Machine Learning on Physical Robots

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Research Question

To what degree can autonomous intelligent agents learn in the presence of teammates and/or adversaries in real-time, dynamic domains?

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

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

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Several Different Leagues

RoboCup Soccer

Small-sized League

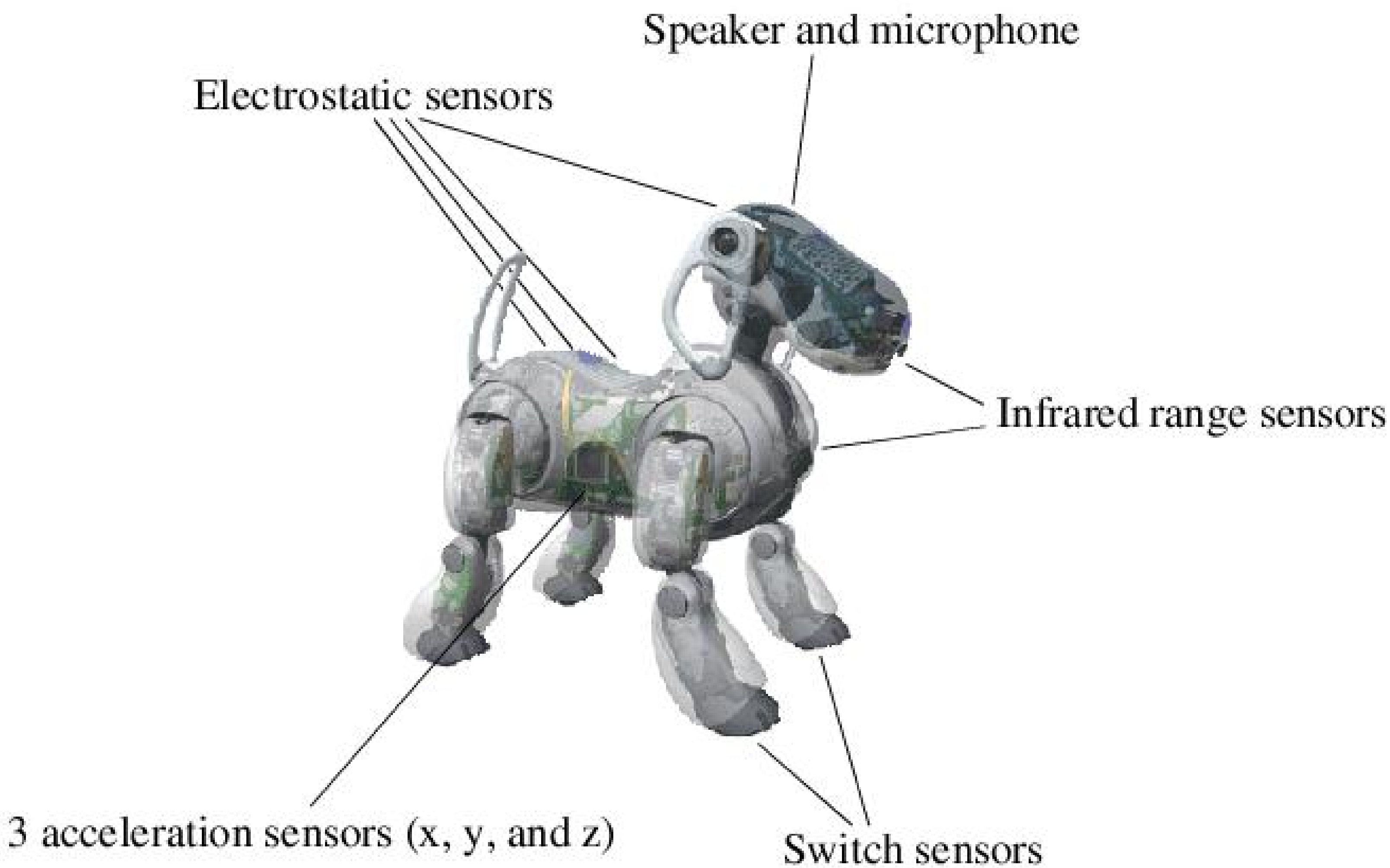
Middle-sized League

Legged Robot League

Simulation League

Humanoid League

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



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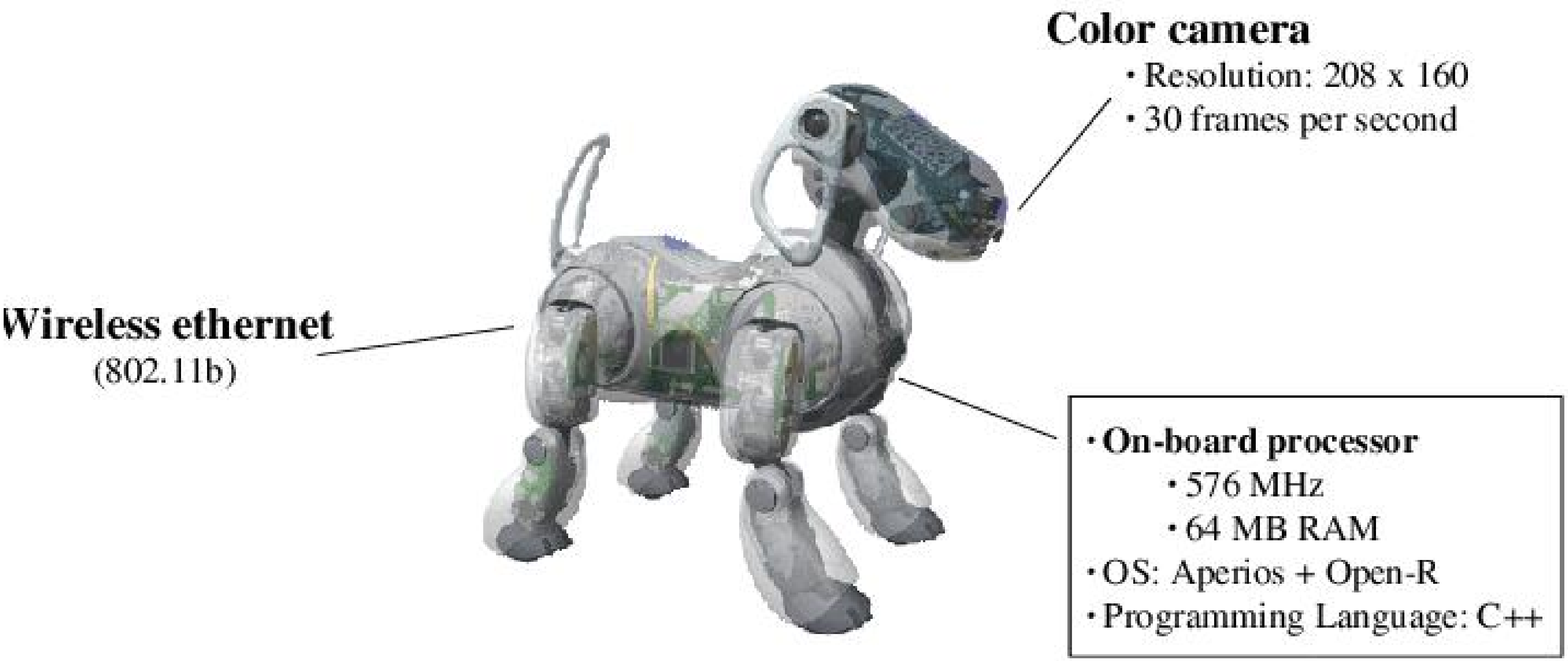
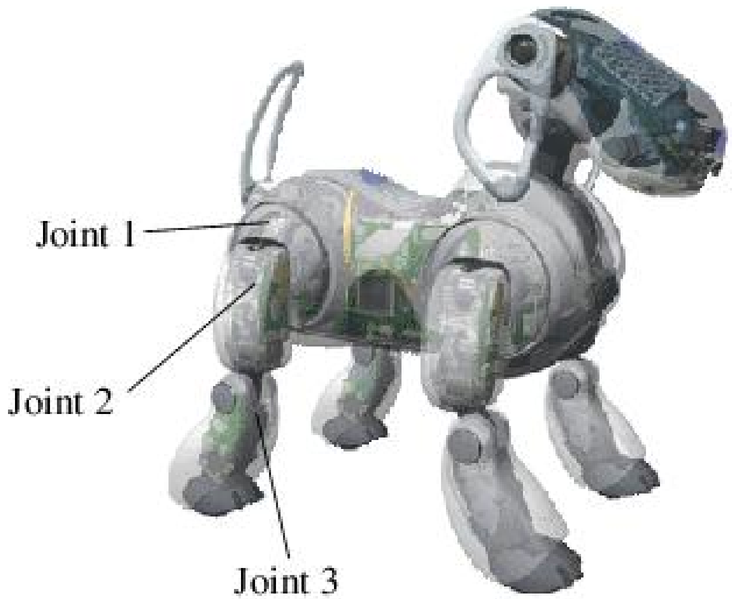


