtasks

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- Vision
- Localization
- Walking
- Ball manipulation (kicking)
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- Won **3rd place** at US Open **(2004, 2005)**
- **Quarterfinalist** at RoboCup **(2004, 2005)**
- Highlights:
  - Many saves: 1; 2; 3; 4;
  - Lots of goals: CMU; Penn; Penn; Germany;

  - A nice clear
  - A counterattack goal

Post-competition: the CS research

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- Model-based joint control (Stronger, S, '04)
- Learning sensor and action models (Stronger, S, '06)
- **Machine learning for fast walking** (Kohl, S, '04)
- **Learning to acquire the ball** (Fidelman, S, '06)
- **Color constancy on mobile robots** (Sridharan, S, '04)
- **Robust particle filter localization** (Sridharan, Kuhlmann, S, '05)
- **Autonomous Color Learning** (Sridharan, S, '05)

Policy Gradient RL to learn fast walk

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- Start with a **parameterized walk**
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- **No simulator** available:
  - Learn entirely on robots
  - Minimal human intervention

Walking Aibos

- Walks that "come with" Aibo are **slow**
- **RoboCup** soccer: **25+ Aibo teams** internationally
  - Motivates faster walks

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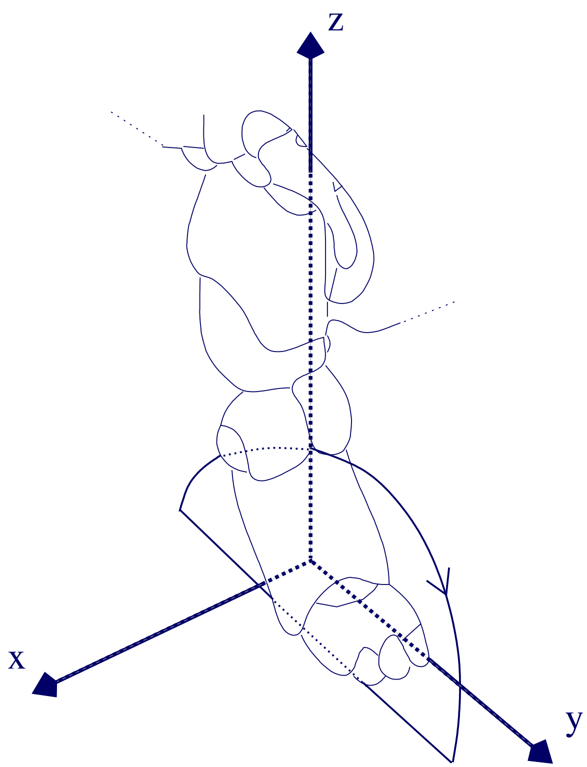
Hand-tuned gaits (2003)			Learned gaits	
German Team	UT Austin Villa	UNSW	Hornby et al. (1999)	Kim & Uther (2003)
230 mm/s	**245**	**254**	**170**	**270** (± 5)

A Parameterized Walk

- Developed from scratch as part of **UT Austin Villa** 2003
- **Trot gait** with elliptical locus on each leg

Locus Parameters



- Ellipse length
- Ellipse height
- Position on x axis
- Position on y axis
- Body height
- Timing values

12 continuous parameters

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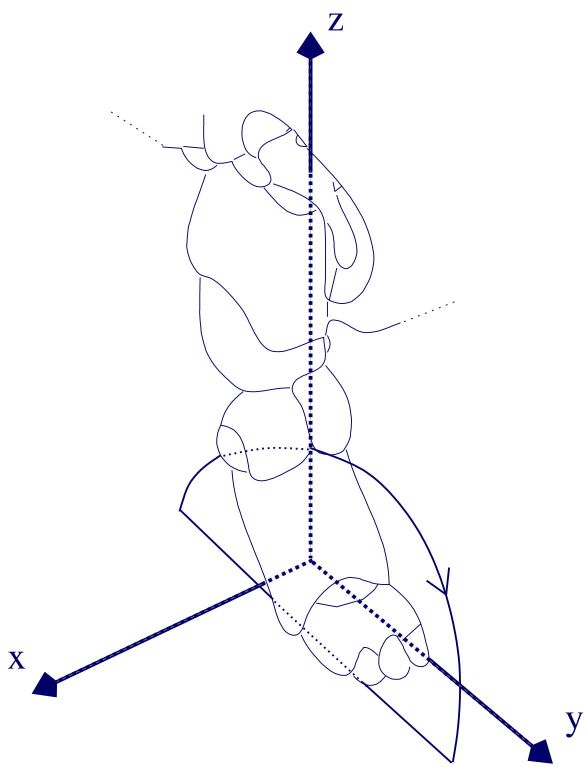

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- Hand tuning by April, '03: **140 mm/s**
- Hand tuning by July, '03: **245 mm/s**

Experimental Setup

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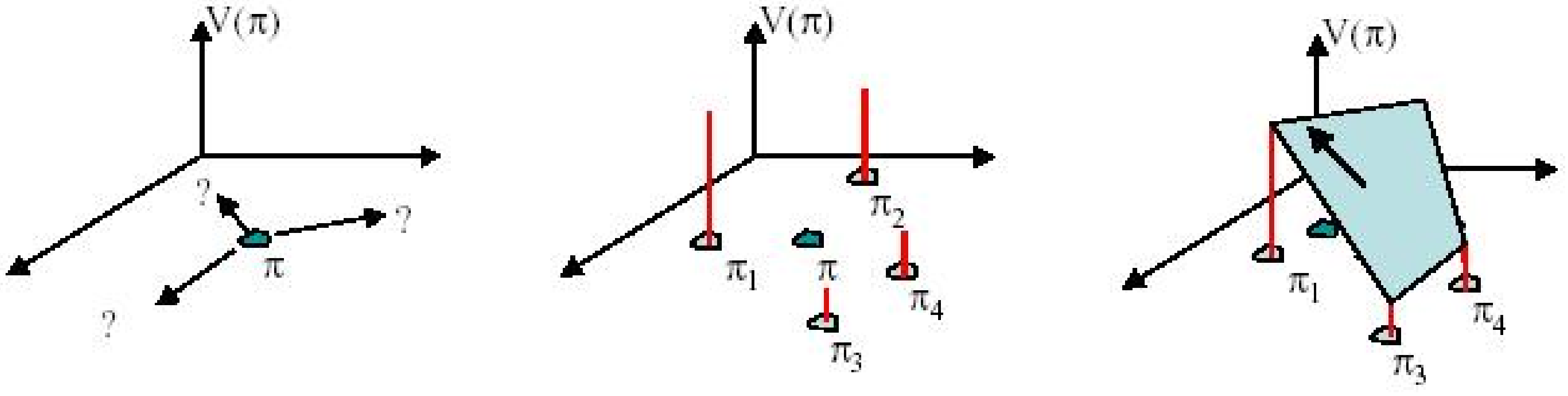
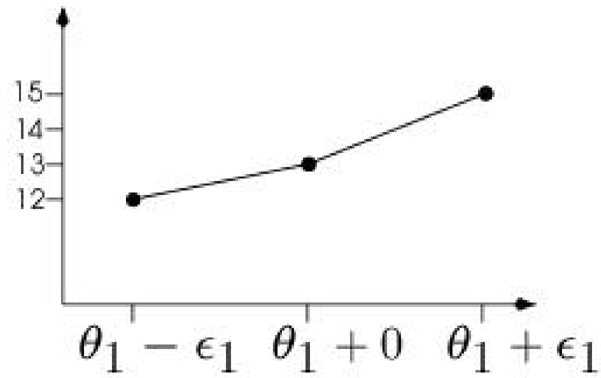
  - Expect $t/3$ estimates for each of $\theta_i \pm \epsilon$, 0
  - Each evaluation contributes to **all 12** estimates

