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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- Improve performance from experience **(Learning agents)**

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

RoboCup

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Several Different Leagues

RoboCup Soccer

Small-sized League

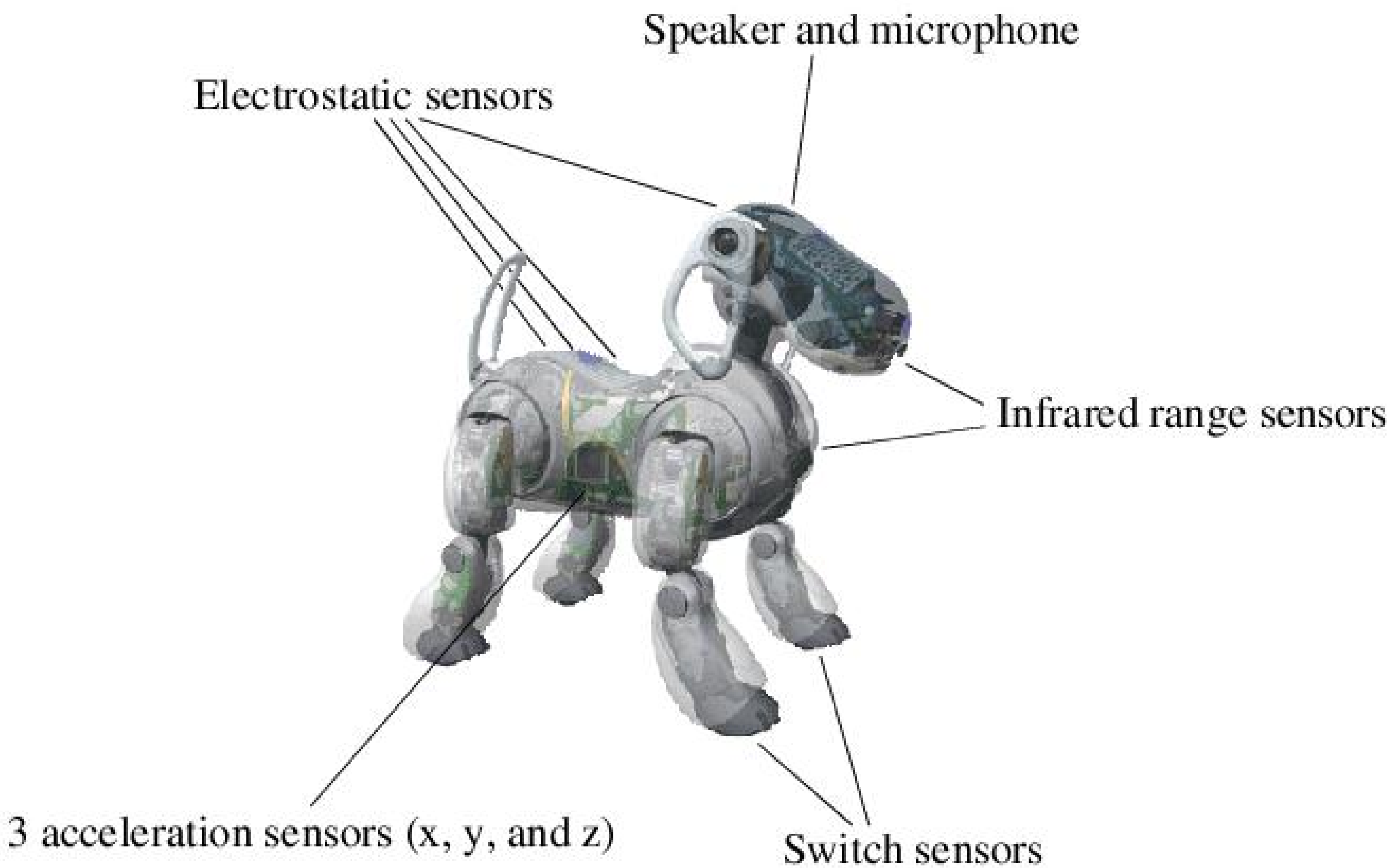
Middle-sized League

Legged Robot League

Simulation League

Humanoid League

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



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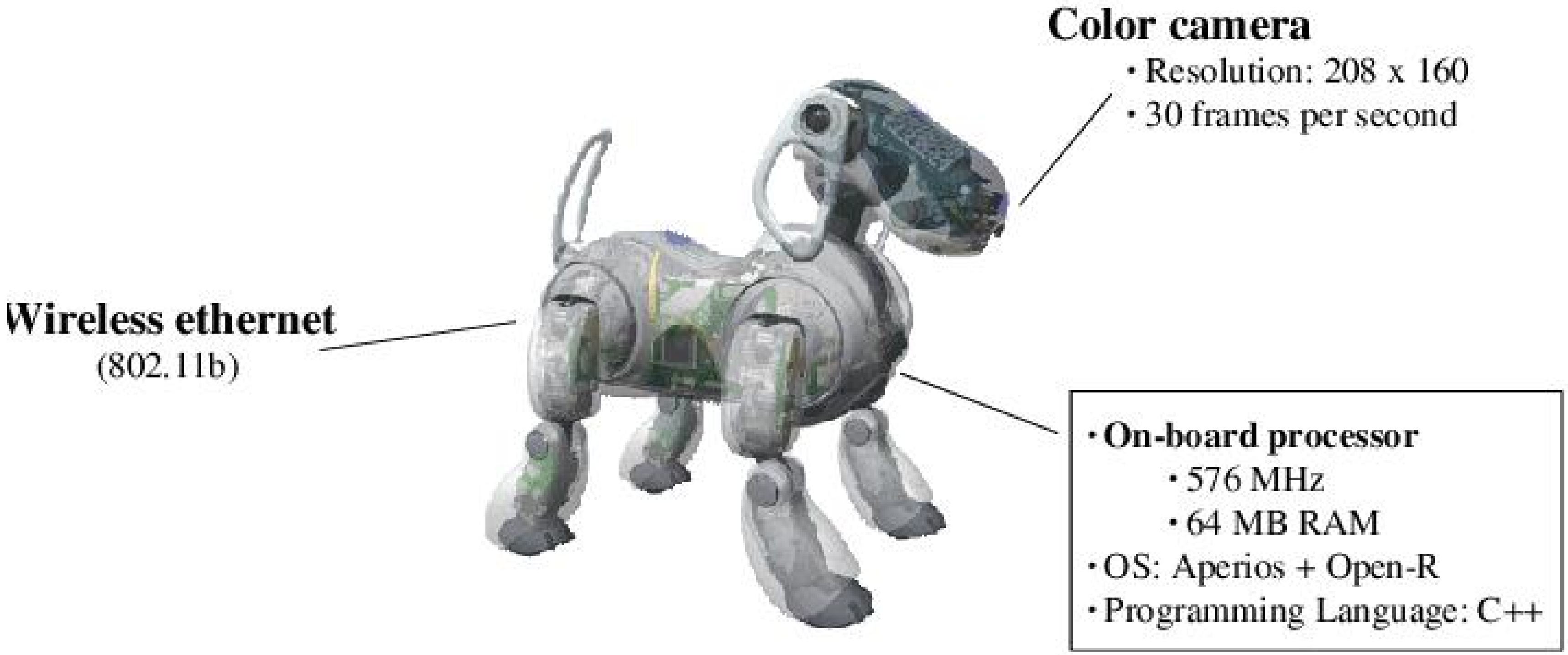
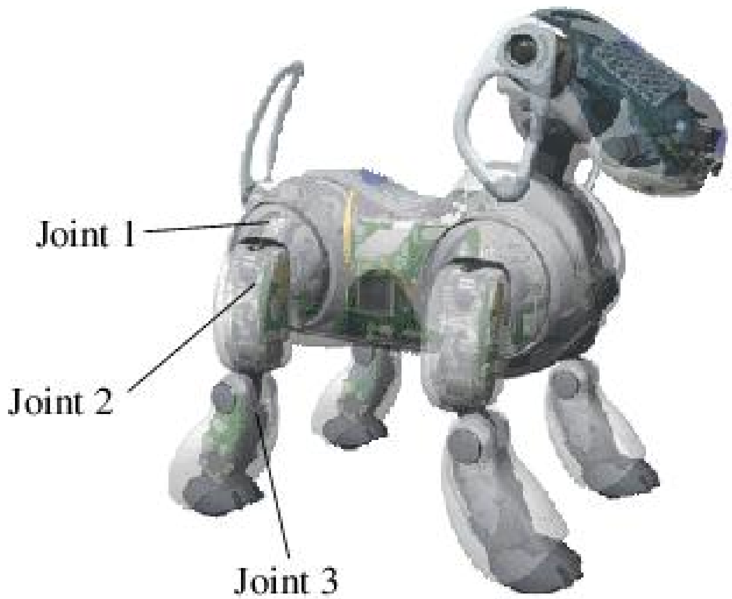


Sony Aibo (ERS-210A, ERS-7)

20 degrees of freedom



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

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- **Vision**
- **Localization**
- **Walking**
- **Ball manipulation** (kicking)
- 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, Stone)
- **Machine learning for fast walking** (Kohl, Stone)
- **Learning to acquire the ball** (Fidelman, Stone)
- **Learning sensor and action models** (Stronger, Stone)
- **Color constancy on mobile robots** (Sridharan, Stone)
- Robust particle filter localization (Sridharan, Kuhlmann, Stone)
- **Autonomous Color Learning** (Sridharan, Stone)

Policy Gradient RL to learn fast walk

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- Start with a **parameterized walk**
- **Learn** fastest possible parameters
- **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
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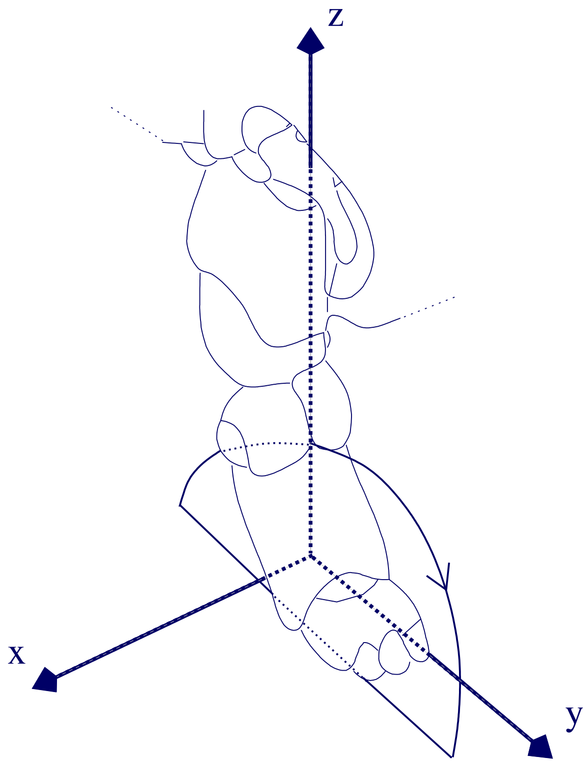
Hand-tuned gaits (2003)			Learned gaits	
German Team	UT Austin Villa	UNSW	Hornby et al. (1999)	Kim & Uther (2003)
230 mm/s	**245**	**254**	**170**	**270** (± 5)

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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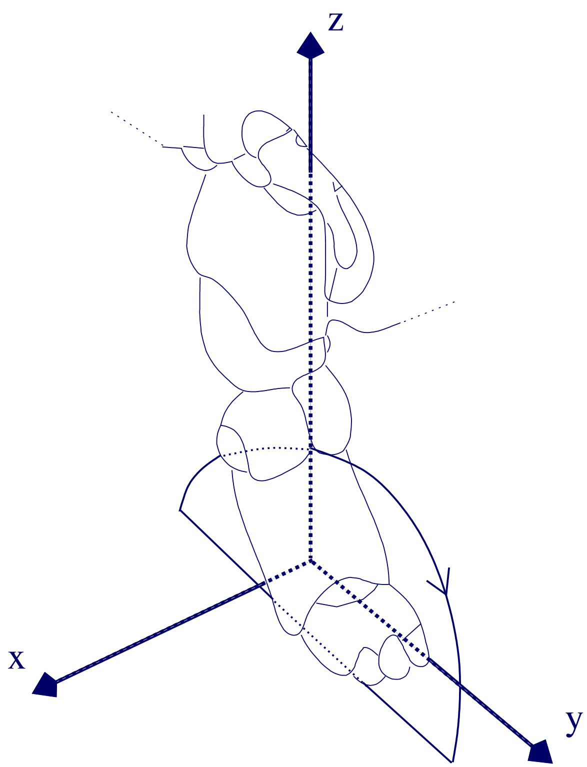

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- Hand tuning by April, '03: **140 mm/s**
- Hand tuning by July, '03: **245 mm/s**

Experimental Setup

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No human intervention except battery changes

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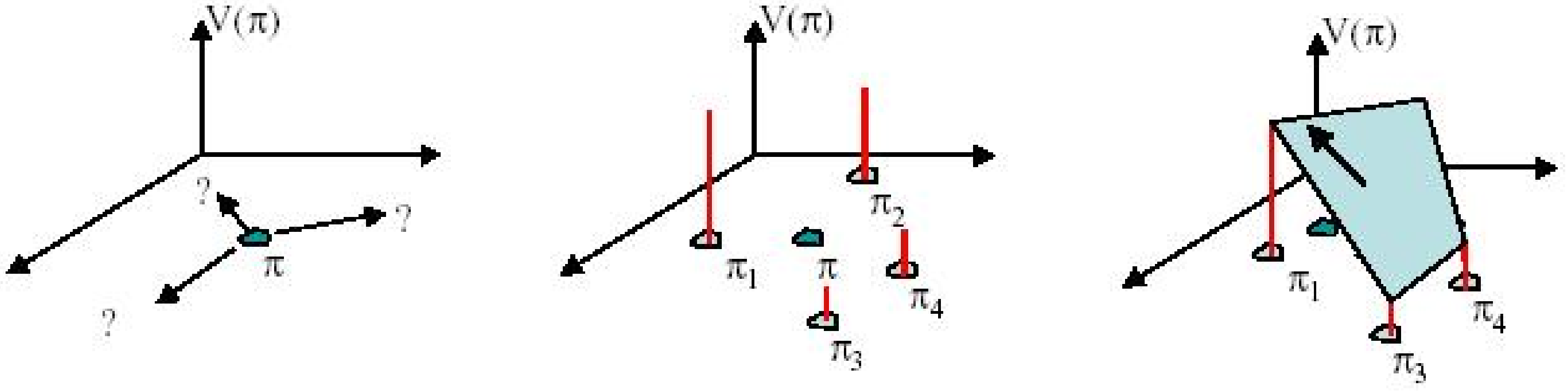