Sony Aibo (ERS-210A, ERS-7)

20 degrees of freedom



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

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- **Localization**
- **Walking**
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- Individual decision making
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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 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)

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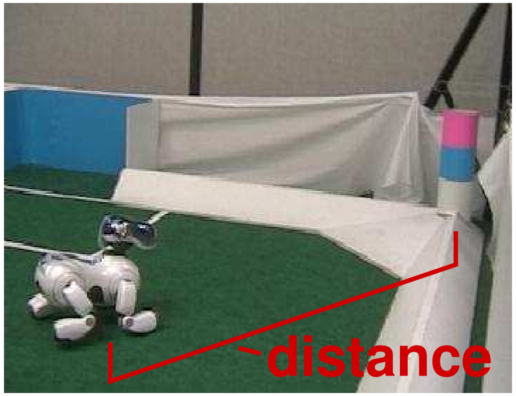
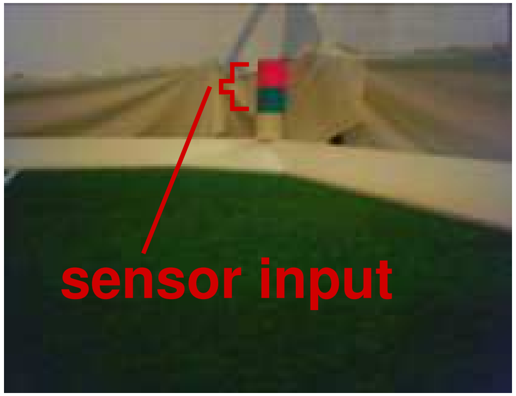
- Implemented and validated on Aibo ERS-7

The Task





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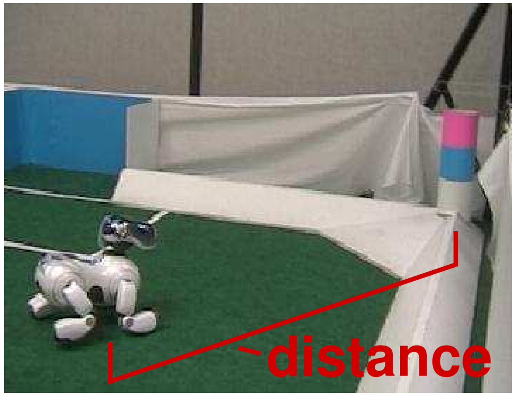

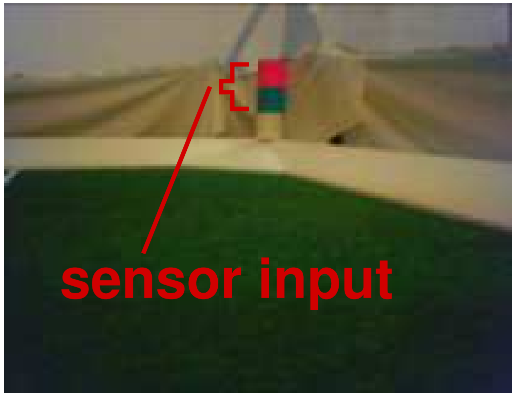

- **Sensor model:** beacon height in image $\mapsto$ distance
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- **Action model:** parametrized walking, W(x) $\mapsto$ velocity
  - W(0) steps in place
  - W(-300) has velocity -300
  - W(300) has velocity 300

Experimental Setup

- Aibo alternates walking forwards and backwards
  - Forwards: random action in $[0, 300]$
  - Backward phase: random action in $[-300, 0]$
  - Switch based on beacon size in image

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- Aibo keeps self pointed at beacon

Learning Action and Sensor Models

- Both models provide info about the robot's location
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$$x_s(t_k) = S(obs_k)$$

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  – Models learned in arbitrary units