Gradient Estimation



Taking a step



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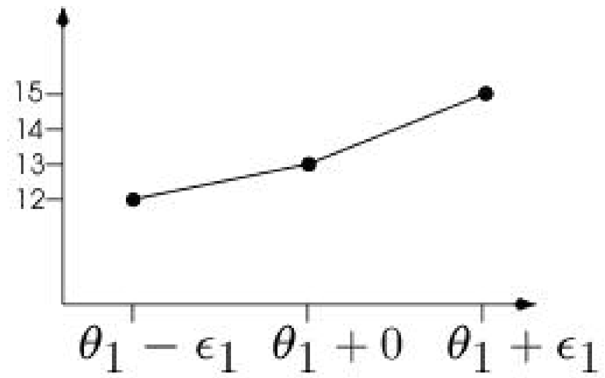

$$A_i = \begin{cases} 0 & \text{if } Avg_{+0,i} > Avg_{+\epsilon,i} \text{ and} \\ & \quad Avg_{+0,i} > Avg_{-\epsilon,i} \\ Avg_{+\epsilon,i} - Avg_{-\epsilon,i} & \text{otherwise} \end{cases} \tag{1}$$

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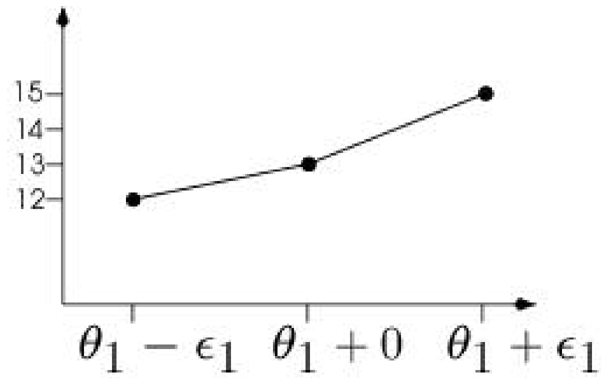

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- **Normalize** A, multiply by scalar **step-size** η
- $\pi = \pi + \eta A$

Experiments

- Started from **stable**, but fairly slow gait
- Used **3 robots** simultaneously
- Each iteration takes 45 traversals, $7\frac{1}{2}$ minutes

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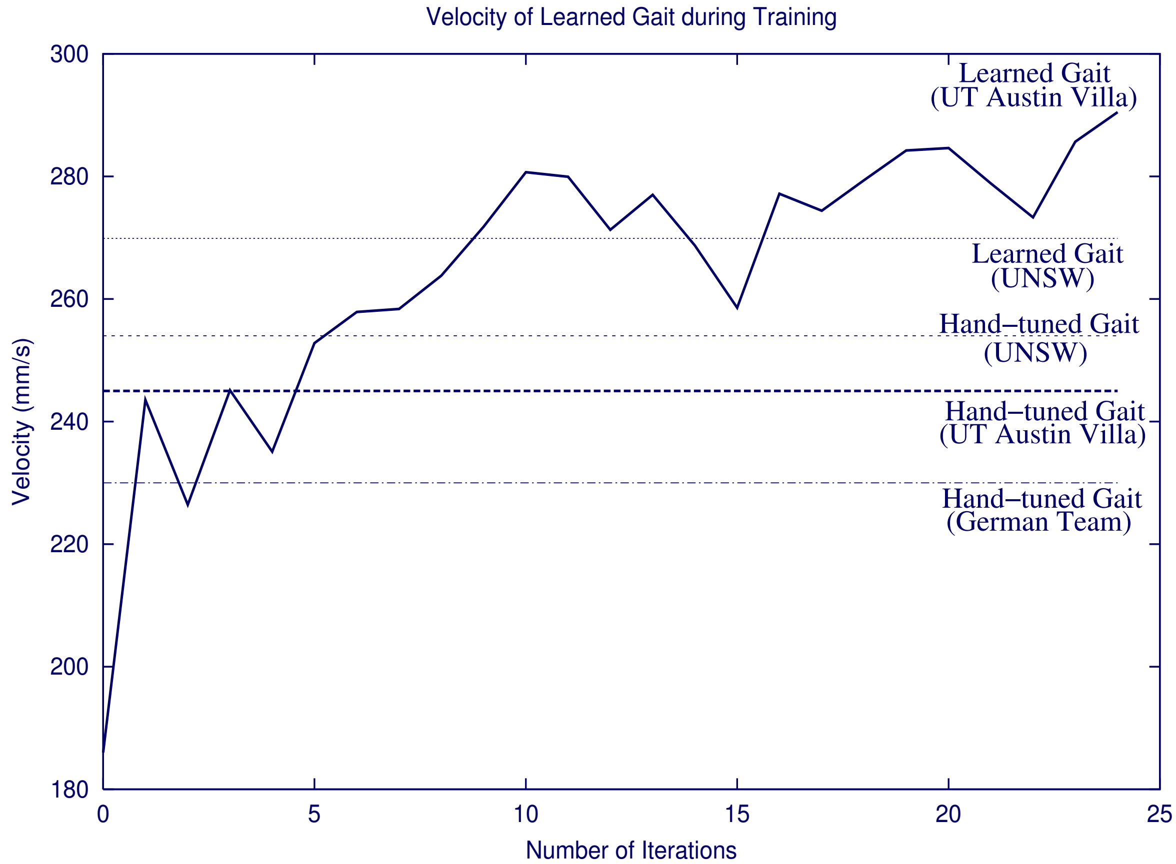
Before learning