Experiments

- Started from **stable**, but fairly slow gait
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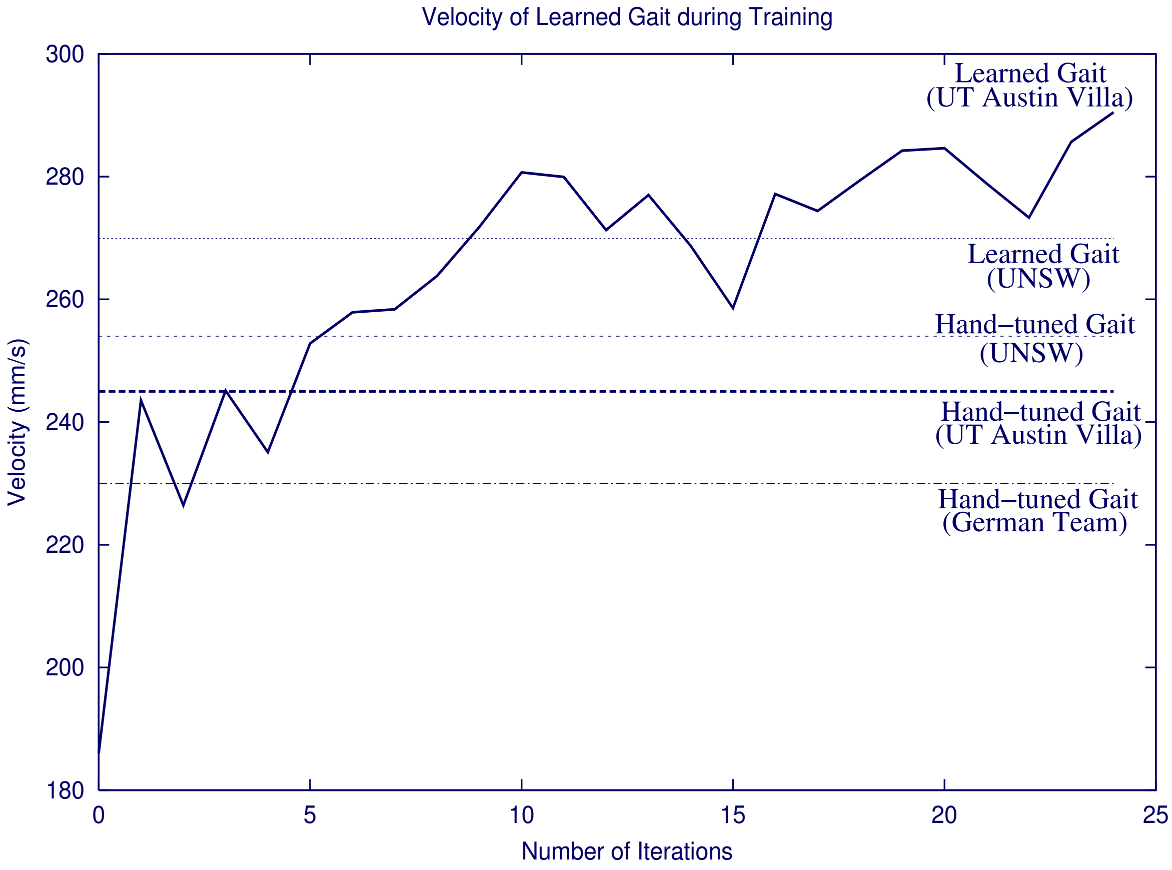
Before learning

After learning

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

Results



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

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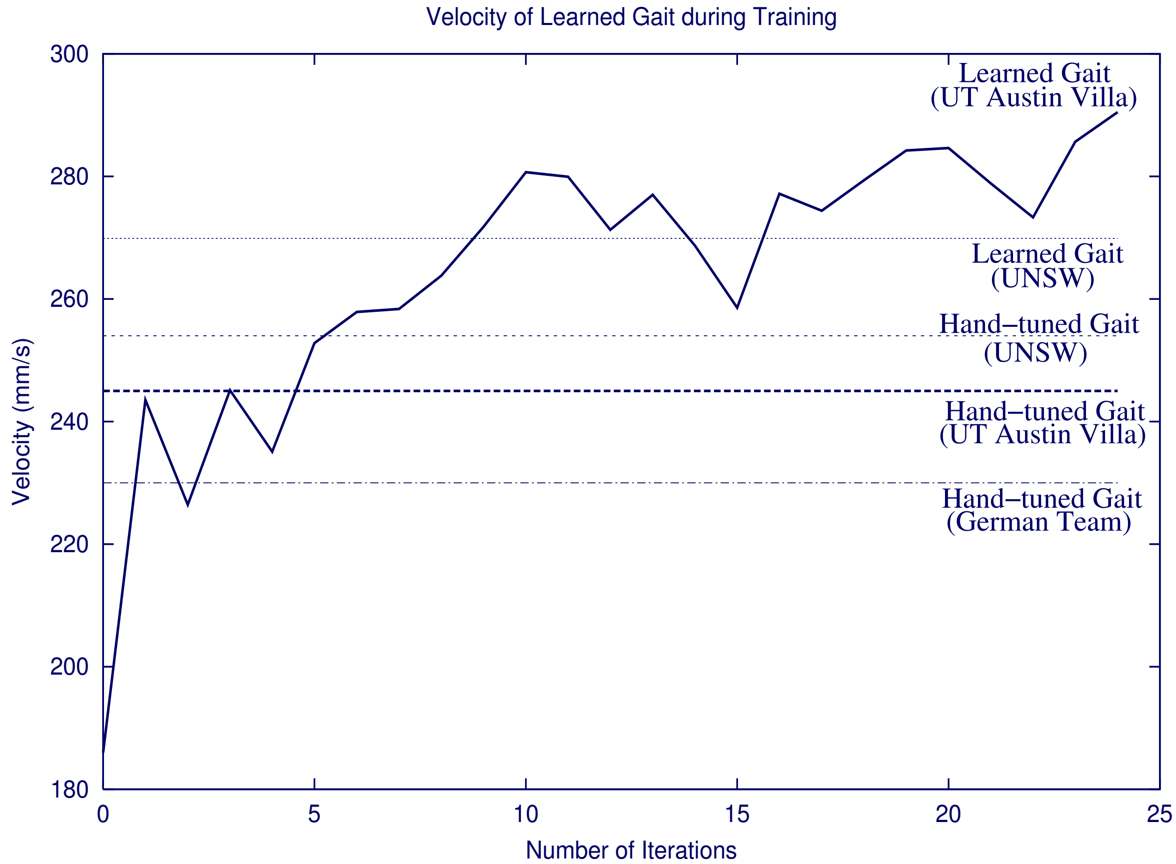
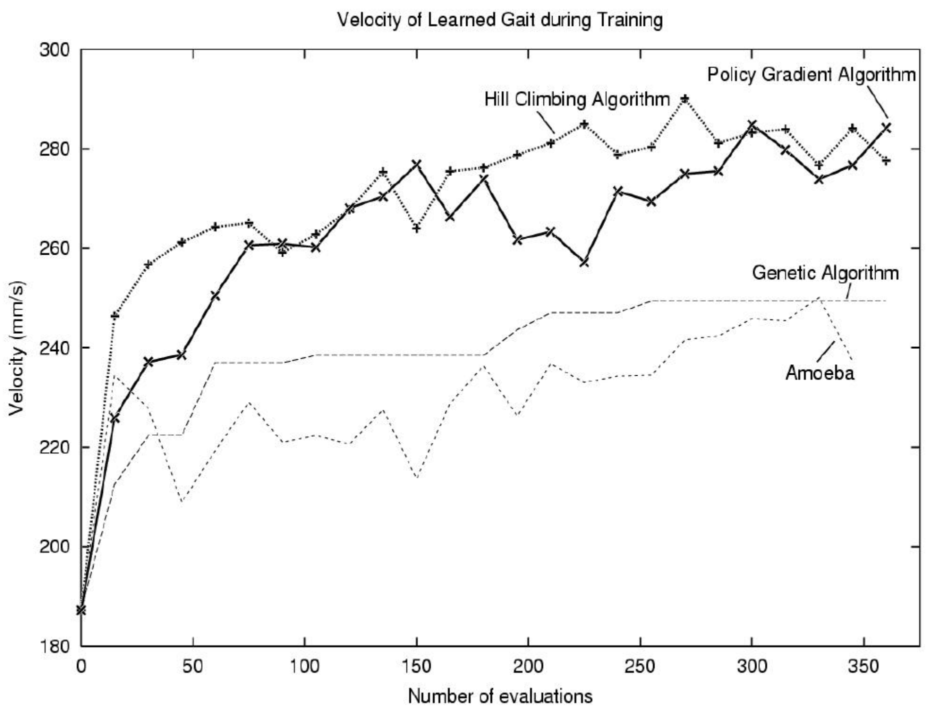


- Additional iterations didn't help
- Spikes: evaluation **noise**? large **step size**?

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

- Machine learning for fast walking (Kohl, Stone)
- **Learning to acquire the ball** (Fidelman, Stone)
- Learning sensor and action models (Stronger, Stone)
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Grasping the Ball

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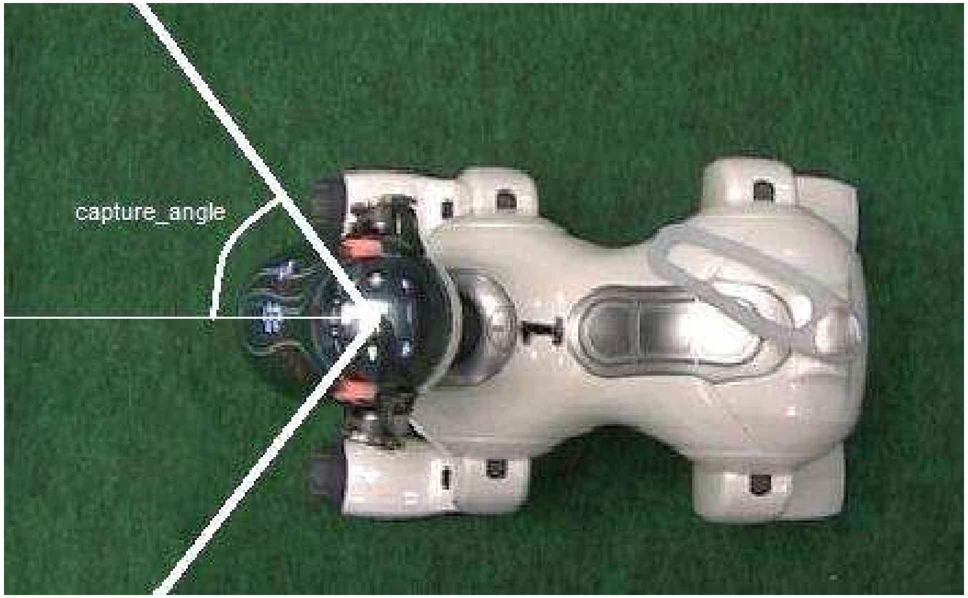
$\boxed{\textbf{Brittle!}}$

Parameterization

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



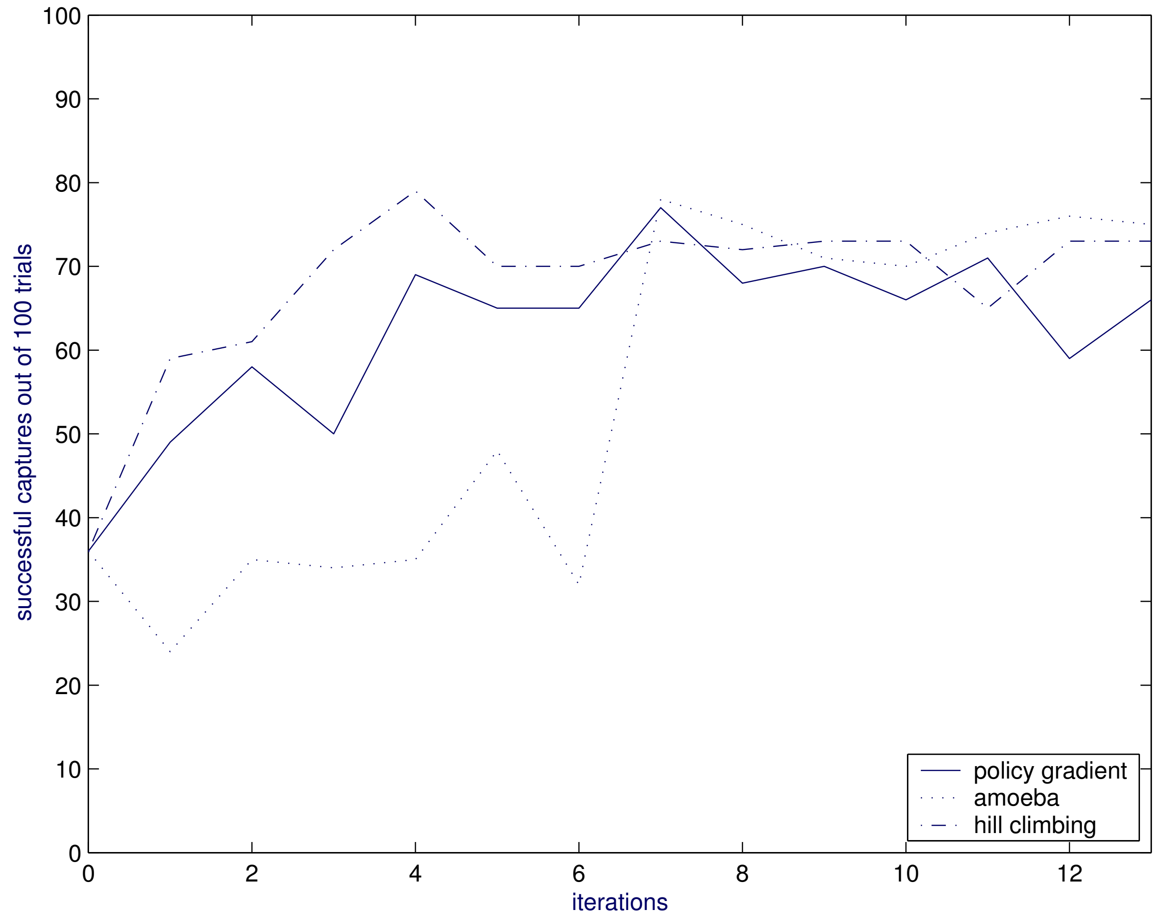
- **capture_dist:** when to put down head