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- Assume accurate action model
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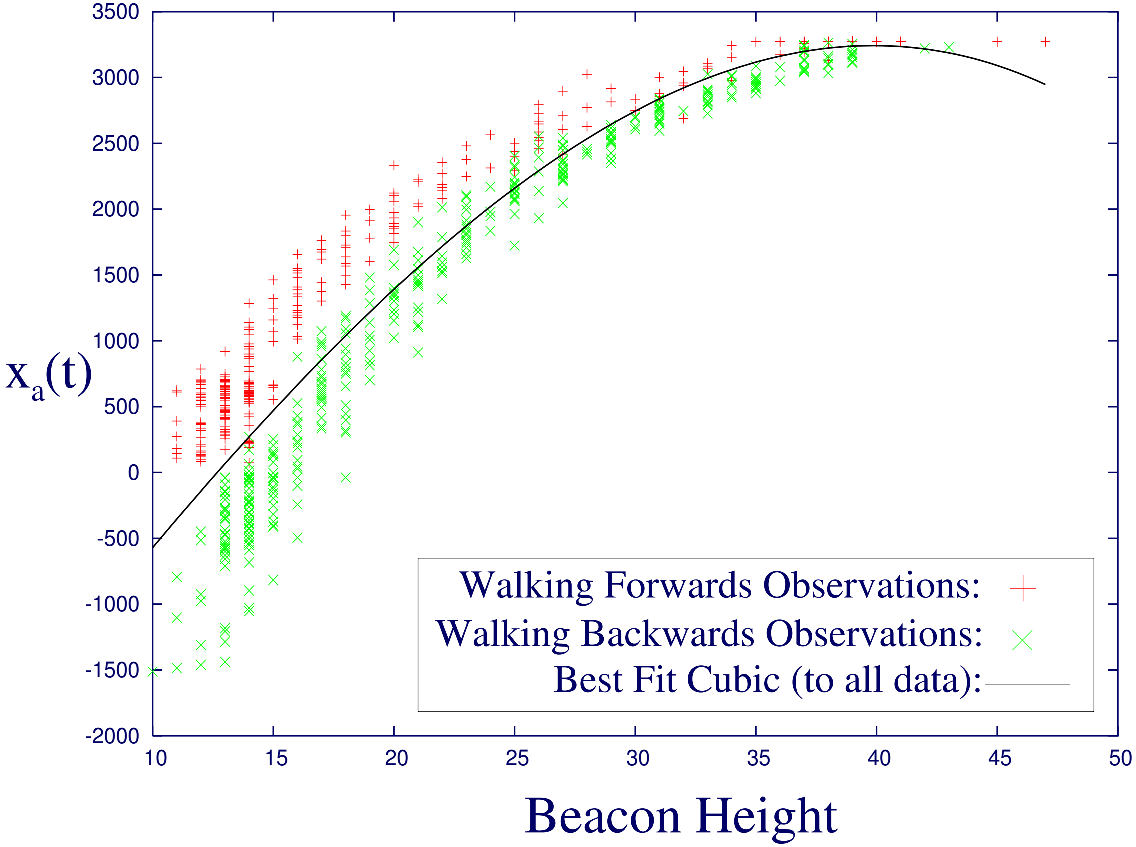

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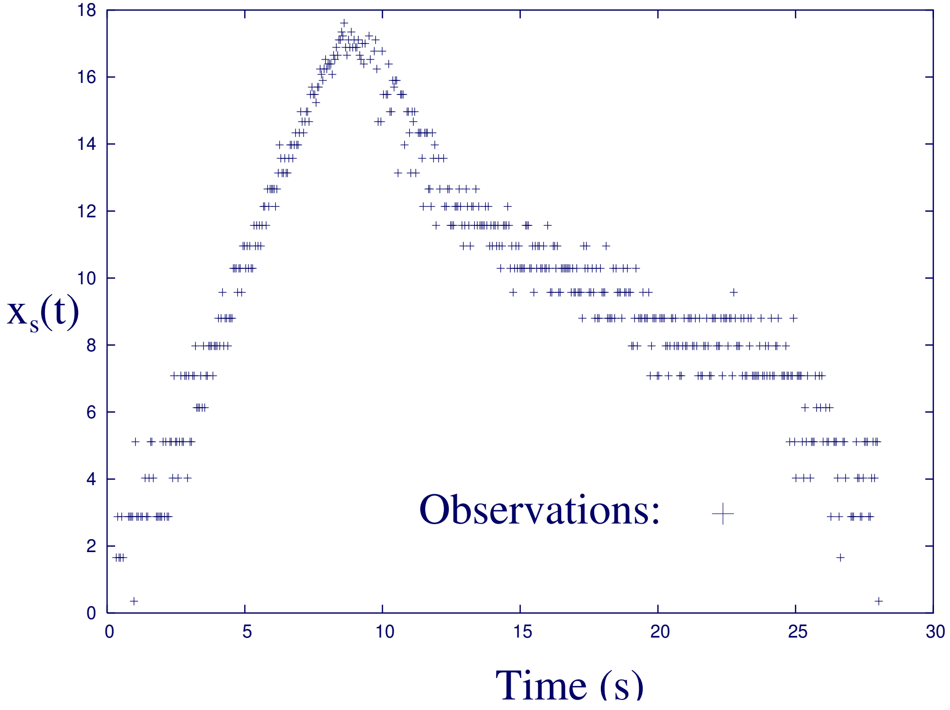

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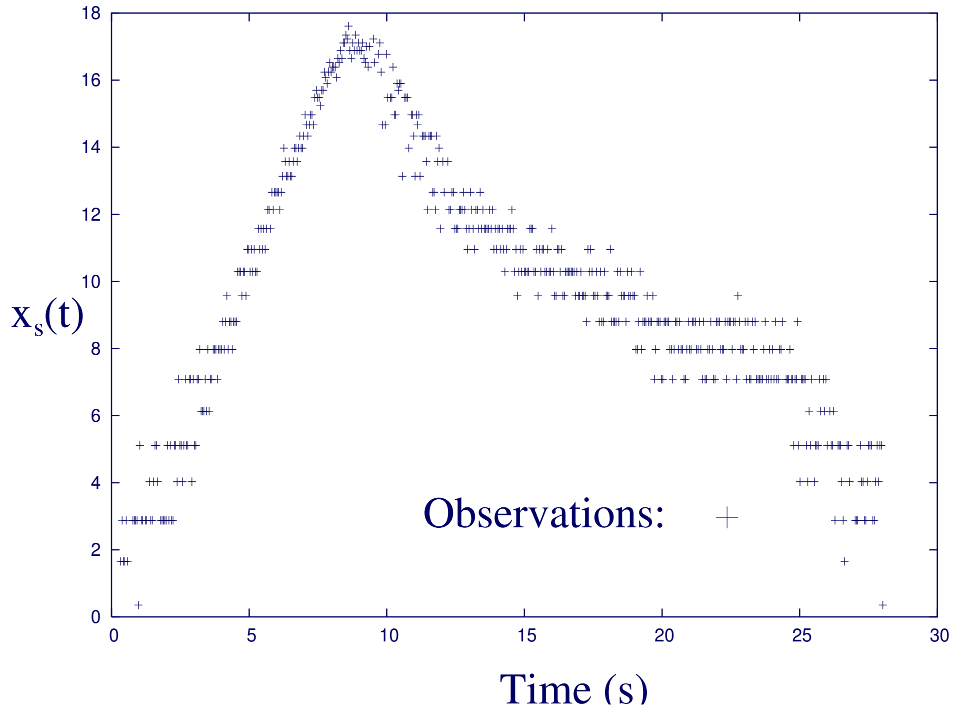