After learning

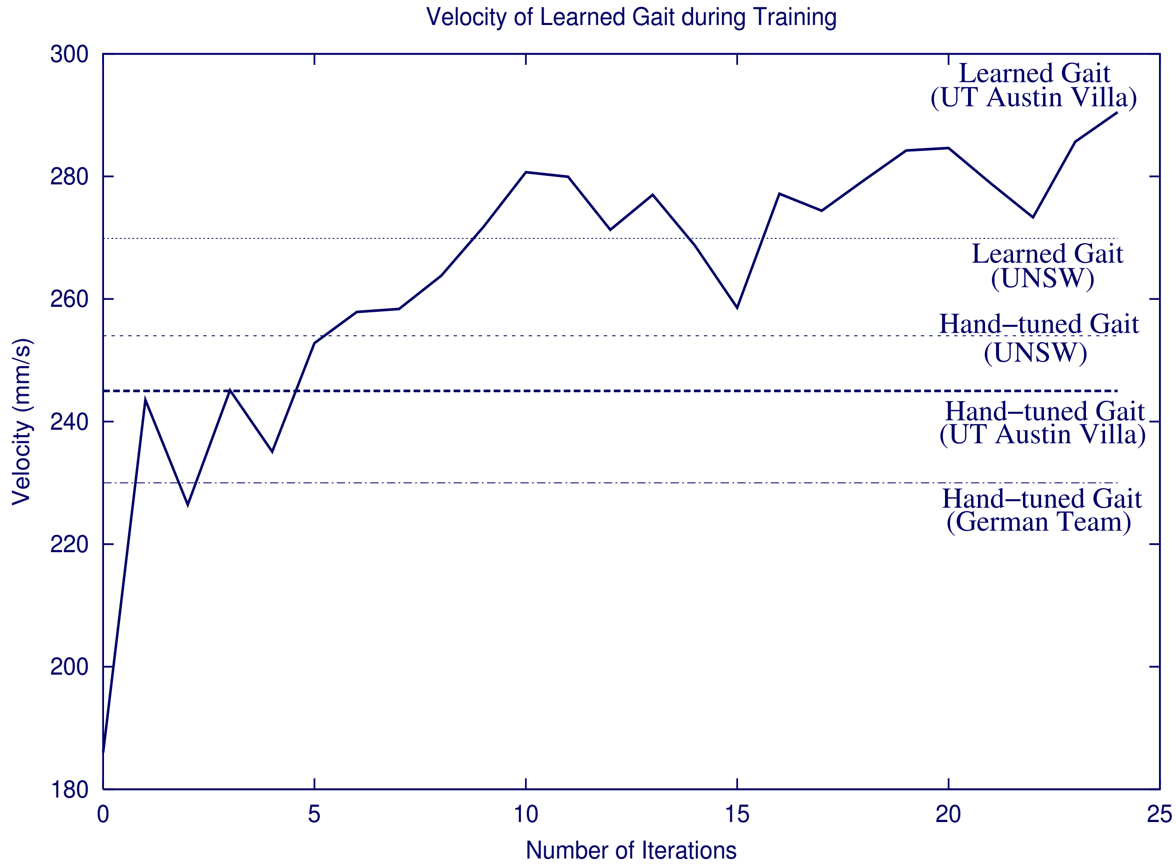
- 24 iterations = **1080 field traversals**, $\approx$ **3 hours**

Results



Velocity of Learned Gait during Training
Velocity (mm/s)
Number of Iterations
300
280
260
240
220
200
180
0
5
10
15
20
25
Learned Gait (UT Austin Villa)
Learned Gait (UNSW)
Hand–tuned Gait (UNSW)
Hand–tuned Gait (UT Austin Villa)
Hand–tuned Gait (German Team)

Results

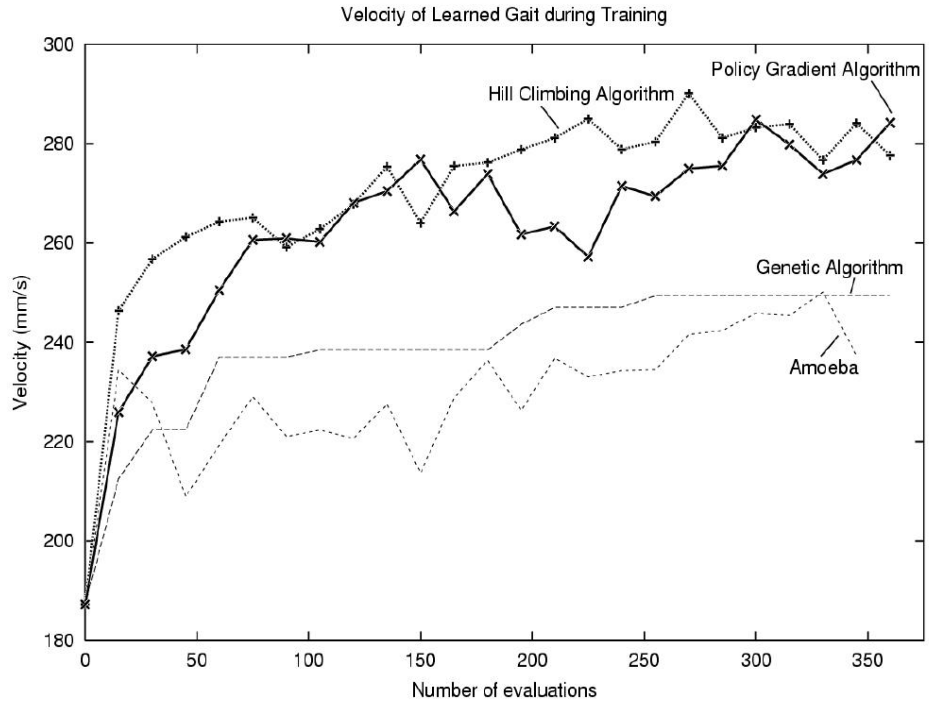


- Additional iterations didn't help
- Spikes: evaluation **noise**? large **step size**?