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%

Instance of Layered Learning

- For domains too **complex** for tractably mapping state features $S \longmapsto$ outputs O
- Hierarchical subtask decomposition **given**: $\{L_1, L_2, \ldots, L_n\}$
- Machine learning: **exploit data** to train, adapt
- **Learning in one layer feeds into next layer**

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- Techinique is implemented and tested in:
  - **One-dimensional scenario: Sony Aibo ERS-7**
  - Aibo in two-dimensional area
  - Second robotic platform: an autonomous car

Action and Sensor Models

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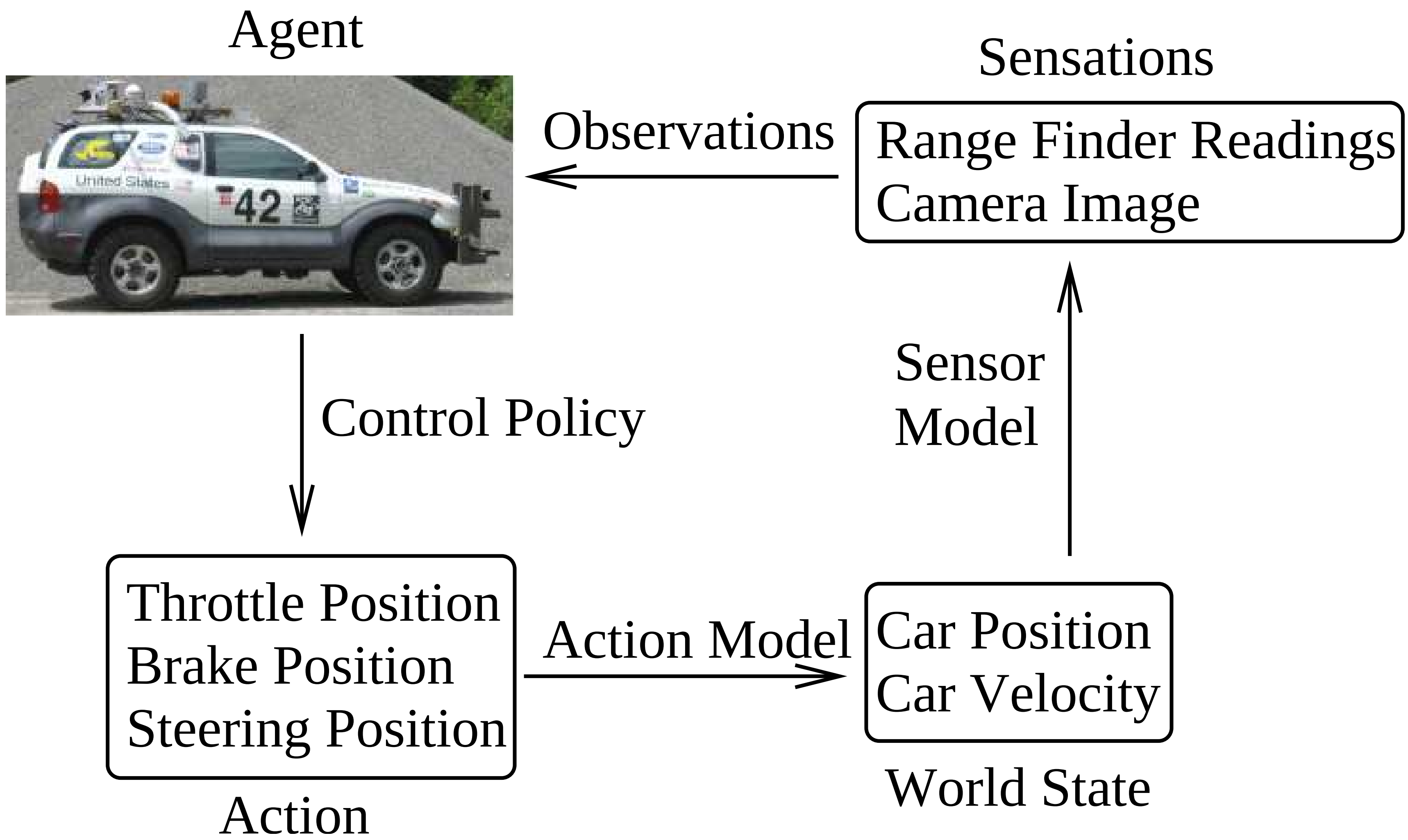

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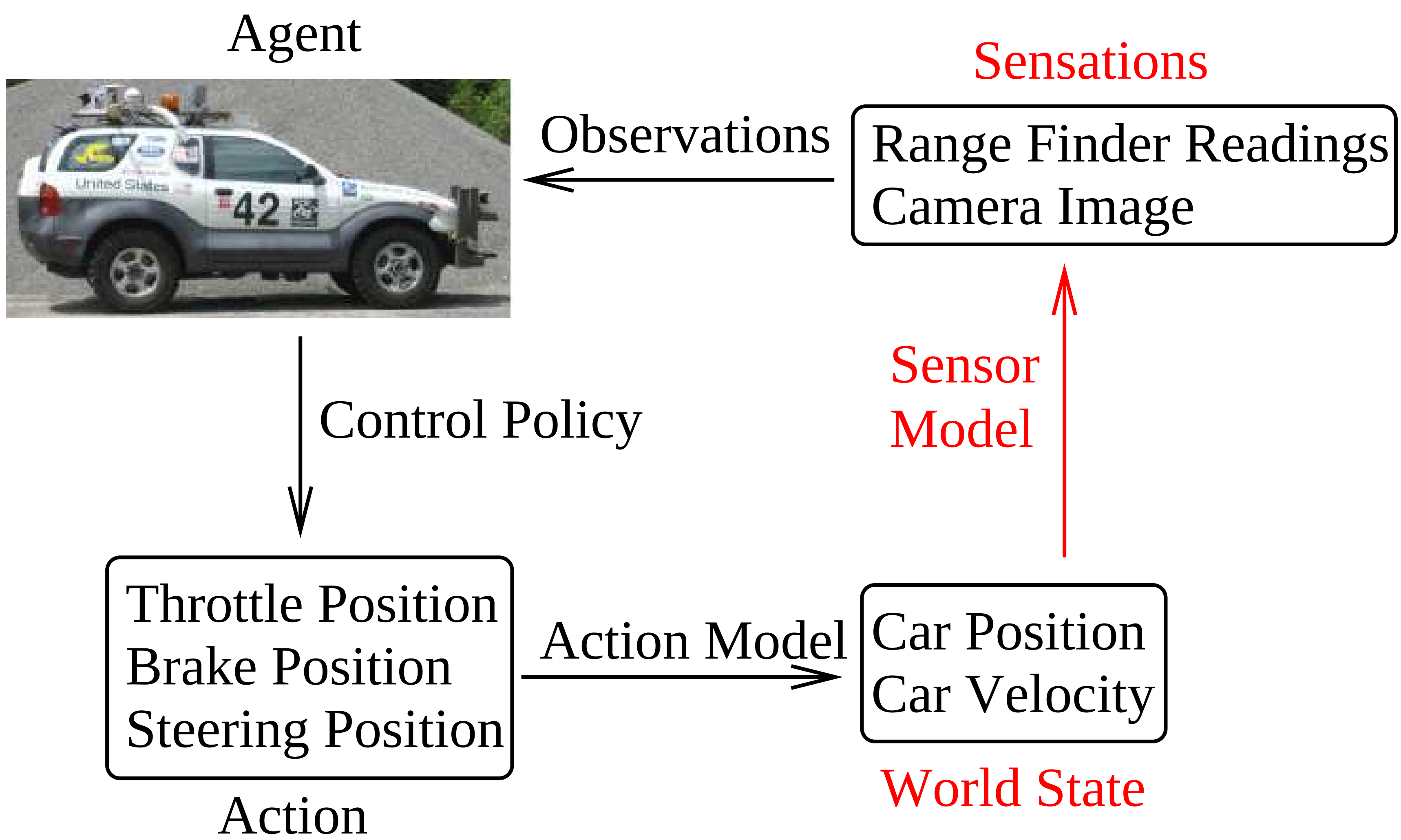

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Agent

Sensations

Observations

Range Finder Readings
Camera Image

Control Policy

Sensor
Model

Throttle Position
Brake Position
Steering Position

Action Model

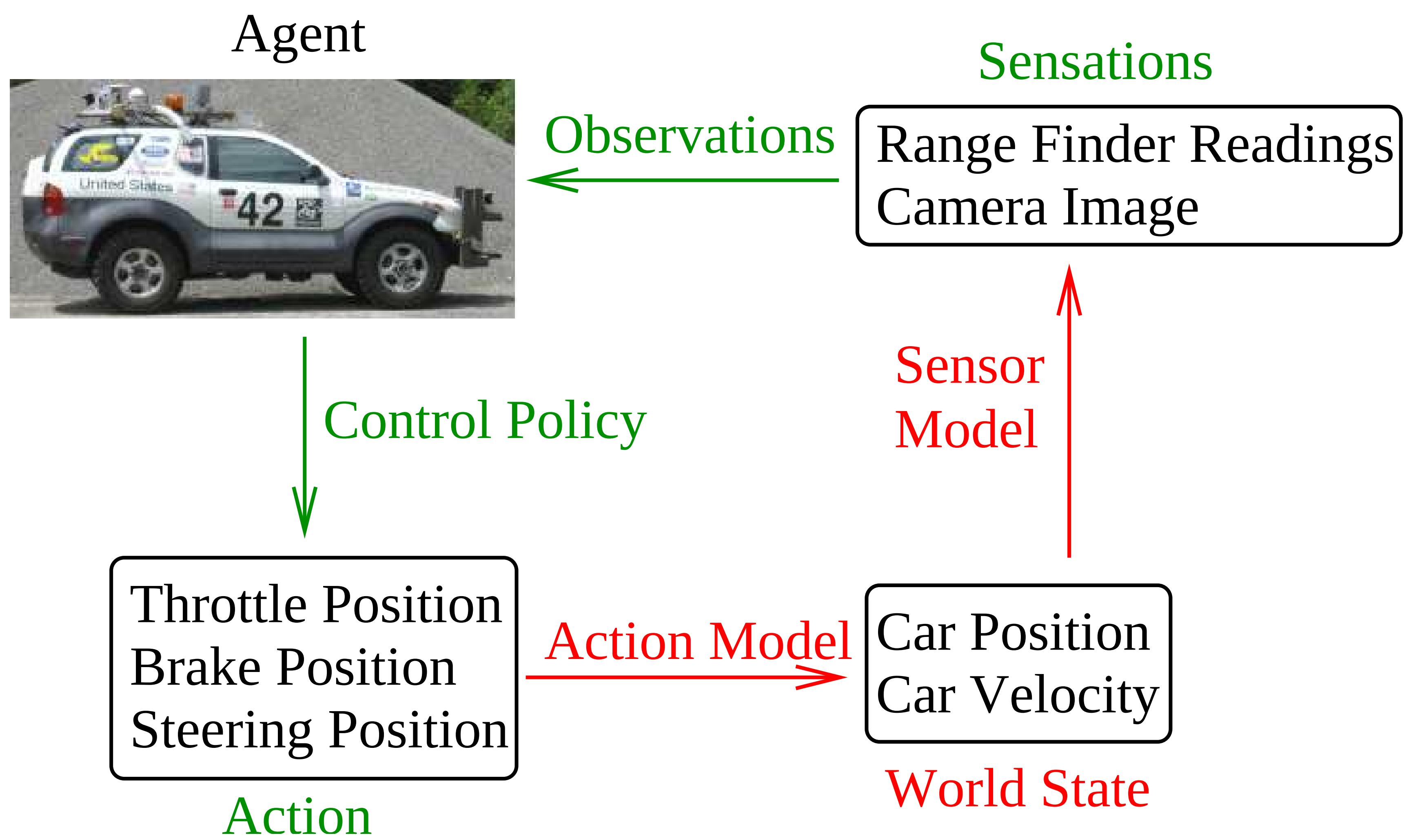
Car Position
Car Velocity

Action

World State

General Methodology

- Action model, sensor model, world state unknown:



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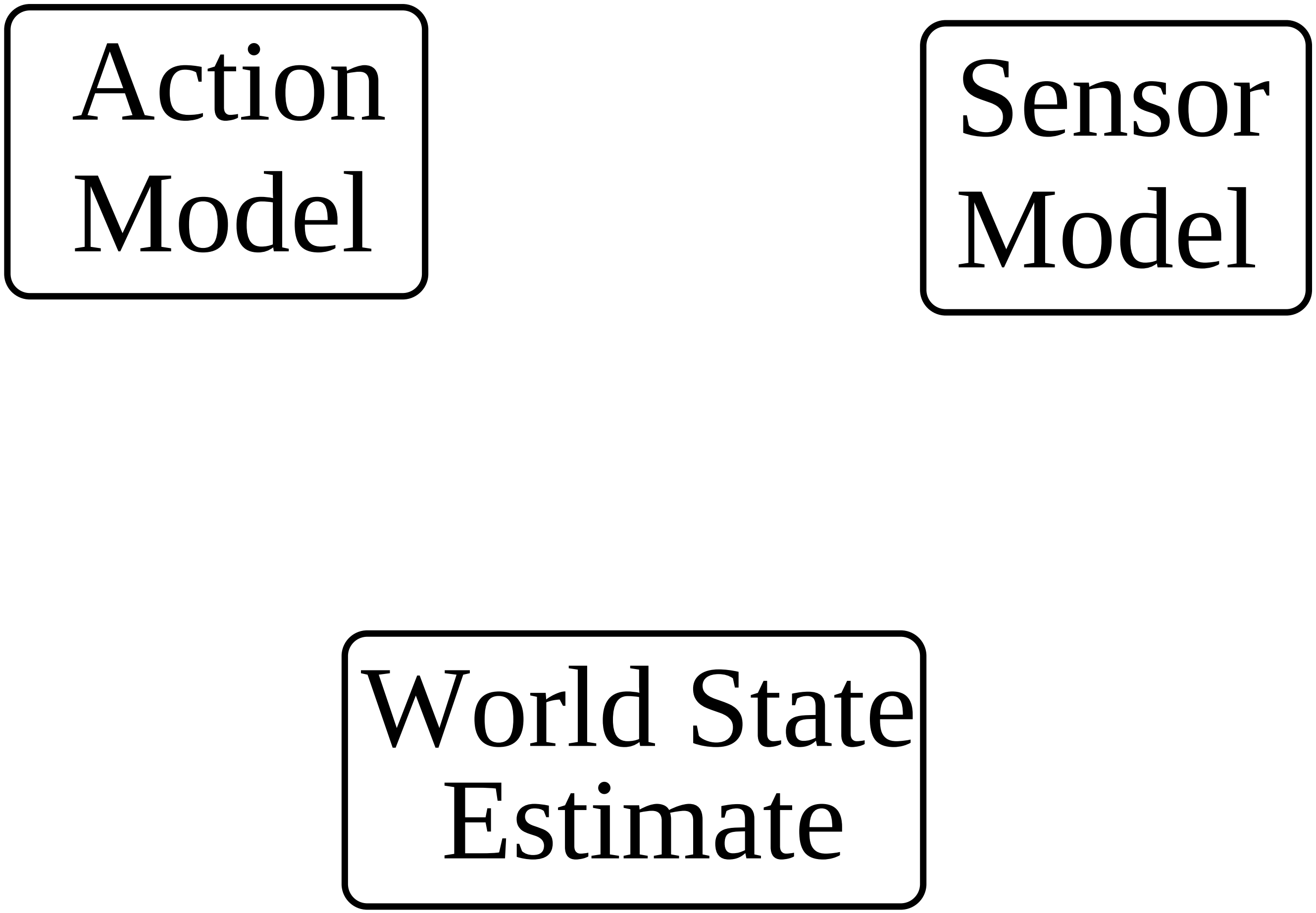

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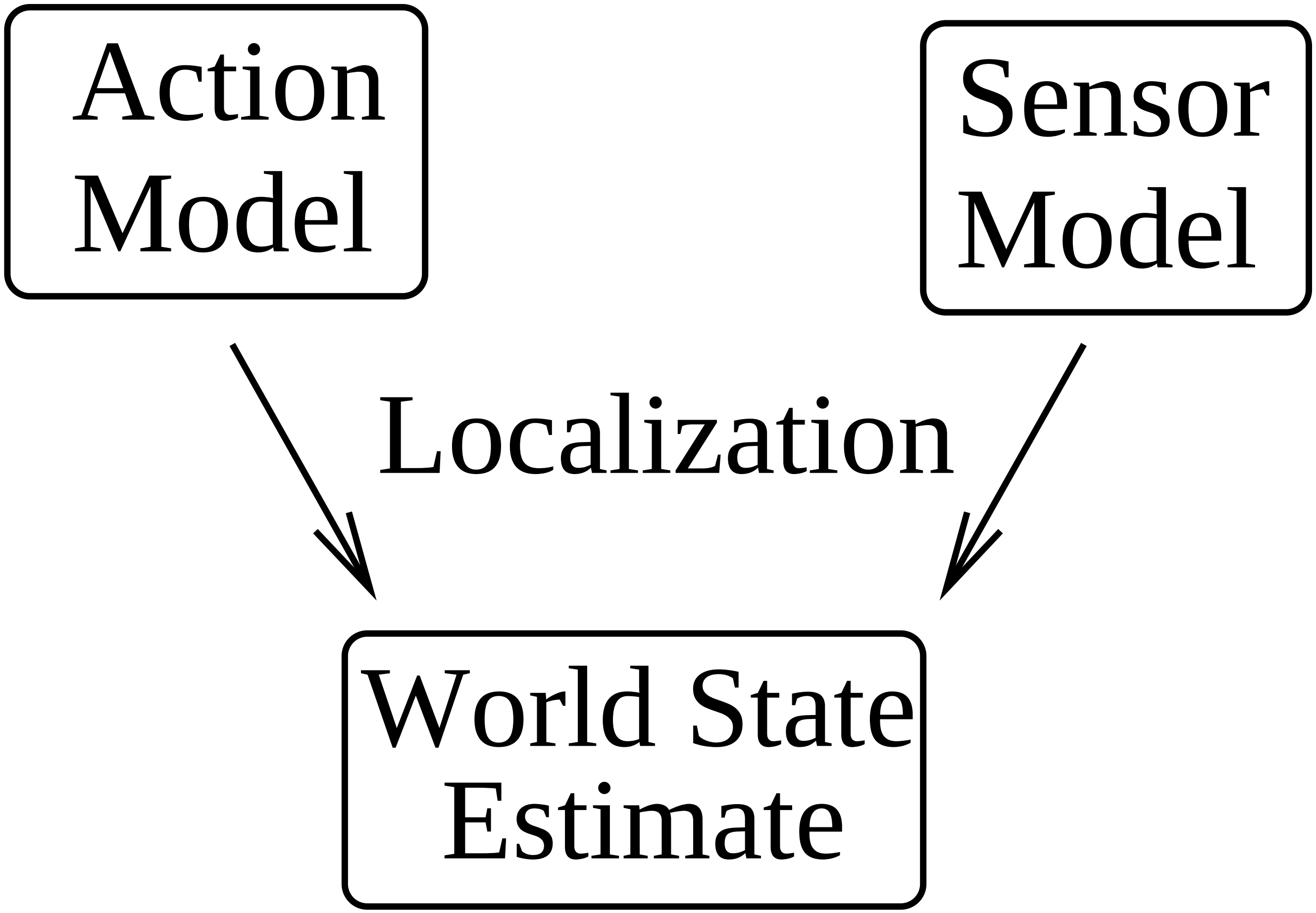

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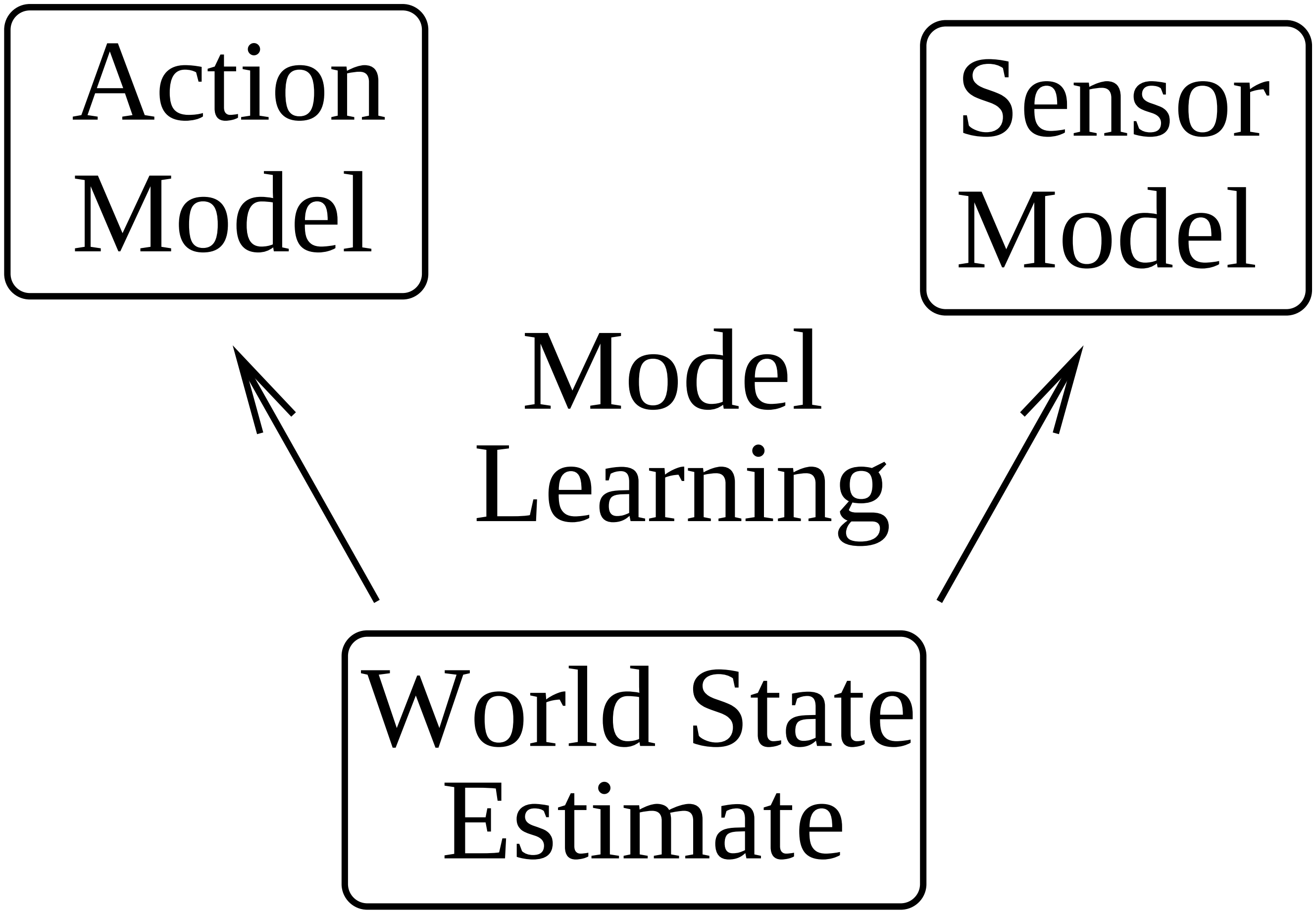

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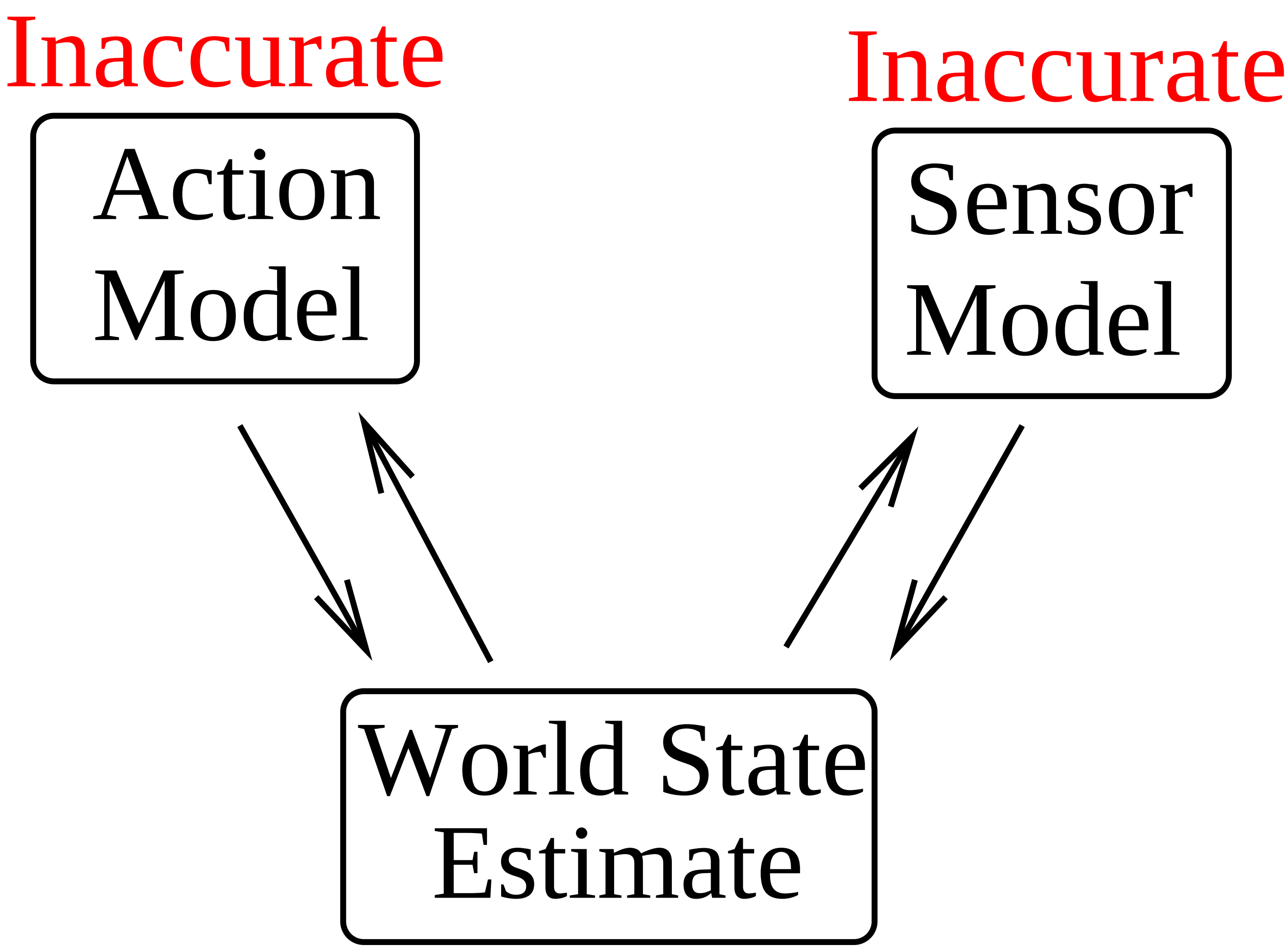