- Compute action model that minimizes the error
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Learning an Action Model

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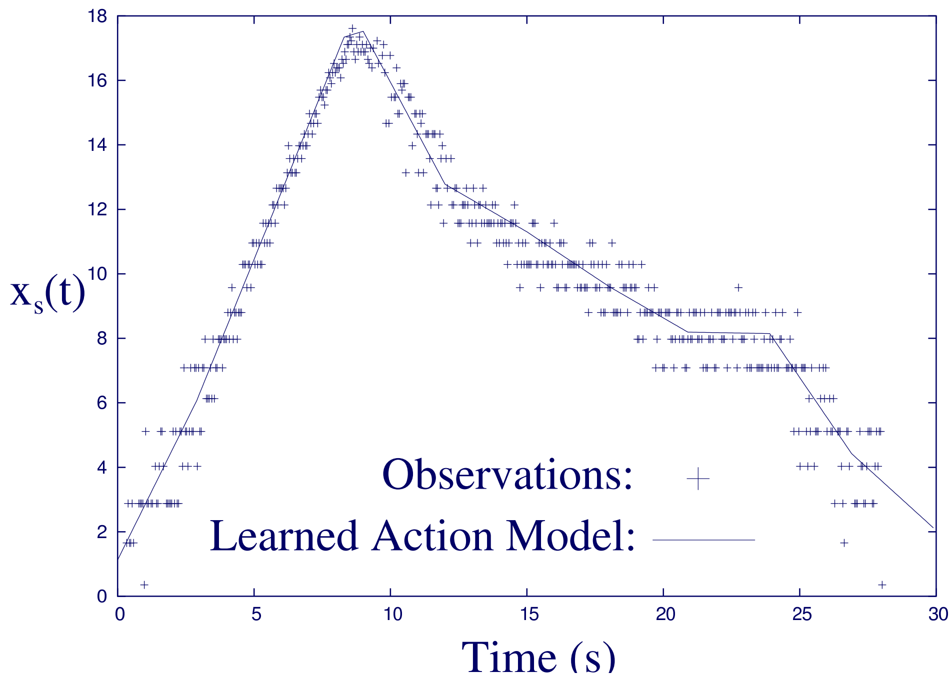

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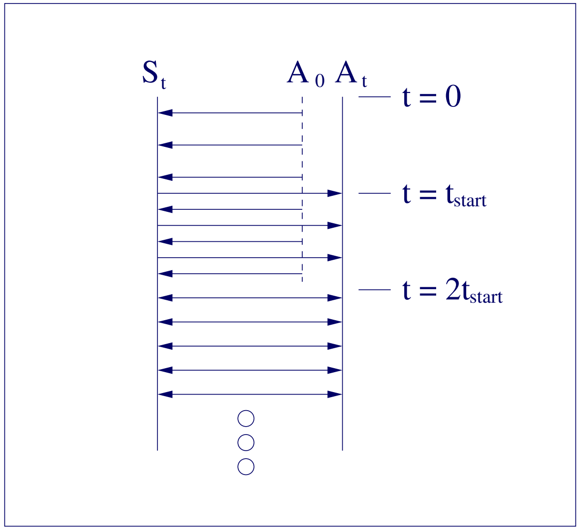
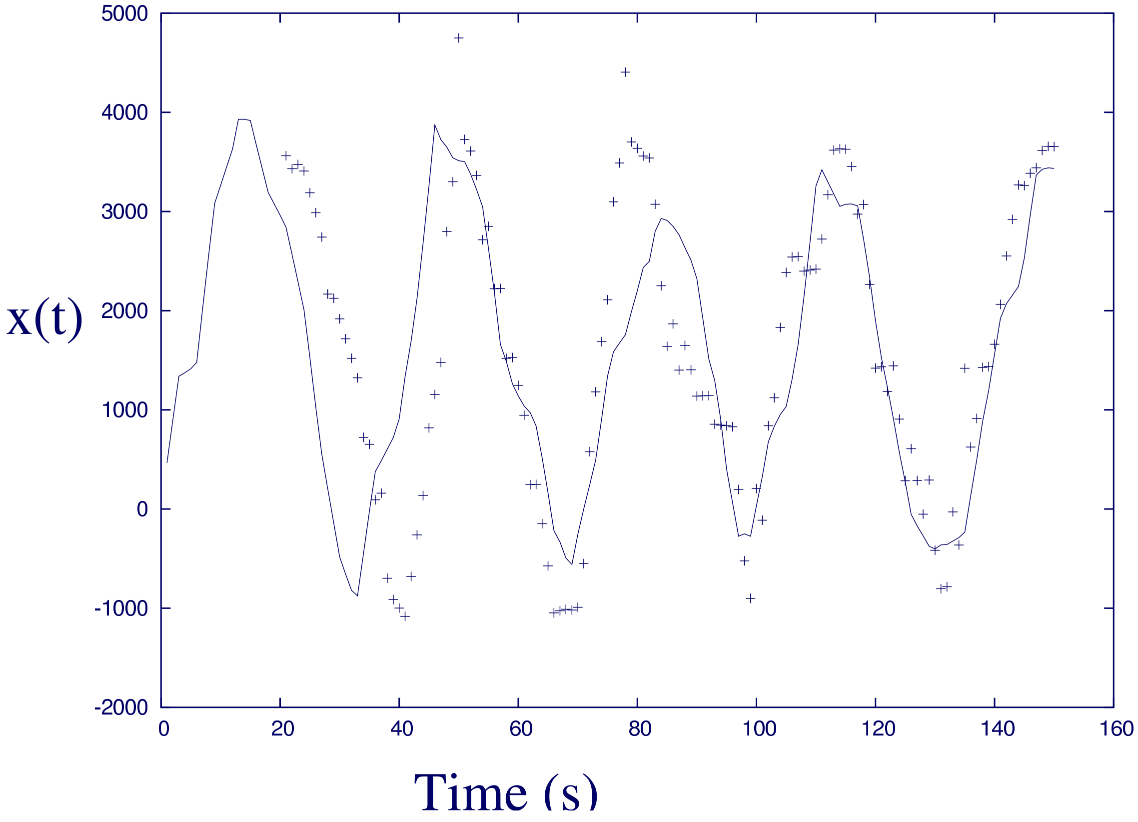
- Ramping up