Learned Parameters

Parameter	Initial Value	ϵ	Best Value
Front ellipse:			
(height)	4.2	0.35	4.081
(x offset)	2.8	0.35	0.574
(y offset)	4.9	0.35	5.152
Rear ellipse:			
(height)	5.6	0.35	6.02
(x offset)	0.0	0.35	0.217
(y offset)	-2.8	0.35	-2.982
Ellipse length	4.893	0.35	5.285
Ellipse skew multiplier	0.035	0.175	0.049
Front height	7.7	0.35	7.483
Rear height	11.2	0.35	10.843
Time to move through locus	0.704	0.016	0.679
Time on ground	0.5	0.05	**0.430**

Algorithmic Comparison, Robot Port



Before learning

After learning

Summary

- Used policy gradient RL to **learn fastest Aibo walk**
- All learning done **on real robots**
- **No human itervention** (except battery changes)

Outline

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- **Learning to acquire the ball** (Fidelman, S, '06)
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Grasping the Ball

- **Three stages:** walk to ball; slow down; lower chin
- Head proprioception, IR chest sensor $\mapsto$ ball distance
- Movement specified by **4 parameters**

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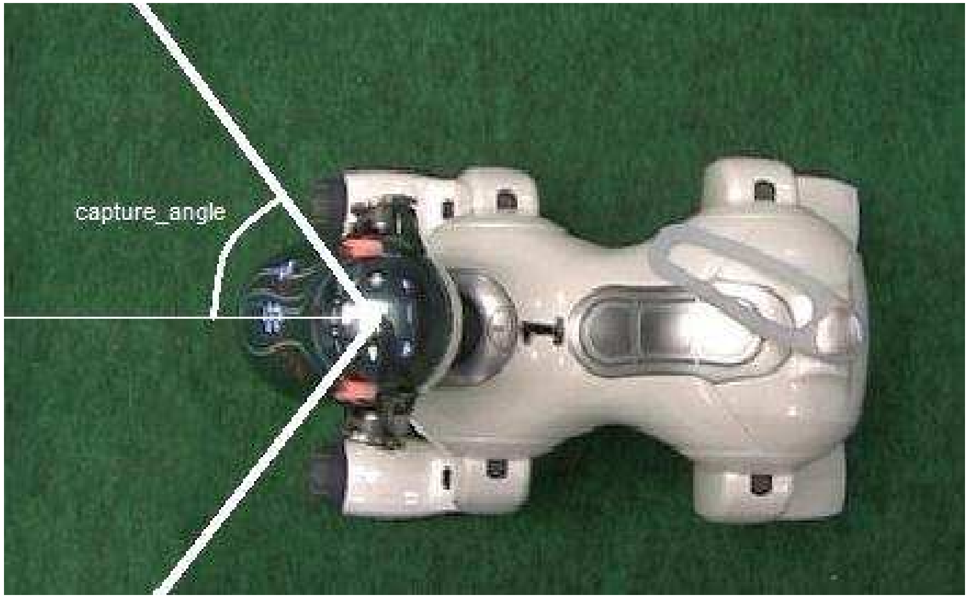
$\boxed{\textbf{Brittle!}}$

Parameterization

- **slowdown_dist:** when to slow down
- **slowdown_factor:** how much to slow down
- **capture_angle:** when to stop turning



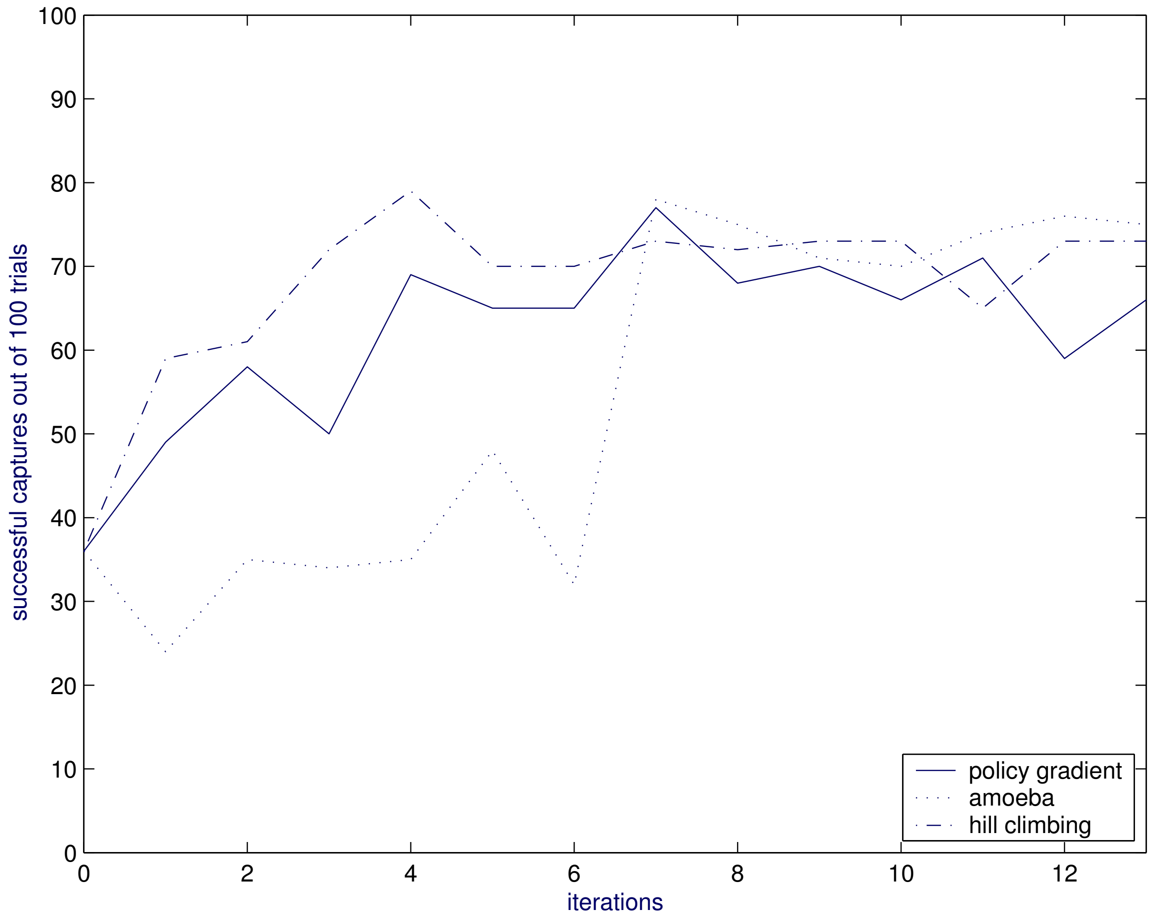
- **capture_dist:** when to put down head