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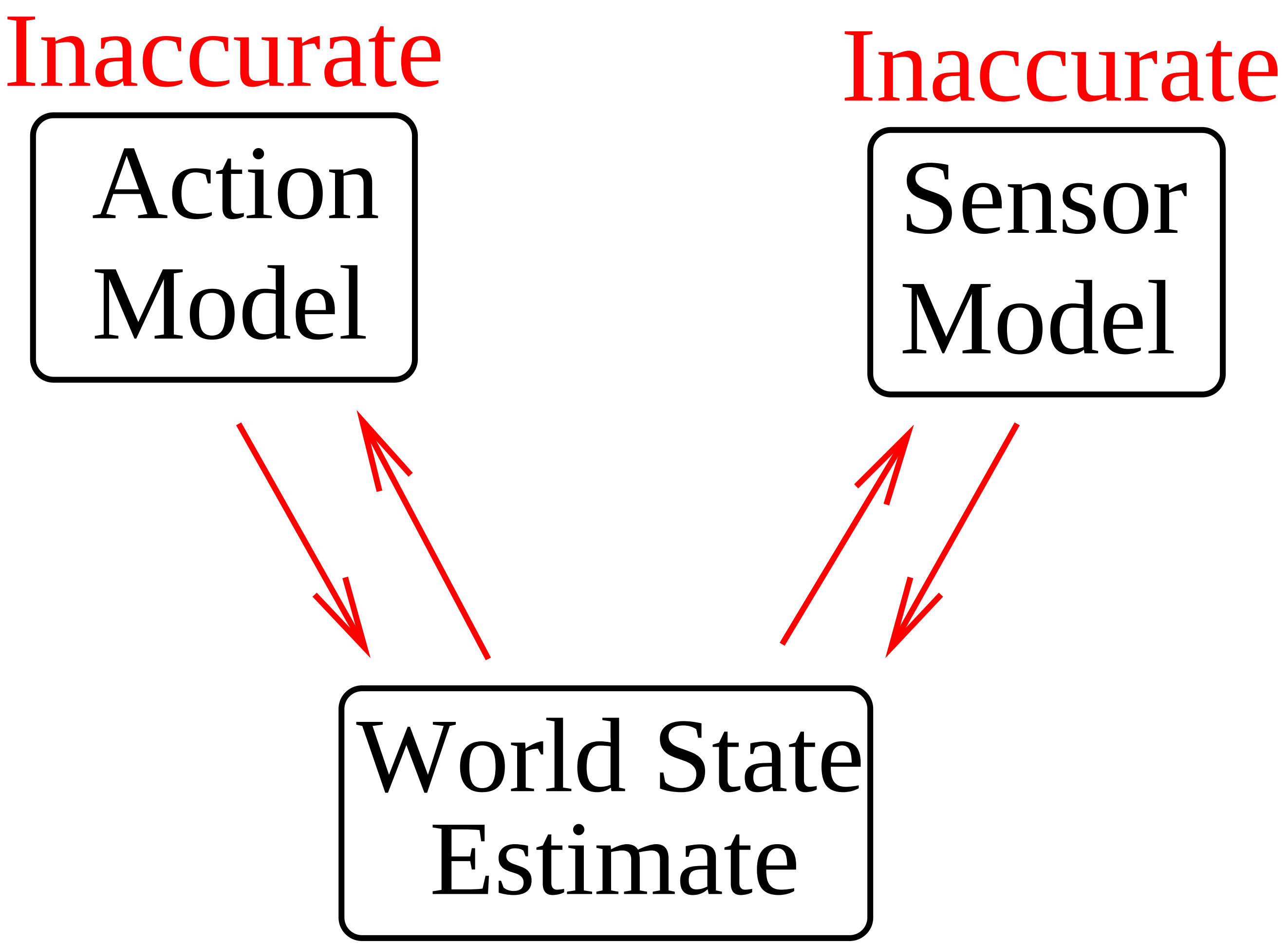

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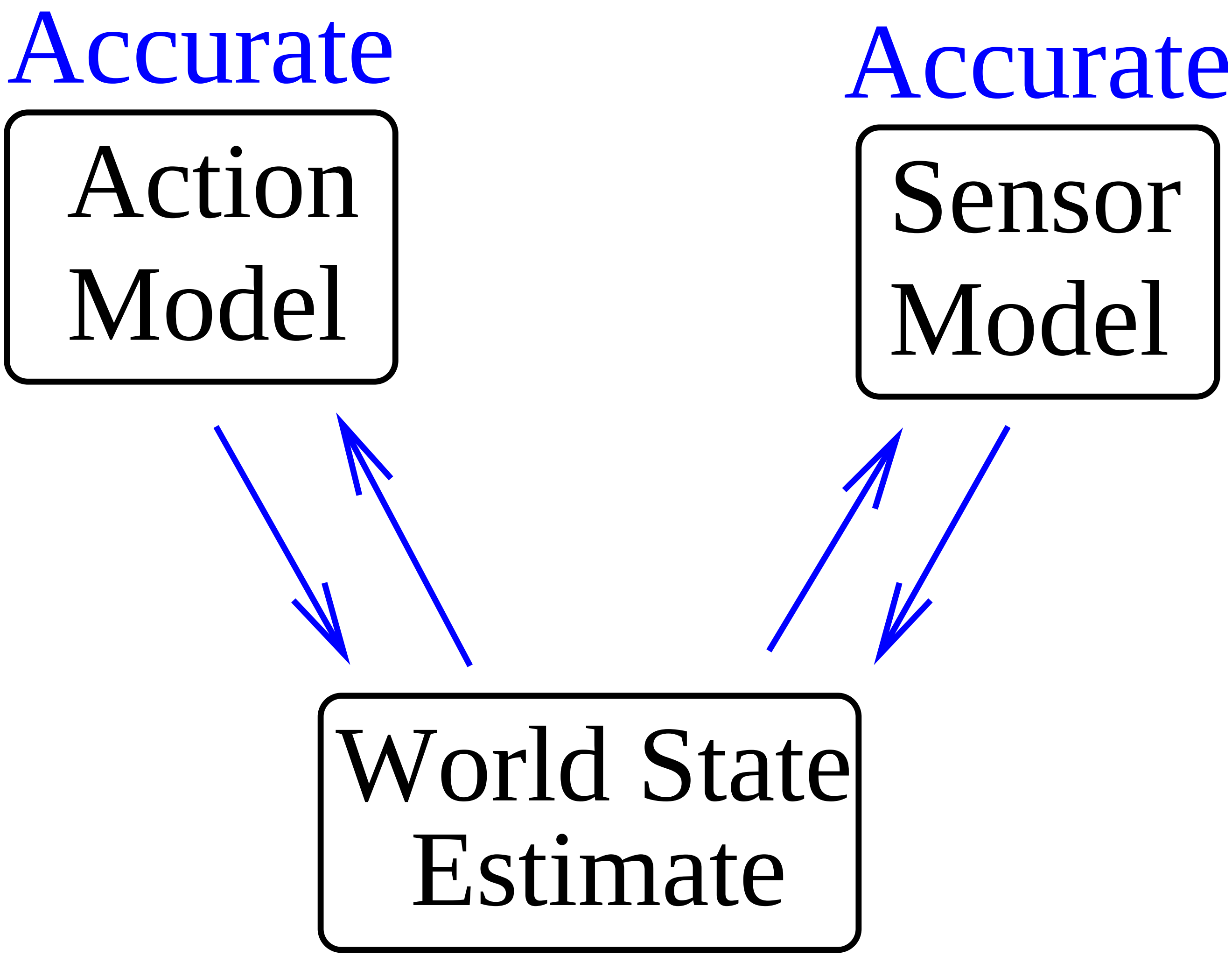

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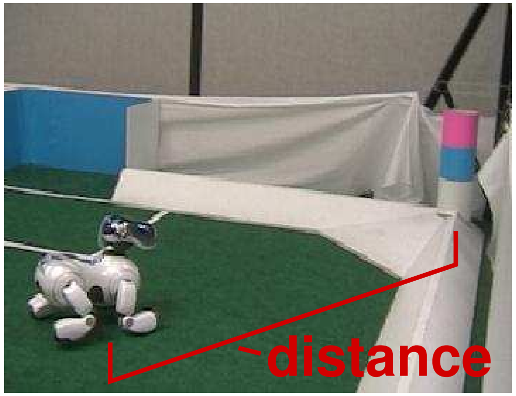

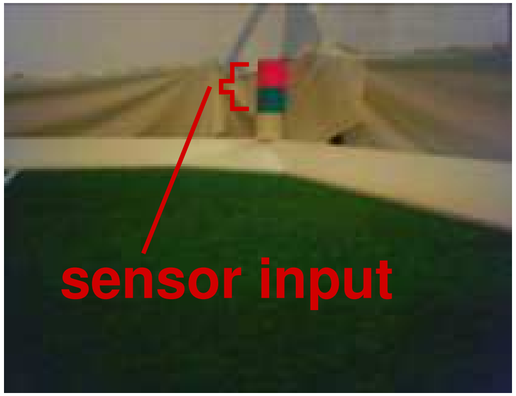

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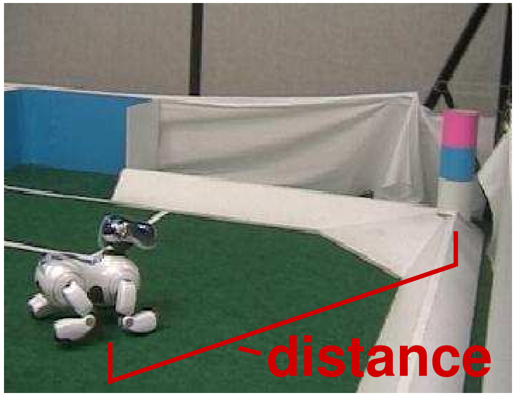

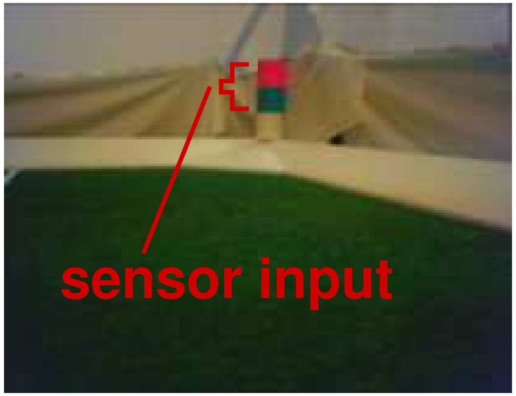

- **Sensor model:** beacon height in image $\mapsto$ distance
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- **Action model:** parametrized walking, W(x) $\mapsto$ velocity
  - x $\in [-300, 300]$ is attempted velocity
  - Not accurate due to friction, joint behavior

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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  – Models learned in arbitrary units

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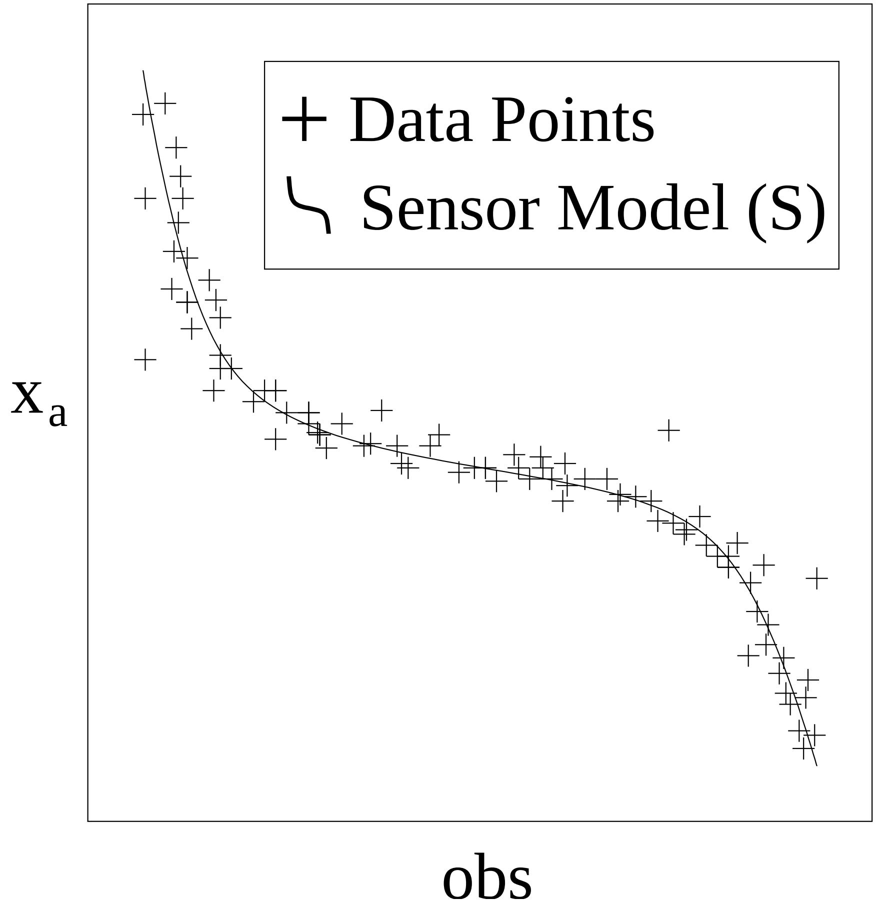