Learning Both Simultaneously

- Over 2.5 min., $x_s(t)$ and $x_a(t)$ converge



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- Run ASAMI for pre-set amount of time (2.5 minutes)
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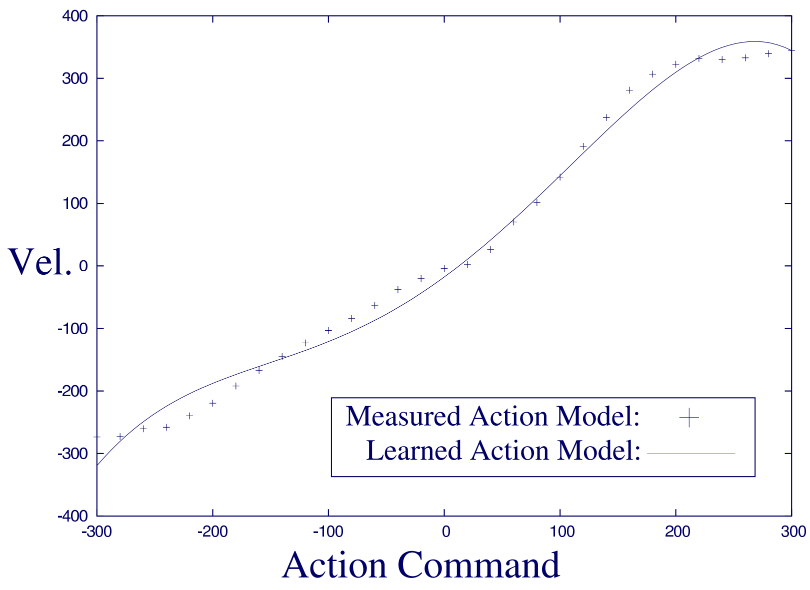
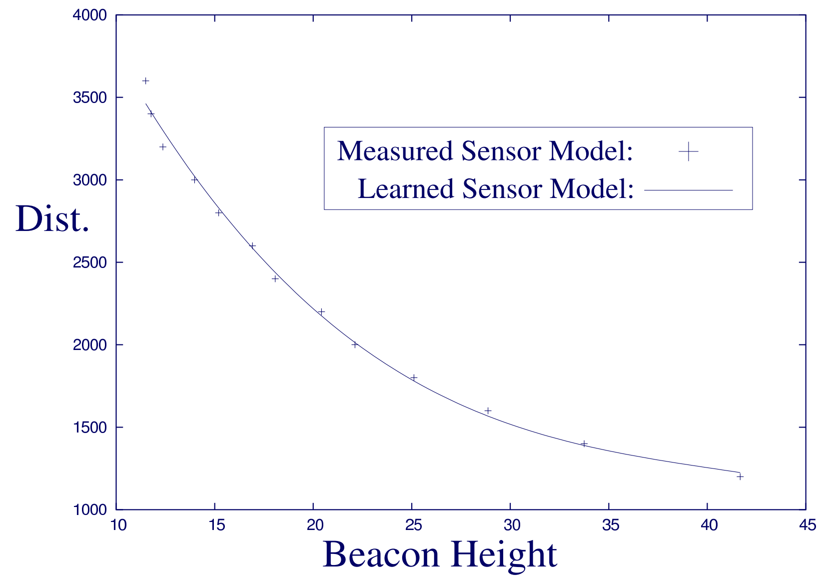
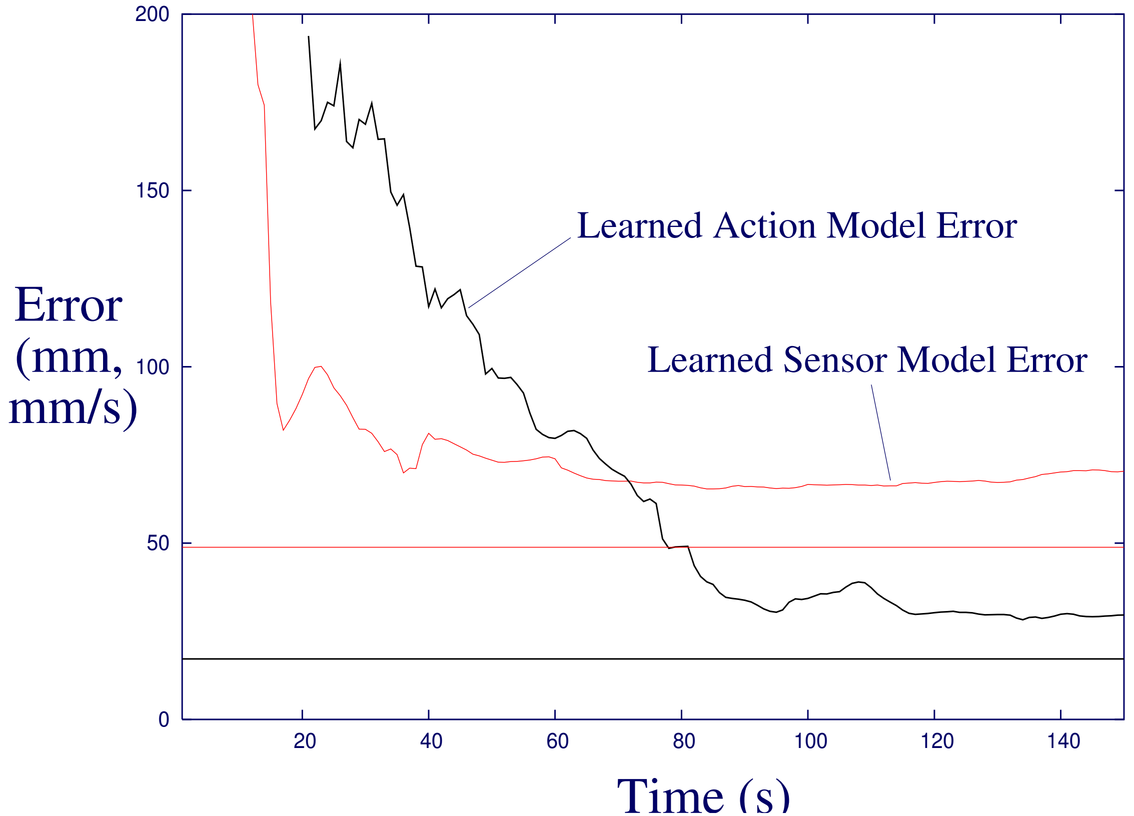




Experimental Results

- Average fitness of model over 15 runs



Summary

- **ASAMI:** Autonomous, no external feedback
- Computationally **efficient**
- Starts with poor action model, no sensor model
  - Learns **accurate** approximations to both models
  - Models are to scale with each other