Learning the Chin Pinch

- **Binary, noisy** reinforcement signal: multiple trials
- Robot evaluates self: **no human intervention**

Results

- Evaluation of **policy gradient**, **hill climbing**, **amoeba**



What it learned

Policy	slowdown dist	slowdown factor	capture angle	capture dist	Success rate
Initial	200mm	0.7	15.0^o	110mm	36%
Policy gradient	125mm	1	17.4^o	152mm	64%
Amoeba	208mm	1	33.4^o	162mm	69%
Hill climbing	240mm	1	35.0^o	170mm	66%

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- Challenge: Nonlinear variations in sensor response with **change in illumination**
- **Mobile robots**:
  - Computational limitations
  - Changing camera positions

Sample Images

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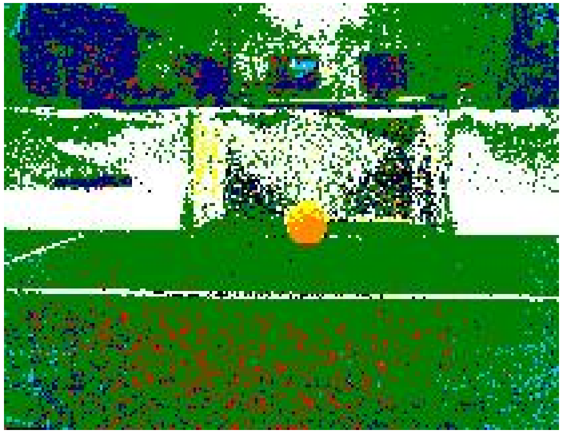

Our Goal

- Match current performance in **changing lighting**
- Experiments on ERS-210A robots

Autonomous Color Learning

- Color Constancy: **more** tediously created maps
  - Hand-labeling many images $\longrightarrow$ hours of **manual effort**

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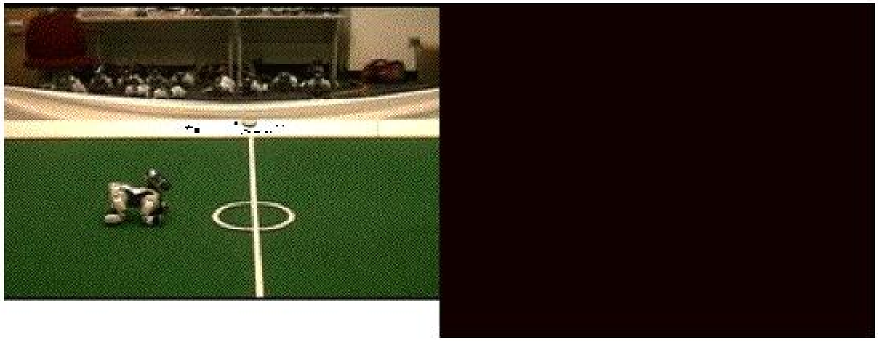
  - Hand-labeling many images $\longrightarrow$ hours of **manual effort**
- Use the **structured environment**
  - Robot learns color **distributions**



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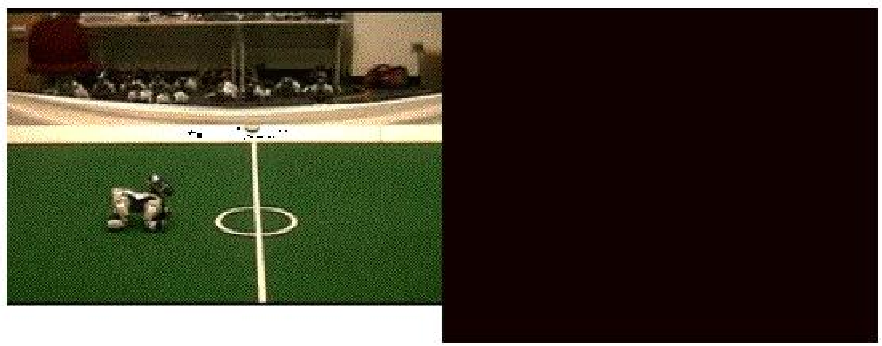

- Comparable accuracy, 5 minutes of **robot effort**

Outline

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  - No simulation, minimal human intervention

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- **Multiagent Strategy:** RL in simulation

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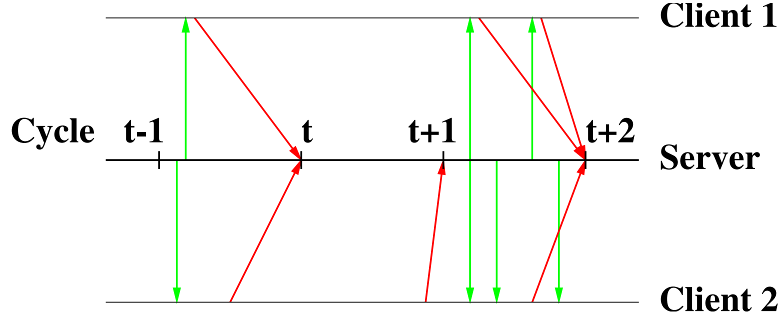

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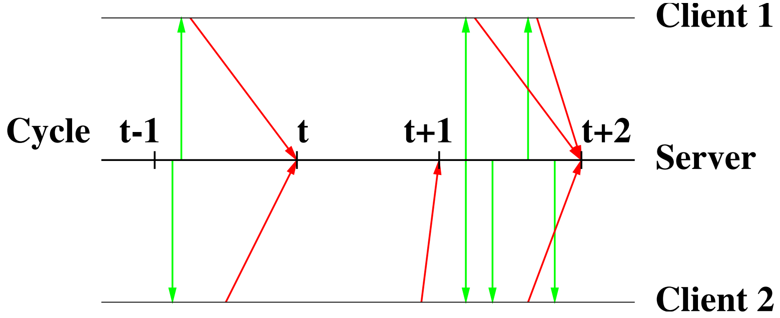