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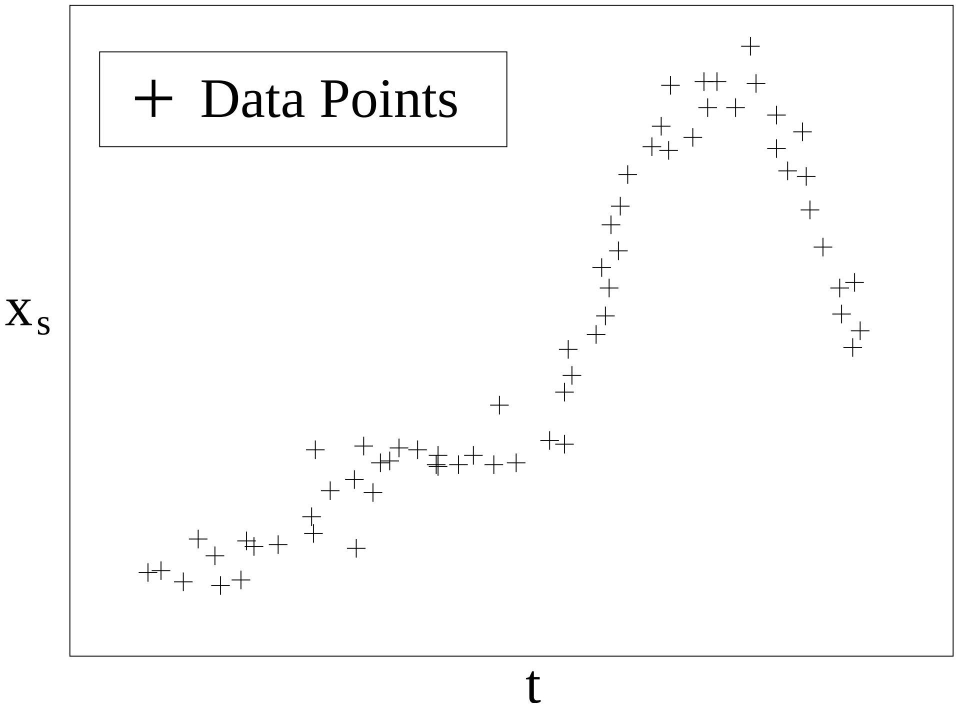

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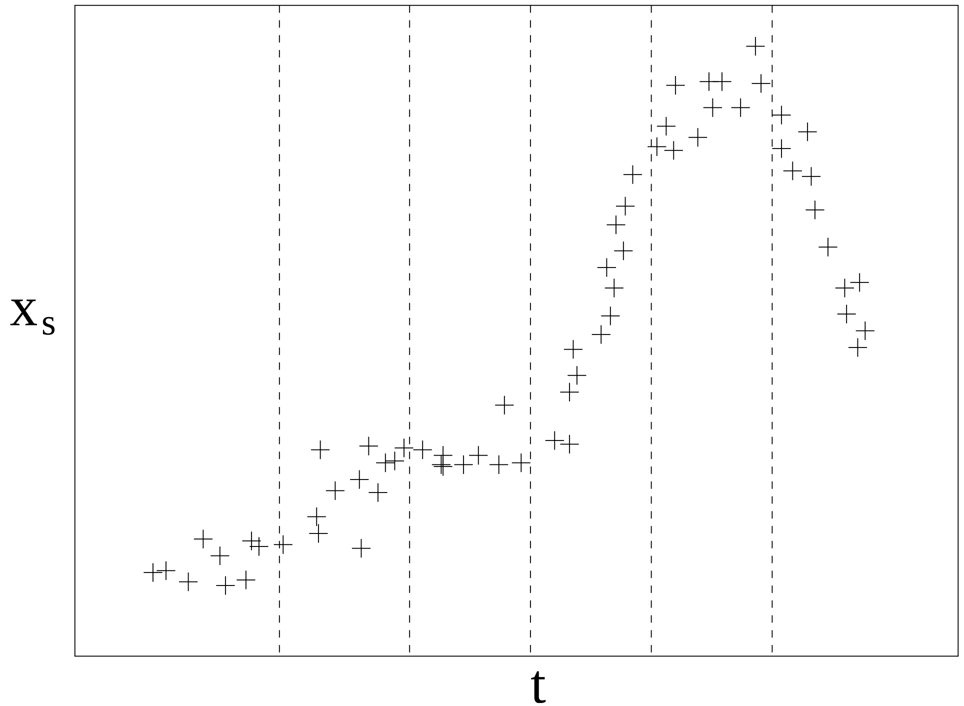
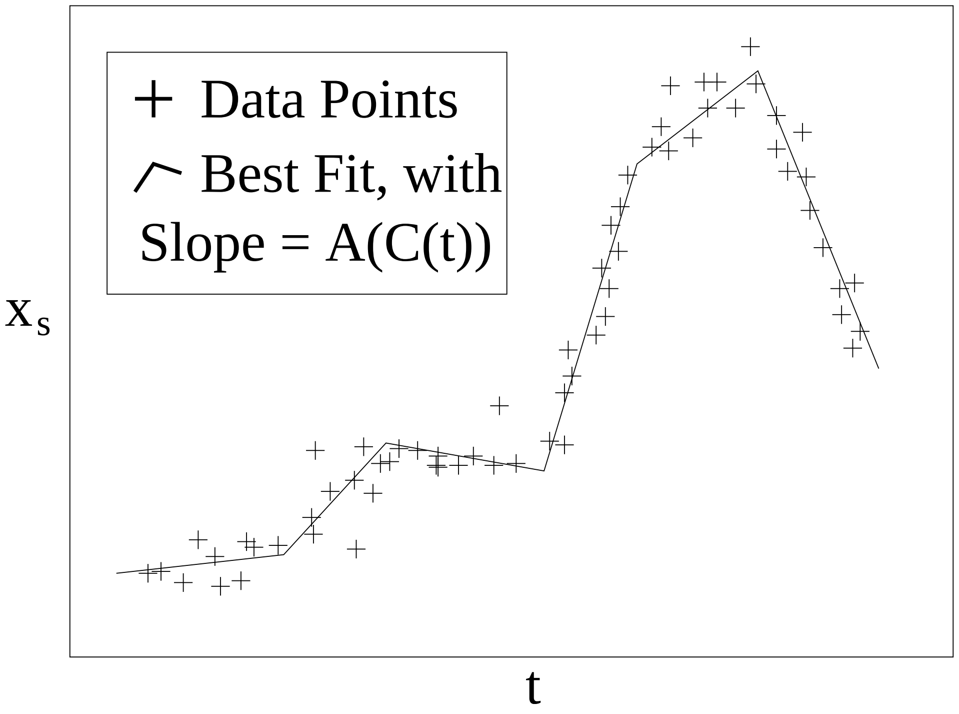


Learning an Action Model (cont.)

- Compute action model that minimizes the error
- Problem equivalent to another multivariate regression



Learning Both Simultaneously

- Both models improve via **bootstrapping**
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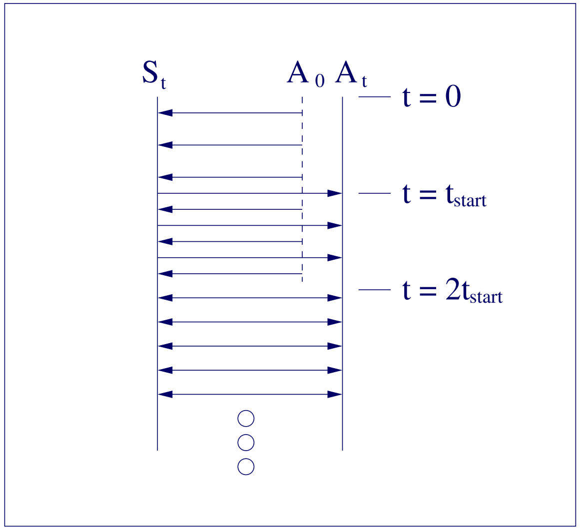
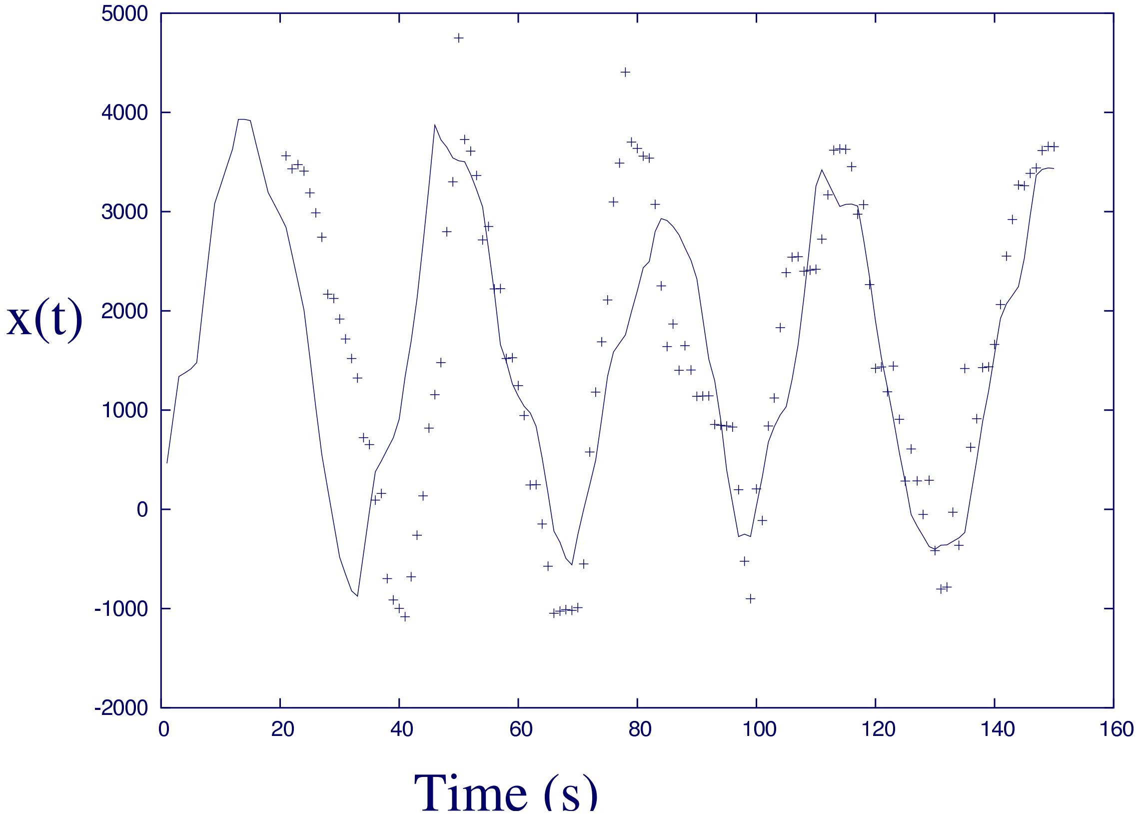


Learning Both Simultaneously

- Over 2.5 min., $x_s(t)$ and $x_a(t)$ come into strong agreement



Experimental Results

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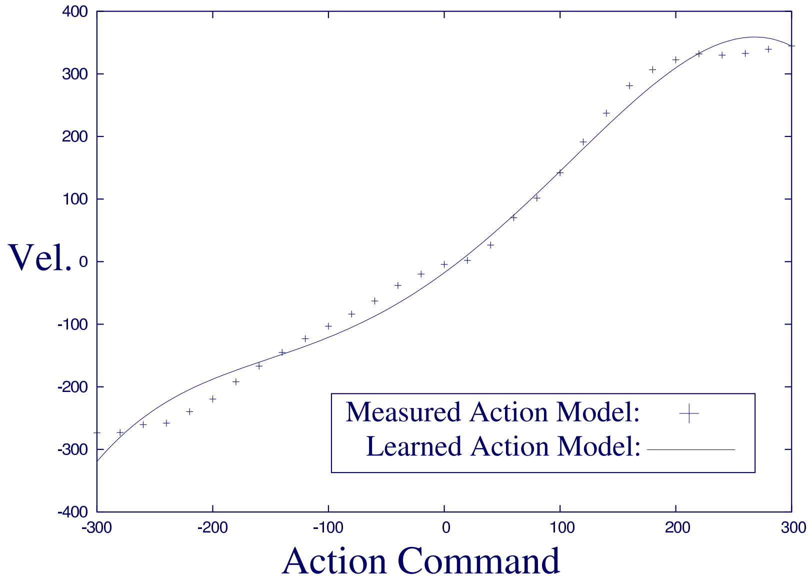
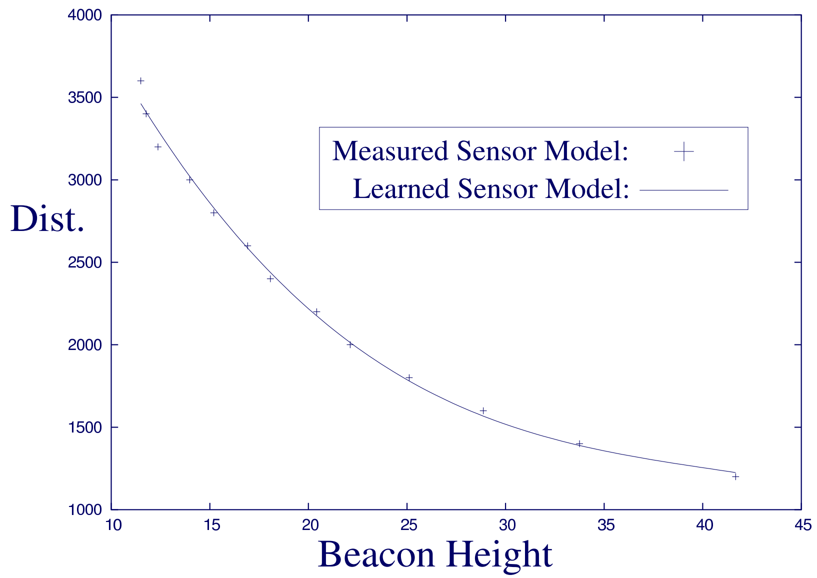
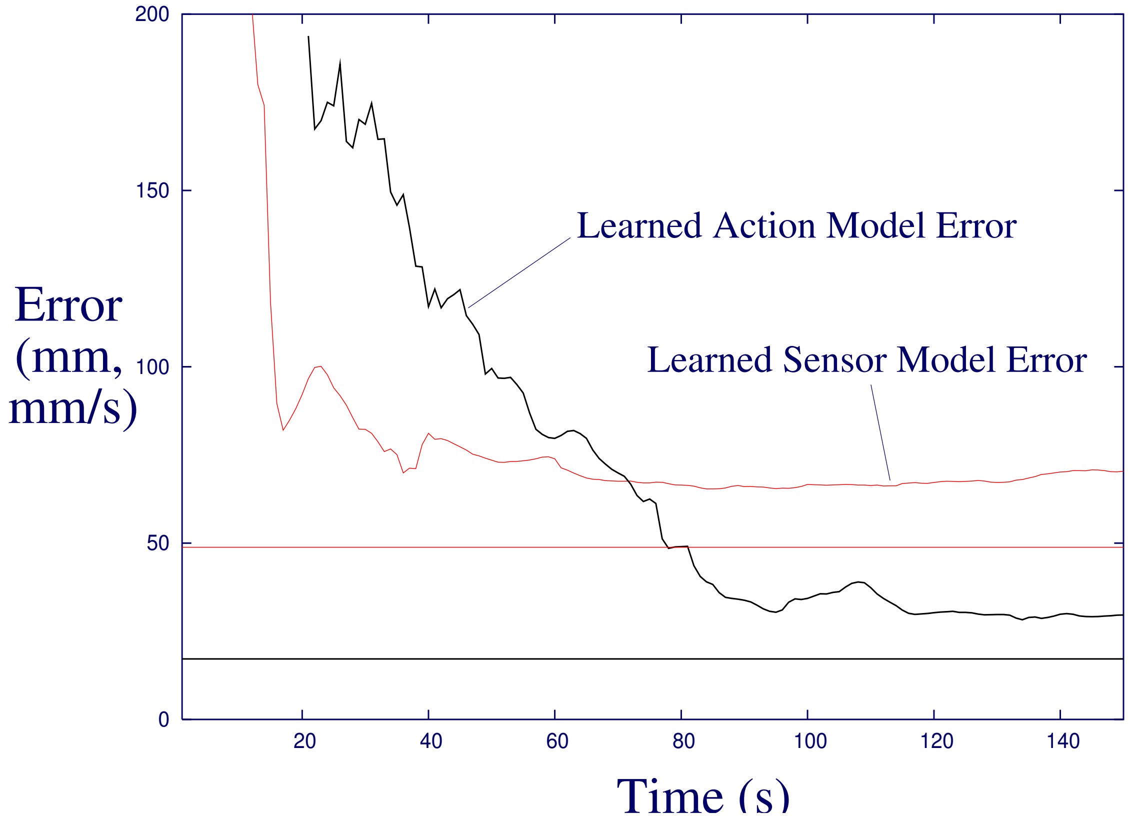