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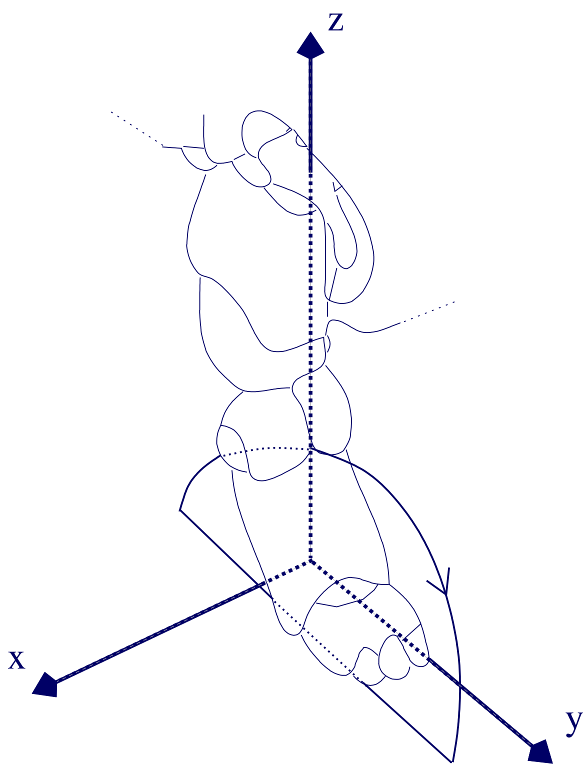
Hand-tuned gaits (2003)			Learned gaits	
German Team	UT Austin Villa	UNSW	Hornby et al. (1999)	Kim & Uther (2003)
230 mm/s	**245**	**254**	**170**	**270** (± 5)

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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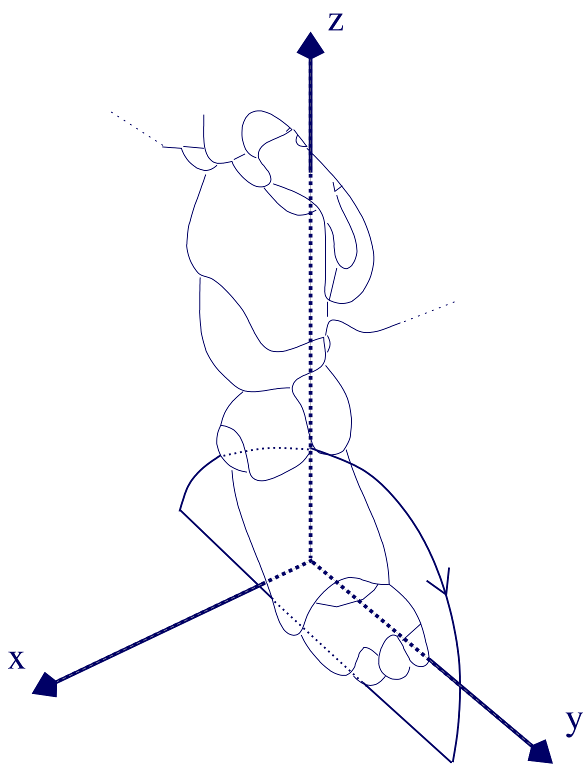

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- Hand tuning by April, '03: **140 mm/s**
- Hand tuning by July, '03: **245 mm/s**

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No human intervention except battery changes

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- Each trial randomly varies **every parameter**

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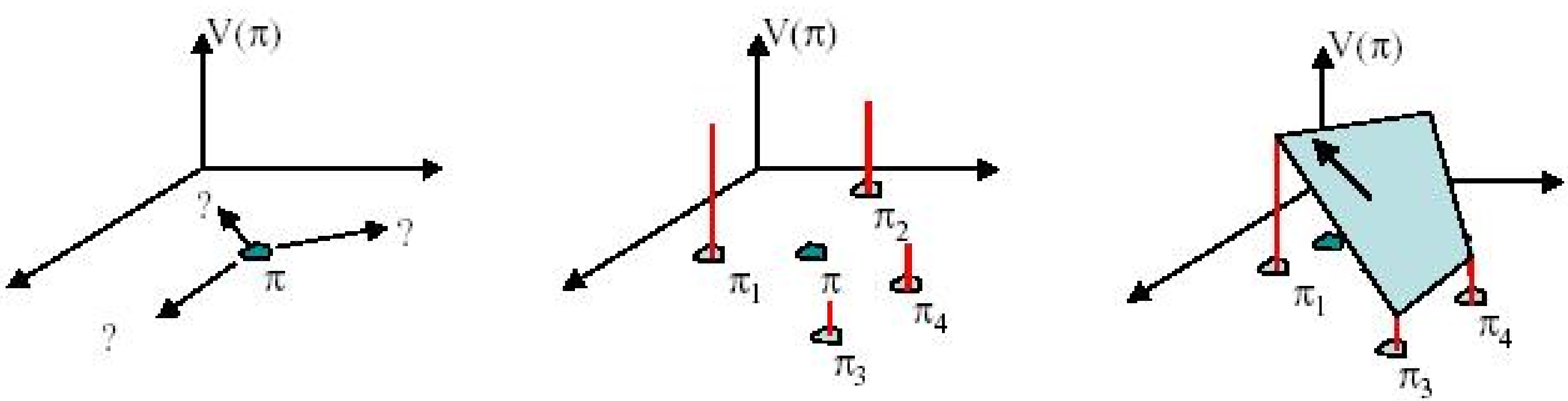