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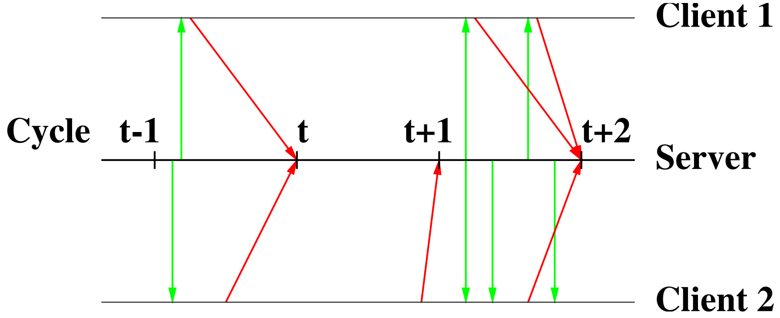

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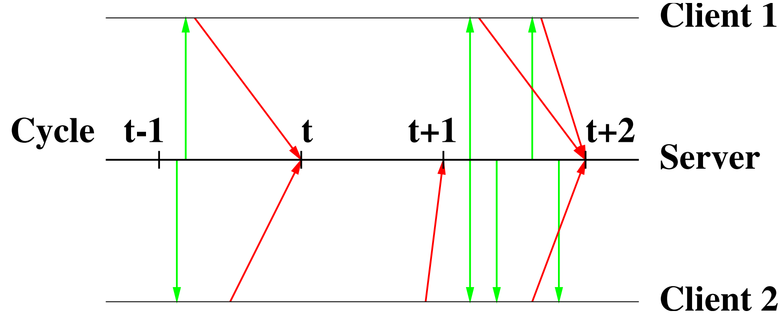

- Parametric actions: dash, turn, kick, say
- Abstract, noisy sensors, hidden state
  - Hear sounds from limited distance
  - See relative distance, angle to objects ahead
- $> 10^{9^{23}}$ states
- Limited resources : stamina
- Play occurs in real time ($\approx$ human parameters)

3 vs. 2 Keepaway

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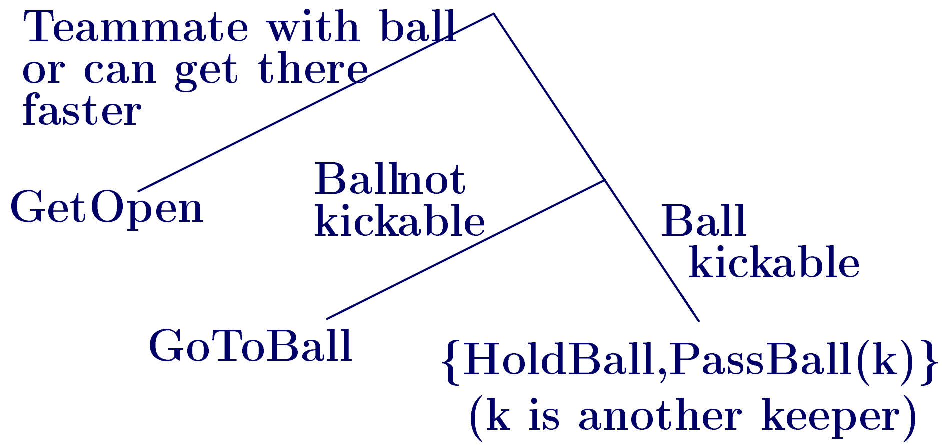
- **Episode:**
  – Players and ball reset randomly
  – Ball starts near a keeper
  – Ends when taker gets the ball or ball goes out
- Performance measure: **average possession duration**
- Use **CMUnited-99 skills**:
  – HoldBall, PassBall(k), GoToBall, GetOpen

The Keepers' Policy Space



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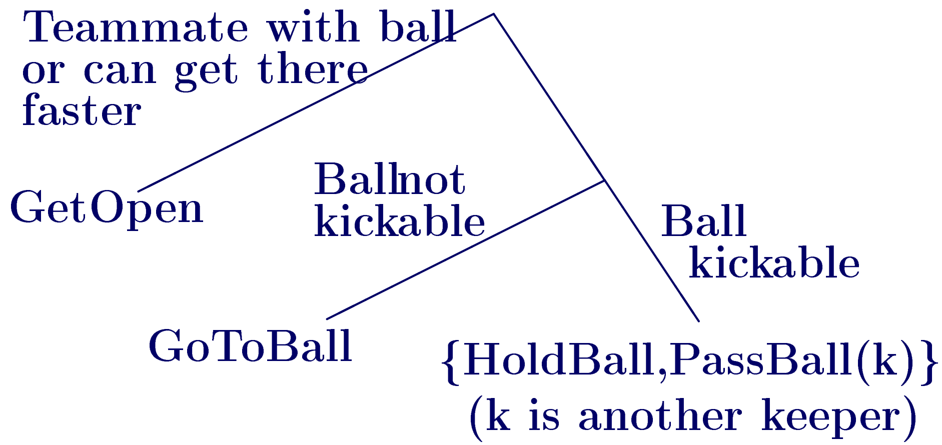

Example Policies

Random: HoldBall or PassBall(k) randomly

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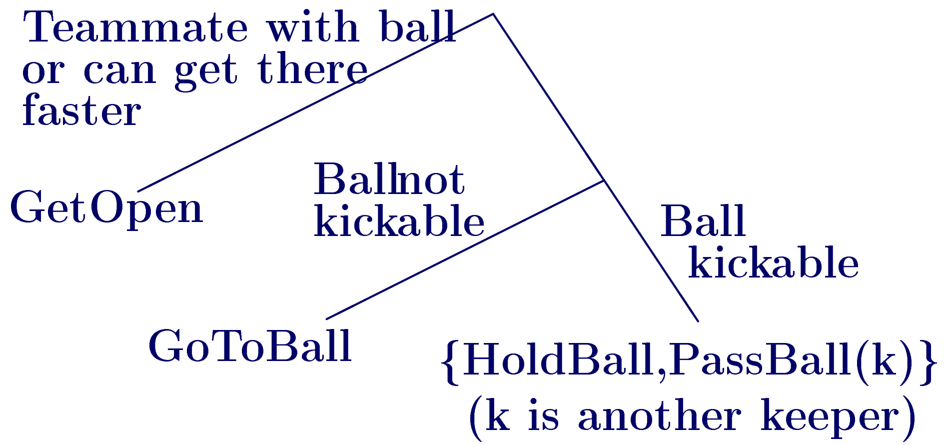