Experimental Results

- Average fitness of model over 15 runs



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- Robot learns while traversing rectangular field
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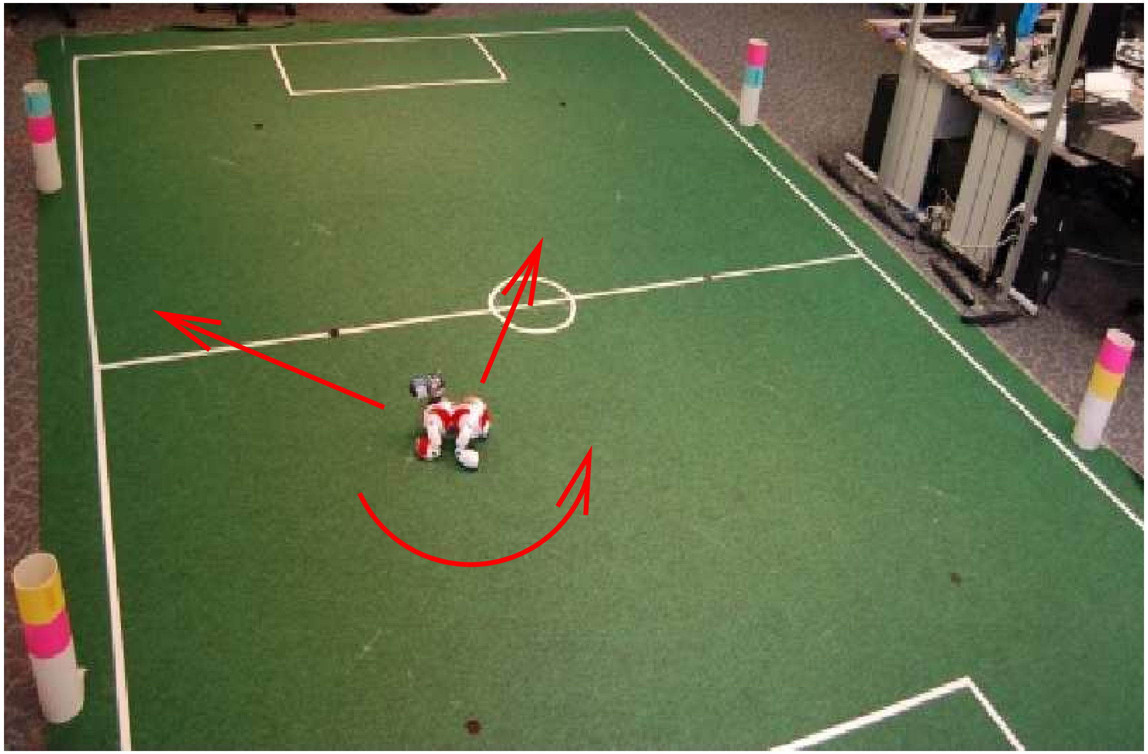

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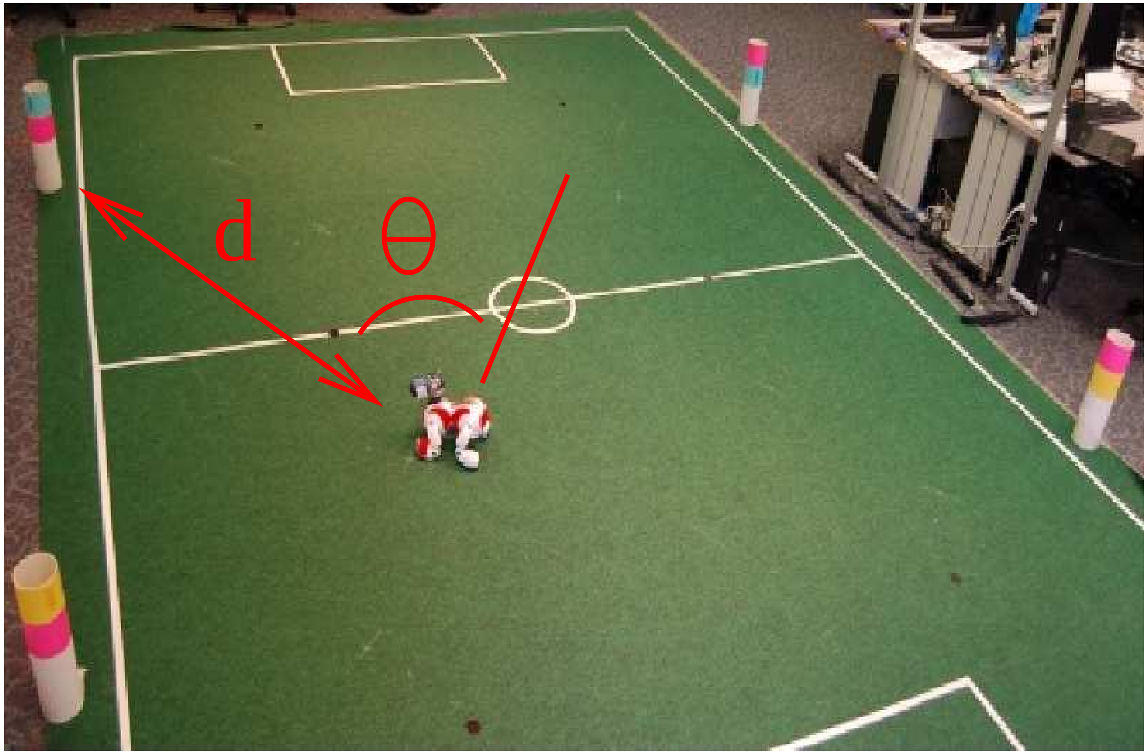


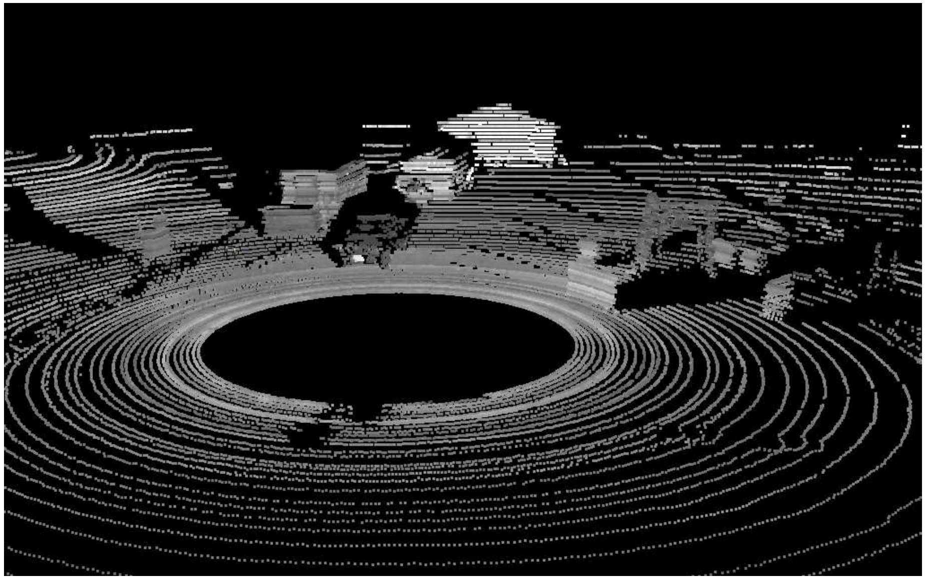
2nd Robotic Platform: Autonomous Car

- **Self-driving car** provides many **challenges** for autonomous model learning

- Actions lead to accelerations, angular velocity:
  – Throttle, brake, and steering position
- Sensors provide information about pose and map:
  – Three-dimensional LIDAR
- Again learn both models starting without accurate estimate of either

3d LIDAR for Autonomous Cars

- The Velodyne LIDAR sensor:



- 64 lasers return distance readings
- Each laser is at a different vertical angle and different horizontal offset
- Unit spins around vertical axis at 10Hz

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

Outline

- Machine learning for fast walking (Kohl, Stone)
- Learning to acquire the ball (Fidelman, Stone)
- Learning sensor and action models (Stronger, Stone)
- **Color constancy on mobile robots** (Sridharan, Stone)
- **Autonomous Color Learning** (Sridharan, Stone)

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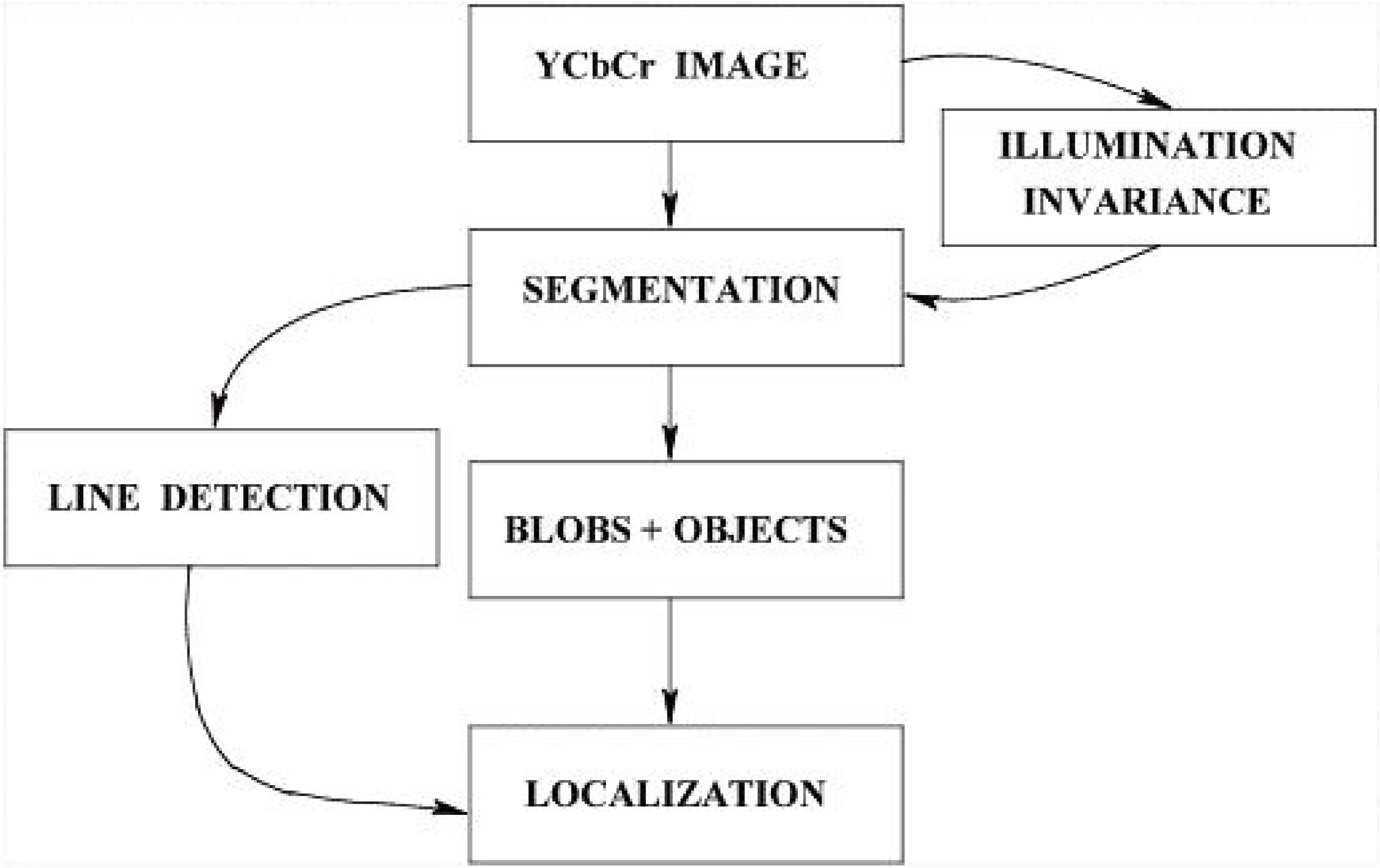
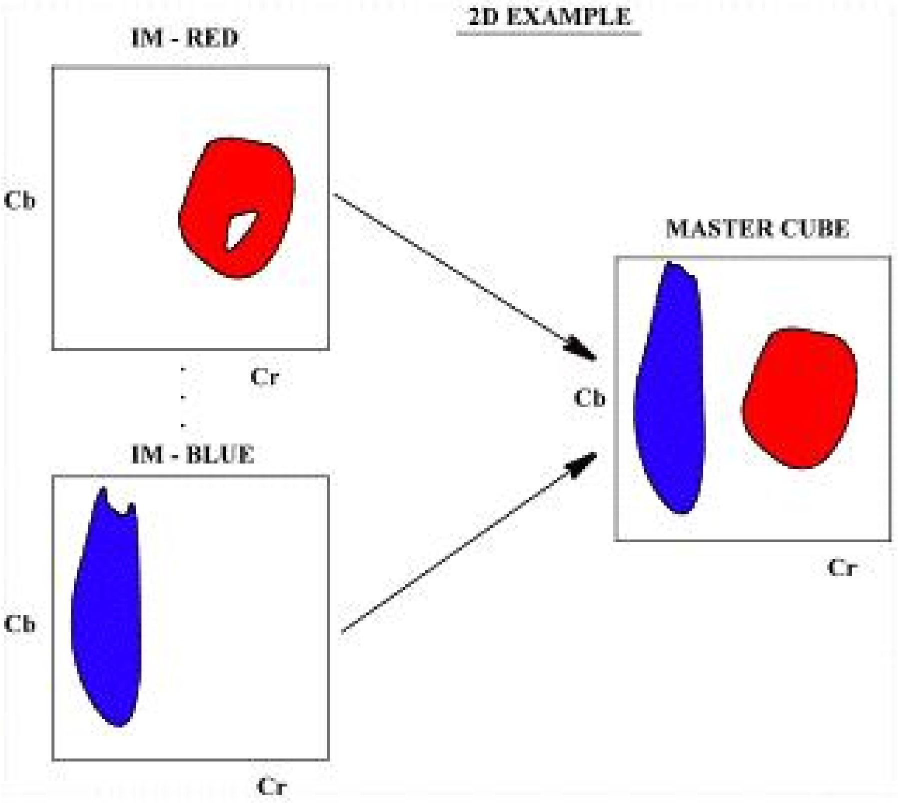
- **Mobile robots**:
  - Computational limitations
  - Changing camera positions