Experiments

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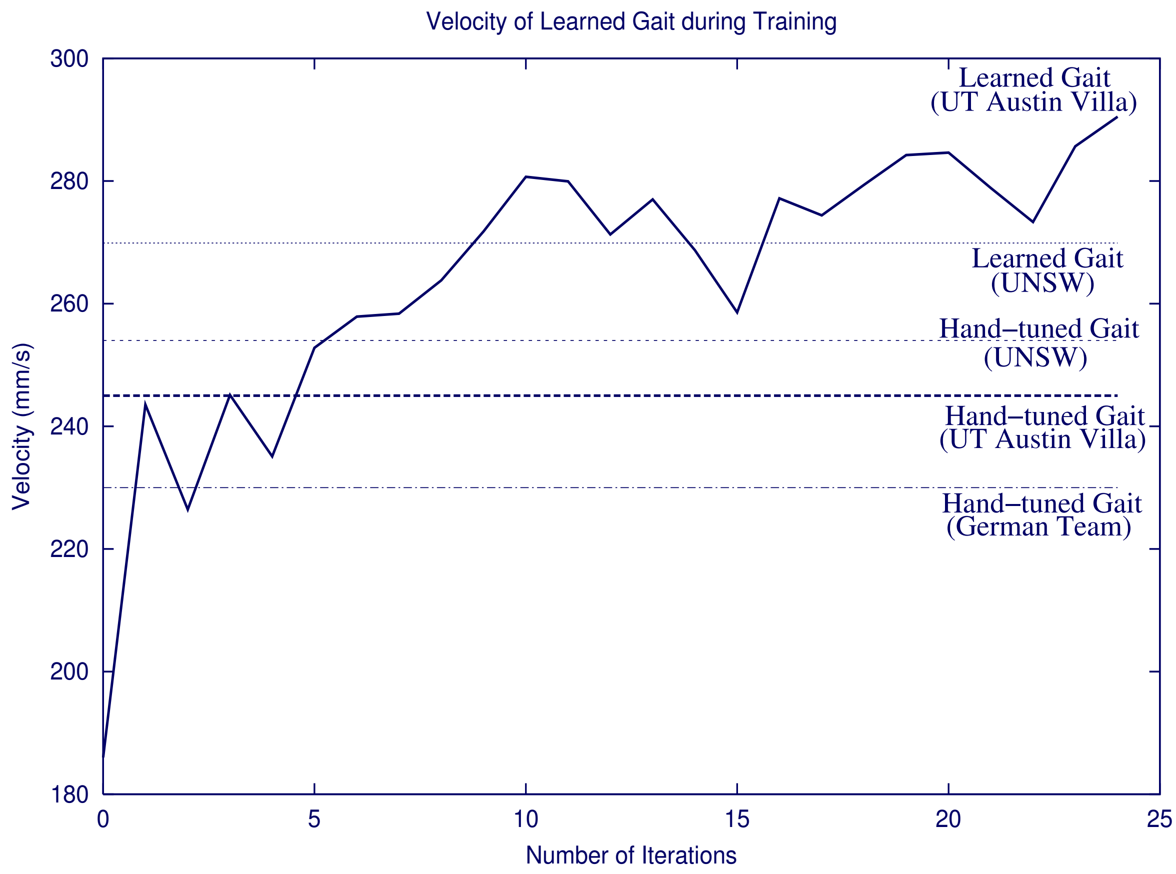
Before learning

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
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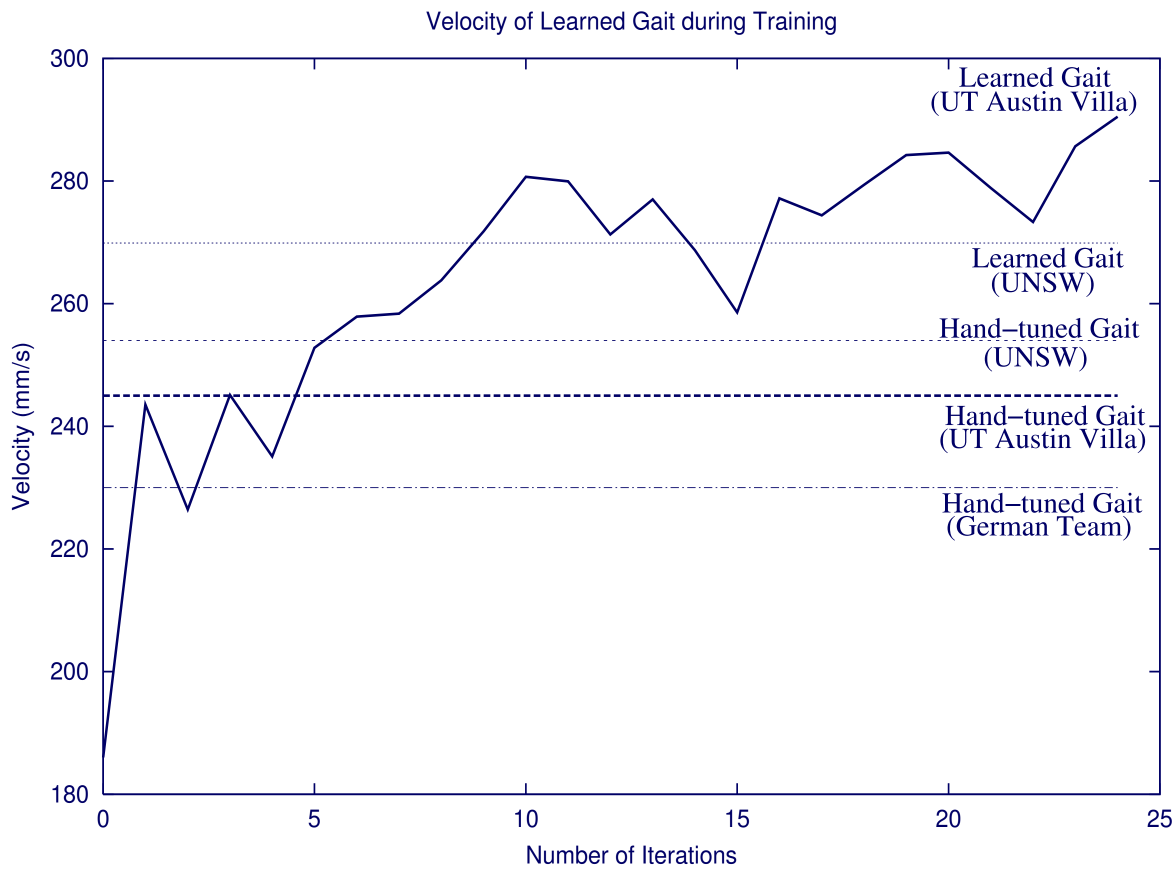
Results

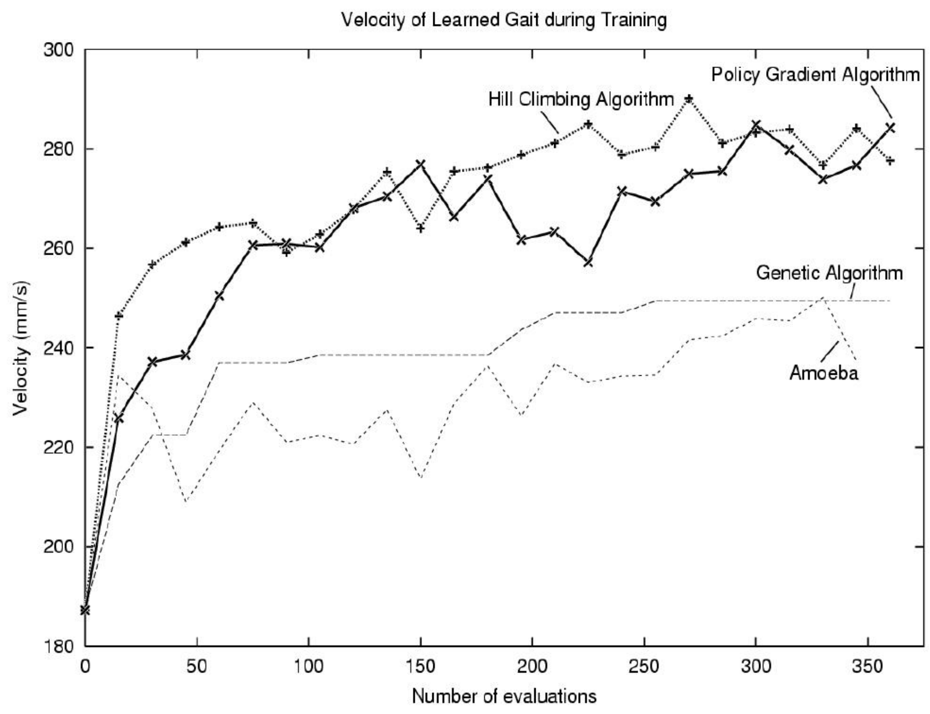


- Additional iterations didn't help
- Spikes: evaluation **noise**? large **step size**?