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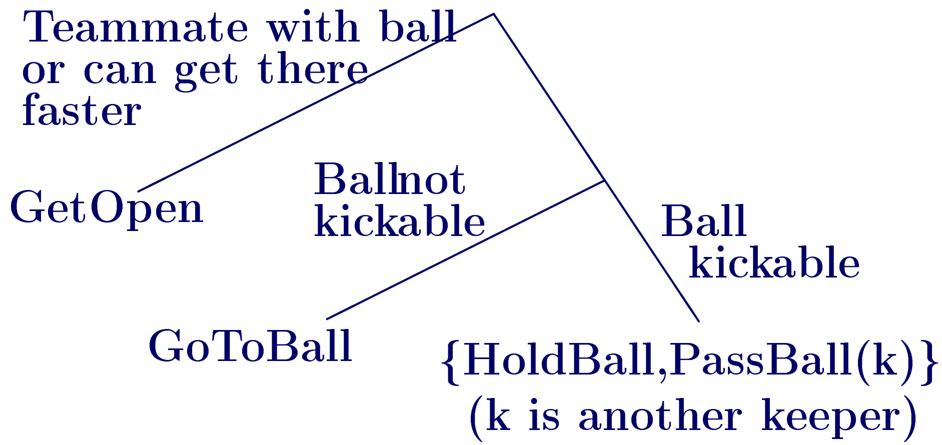


Example Policies

Random: HoldBall or PassBall(k) randomly

Hold: Always HoldBall

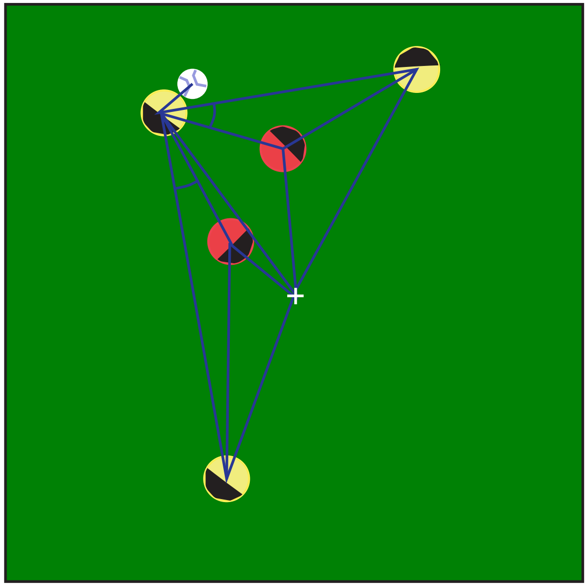
Hand-coded:

If no taker within 10m: HoldBall

Else If there's a good pass: PassBall(k)

Else HoldBall

Keeper's State Variables



- 11 distances among players, ball, and center
- *2 angles* to takers along passing lanes

Function Approximation: Tile Coding

- Form of sparse, coarse coding based on CMACS (Albus, 1981)