Vision Flowchart



Segmentation

- Color Segmentation:
  - Hand-label discrete colors.
  - Intermediate color maps.
  - NNr weighted average – Master color cube.
  - 128x128x128 color map – 2MB.



Sample Images

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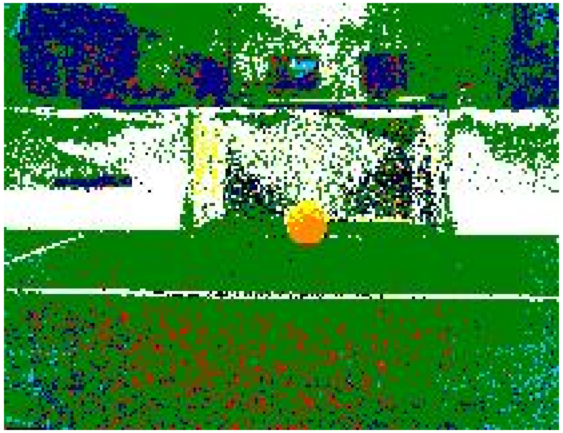

Our Goal

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

Training/Testing

Off-board training: Recognize **10 different colors**

– **Color cube**: $128 \times 128 \times 128$ pixel values $\mapsto$ color label
– **Nearest Neighbor**/weighted average approach

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Real-time color constancy without degradation

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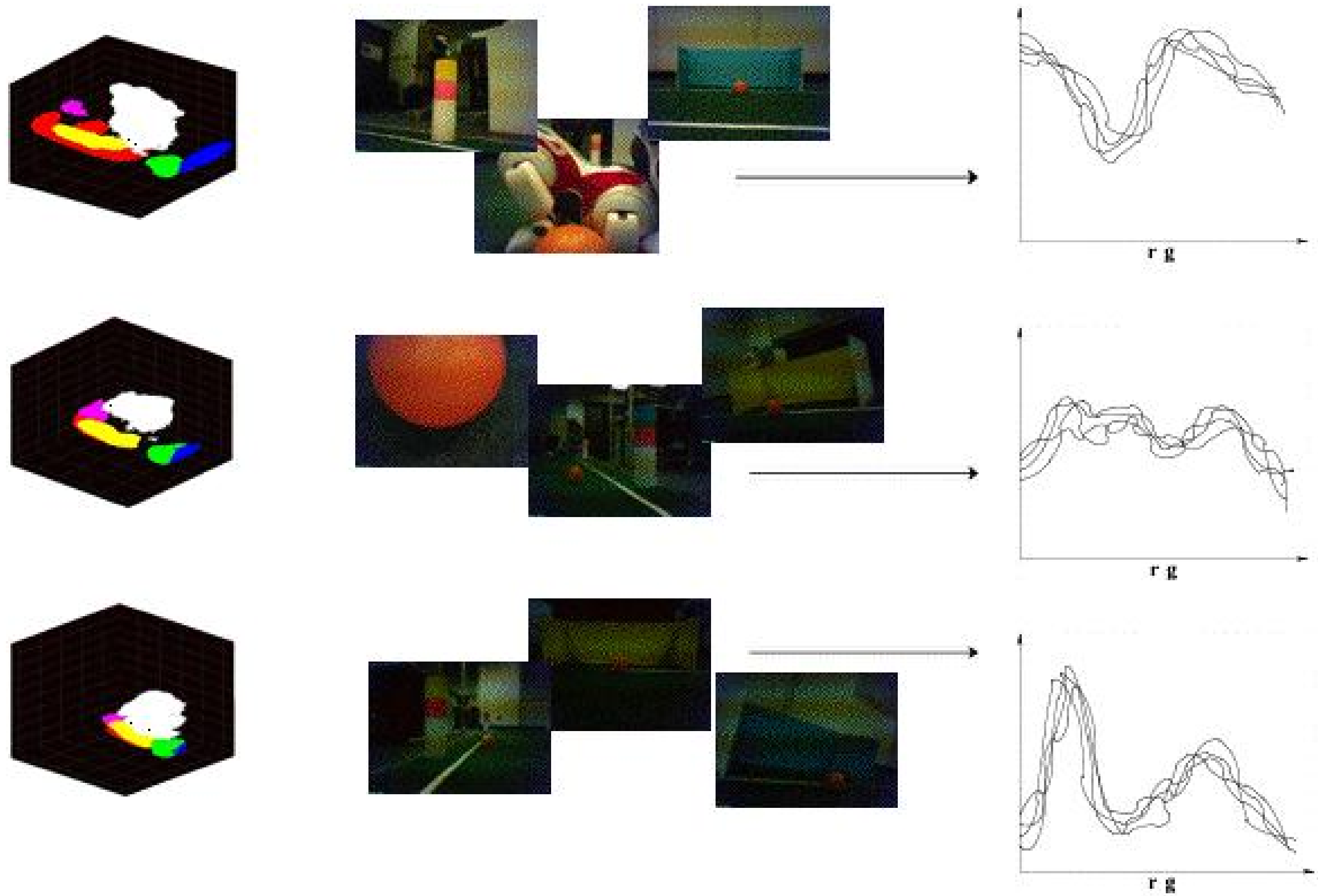
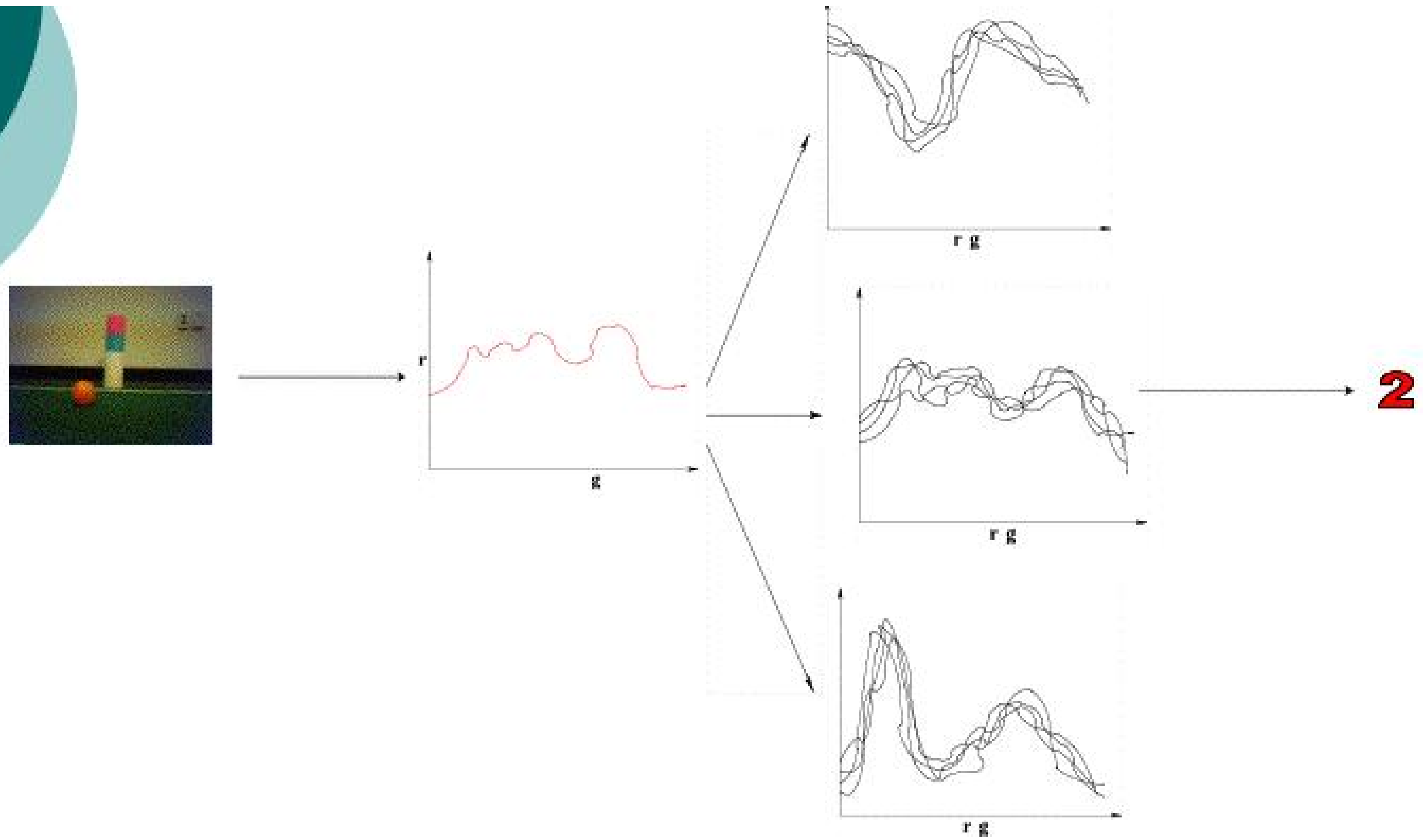
Training Phase



Testing Phase



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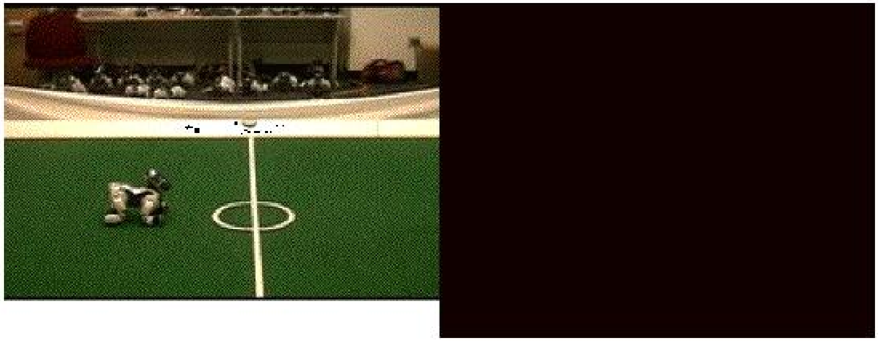

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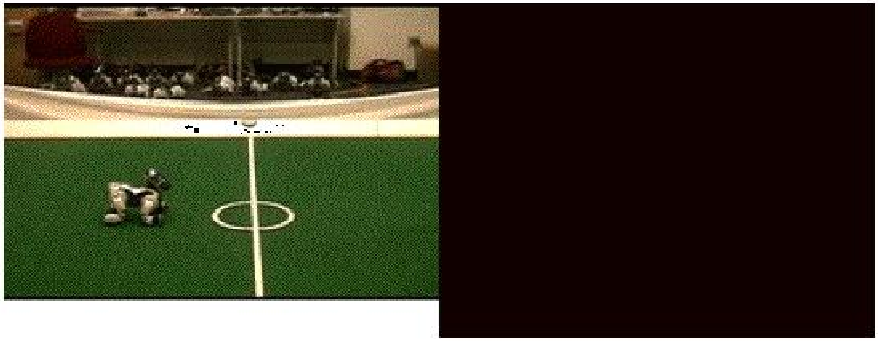

- Comparable accuracy, 5 minutes of **robot effort**

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  - No simulation, minimal human intervention
- **Motion:** learning for fast walking
- **Behavior:** acquiring the ball
- **Localization:** ASAMI
- **Vision:** color constancy, autonomous color learning

Other Robotics Research

- TD learning for **strategy** (Stone, Sutton, Kuhlmann)
- **Collaborative surveillance** (Ahmadi, Stone)
- "**Urban Challenge**:" **autonomous vehicles** (Beeson et al.)
- Autonomous **traffic management** (Dresner, Stone)

Acknowledgements

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- Fox Sports World for inspiration!