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)

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- **Three stages:** walk to ball; slow down; lower chin
- Head proprioception, IR chest sensor $\mapsto$ ball distance
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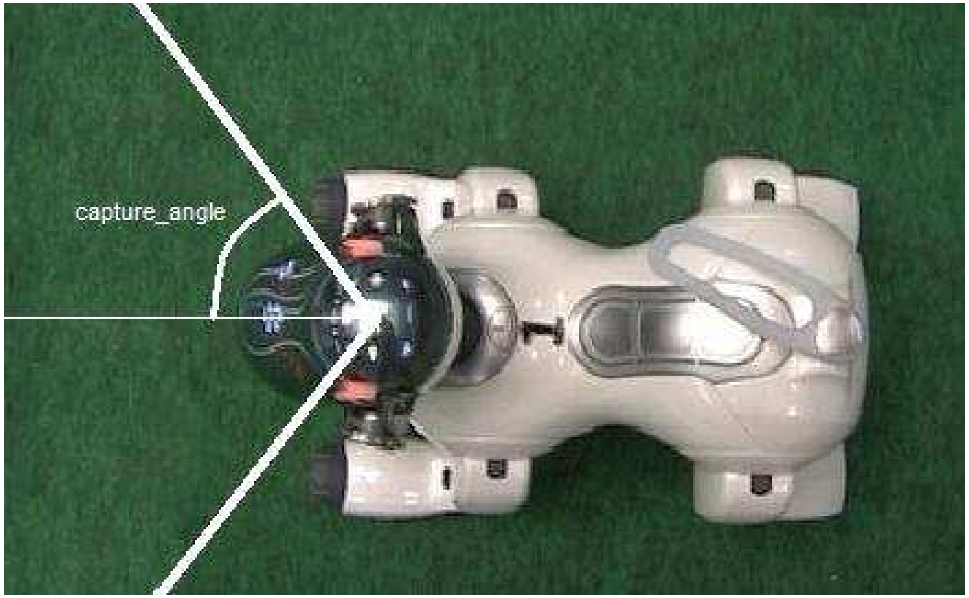
$\boxed{\textbf{Brittle!}}$

Parameterization

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



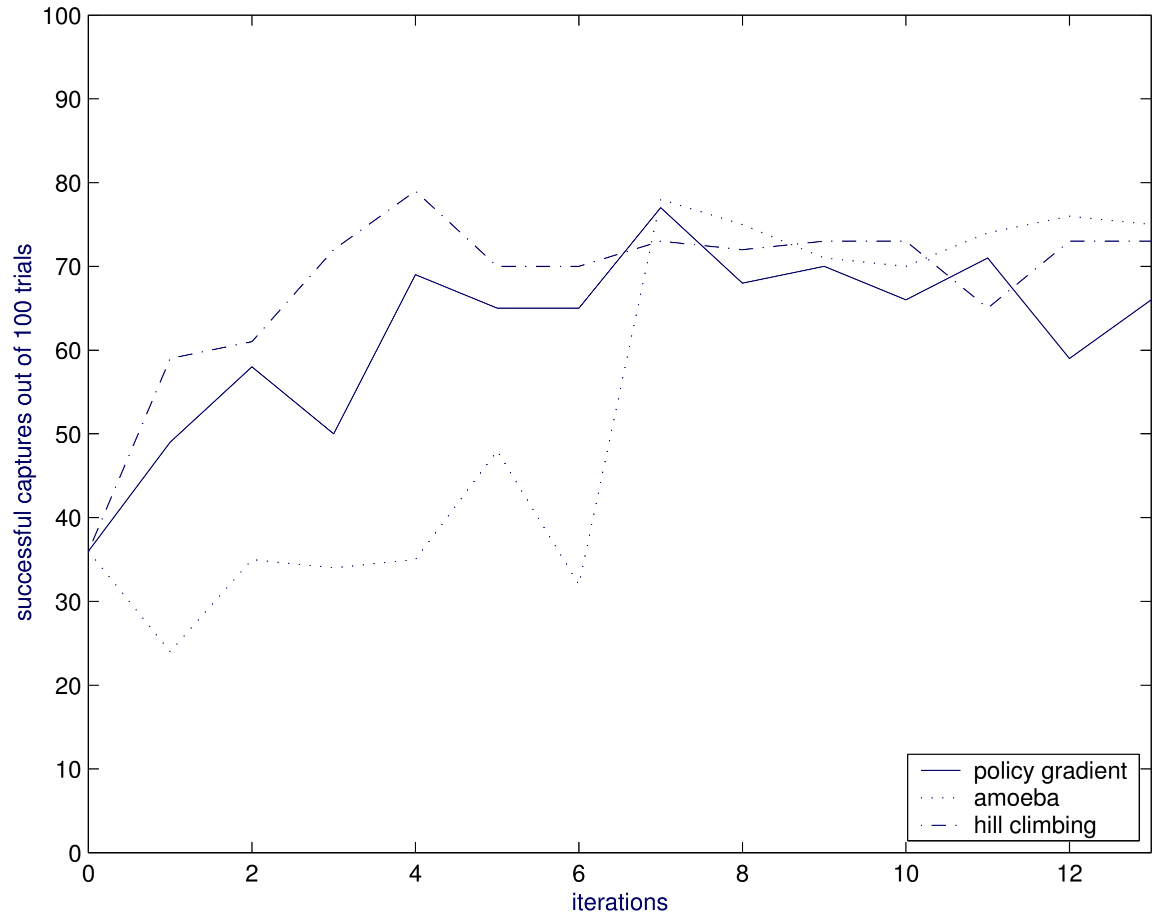
- **capture_dist:** when to put down head

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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- Hierarchical subtask decomposition **given**: $\{L_1, L_2, \ldots, L_n\}$

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Outline

- 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, '05)
- **Autonomous Color Learning** (Sridharan, S, '06)