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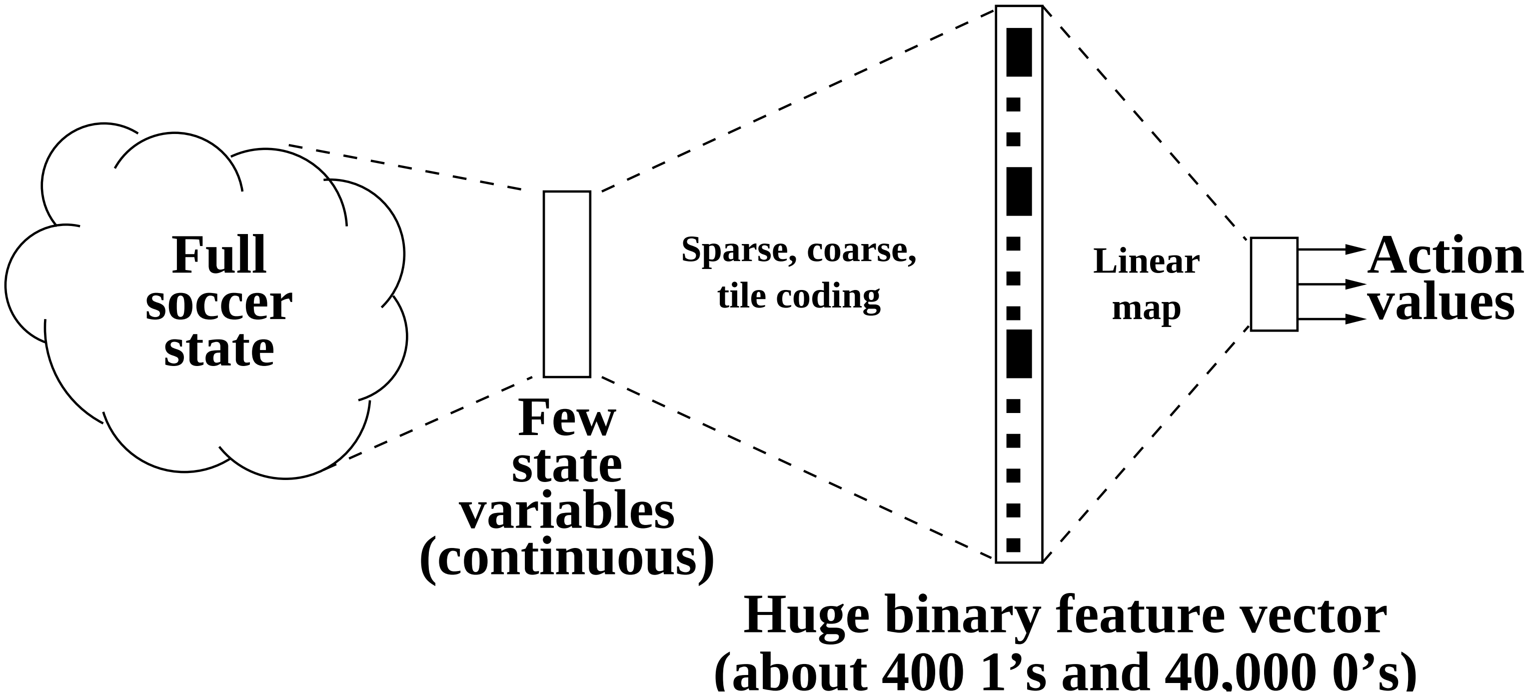
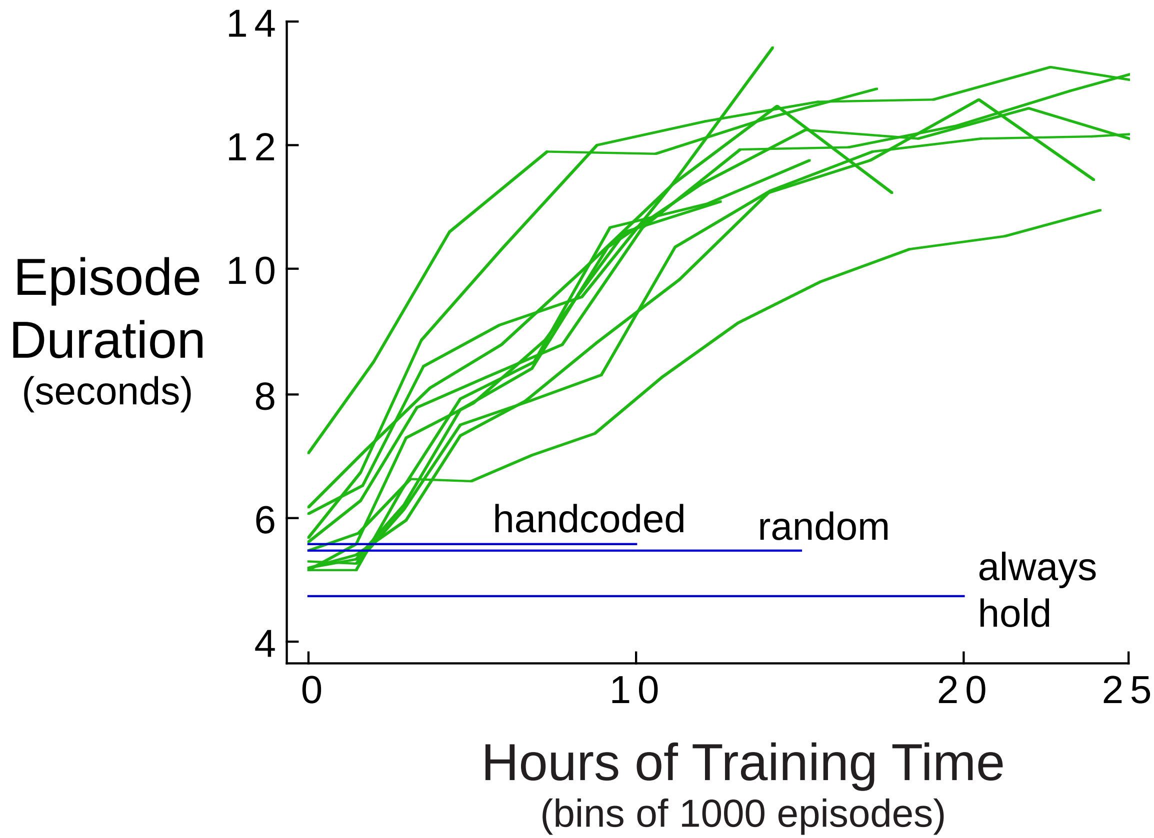
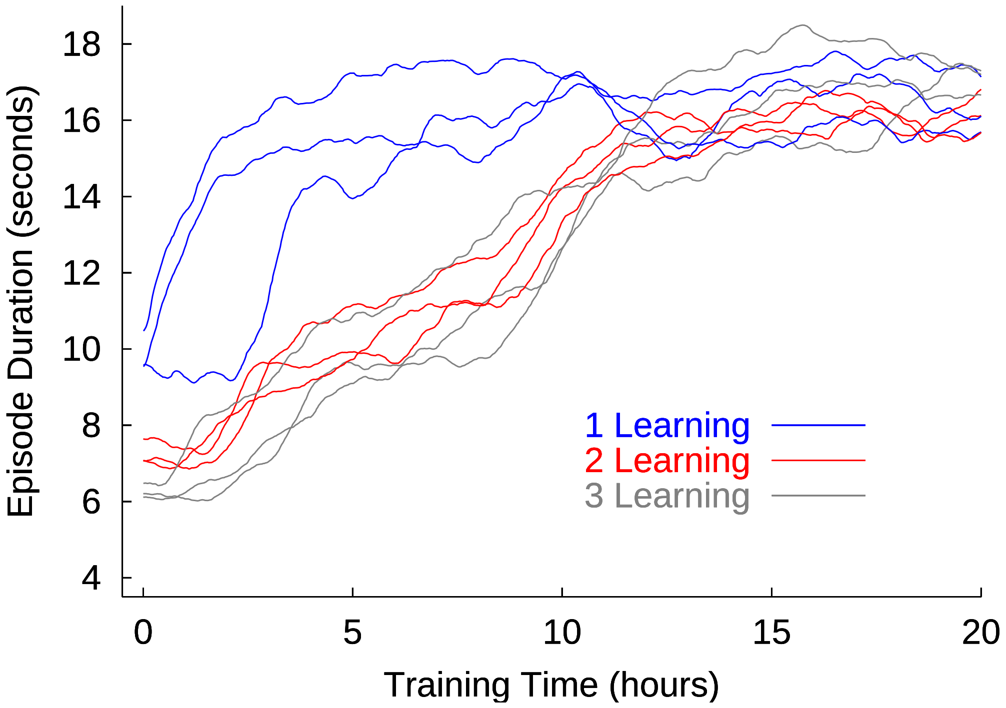


Main Result



1 hour = 720 5-second episodes

Difficulty of Multiagent Learning



- Multiagent learning is harder!

Outline

- Robot soccer on real robots
- Robot soccer in simulation

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- Robot soccer on real robots
- Robot soccer in simulation
- Autonomous driving

Acknowledgements

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- Fox Sports World for inspiration!