Autonomous Robots Playing Soccer and Traversing Intersections

Dr. Peter Stone
October 15, 2010
A Goal of AI

Robust, fully autonomous agents in the real world

How?

• Build complete solutions to relevant challenge tasks
  Complete agents: sense, decide, and act — closed loop
  Challenge tasks: specific, concrete objectives

• Drives research on component algorithms, theory
  – Improve from experience (Machine learning)
  – Interact with other agents (Multiagent systems)

• A top-down, empirical approach

  “Good problems . . . produce good science” [Cohen, ’04]
Goal: By the year 2050, a team of humanoid robots that can beat the human World Cup champion team.

[Kitano, ’97]
RoboCup Soccer

• Still in the **early stages**

• **Many virtues:**
  
  – Incremental challenges, **closed loop at each stage**
  
  – Relatively **easy entry**
  
  – **Multiple robots possible**
  
  – Inspiring to many

• **Visible progress**
The Early Years

RoboCup 1997–1998
A Decade Later

RoboCup 2005–2006

© 2010 Peter Stone
Advances due to RoboCup

- Drives research in many areas:
  - Control algorithms; computer vision, sensing; localization;
  - Distributed computing; real-time systems;
  - Knowledge representation; mechanical design;
  - Multiagent systems; machine learning; robotics

- 200+ publications from simulation league alone

- 200+ from 4-legged league

- 15+ Ph.D. theses
Layered Learning

- For domains too complex for tractably mapping state features $S \rightarrow$ 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
Layered Learning in Practice

First applied in simulated robot soccer [Stone & Veloso, ’97]

<table>
<thead>
<tr>
<th>Strategic Level</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L_1$</td>
<td>individual ball interception</td>
</tr>
<tr>
<td>$L_2$</td>
<td>multiagent pass evaluation</td>
</tr>
<tr>
<td>$L_3$</td>
<td>team pass selection</td>
</tr>
</tbody>
</table>

Recently applied on real robots [Stone, Kohl, & Fidelman, ’06]

<table>
<thead>
<tr>
<th>Strategic Level</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L_1$</td>
<td>individual fast walking</td>
</tr>
<tr>
<td>$L_2$</td>
<td>individual ball control</td>
</tr>
</tbody>
</table>
Robot Vision

- Great progress in computer vision
  - Shape modeling, object recognition, face detection...

- Robot vision offers new challenges
  - Mobile camera, limited computation, color features

- **Autonomous color learning** [Sridharan & Stone, ’05]
  - Learns color map based on known object locations
  - Recognizes and reacts to illumination changes
  - Object detection in real-time, on-board a robot
Other Good AI Challenges

Trading agents

Autonomous vehicles

Autonomic computing

Socially assistive robots
Challenge Problems Drive Research
Outline

• Build complete solutions to relevant challenge tasks
  – Drives research on component algorithms, theory

• Learning Agents

• Multiagent reasoning
Machine Learning

“... resurgence of interest in machine learning” [Mitchell, ‘83]

Supervised learning mature [Kaelbling, ‘97]

For agents, reinforcement learning most appropriate

- Foundational theoretical results
- Challenge problems require innovations to scale up
Success story: $Q$-learning converges to $\pi^*$ [Watkins, 89]

- Table-based representation
- Visit every state infinitely often
Scaling Up

- Backgammon [Tesauro, ’94]
- Helicopter control [Ng et al., ’03]
- RoboCup Soccer Keepaway [Stone & Sutton, ’01]
  - Play in a small area (20m × 20m)
  - Keepers try to keep the ball
  - Takers try to get the ball
  - Performance measure: average possession duration
Function Approximation

In practice, visiting every state impossible

```
s[t]  s[t-1]  a[t-1]
```

```
Q(s, a)
```

```
s[t-1]  a[t]
```

```
r[t]  a[t-1]  s[t]
```

Function approximation of value function

Theoretical guarantees harder to come by
Main Result

Learning: Distributed SMDP SARSA(\(\lambda\)) with CMACs
- Algorithm modified to enable distributed updates

1 hour = 720 5-second episodes
Batch Methods

In practice, often experience is scarce

Save transitions:

\(<r[i], s[i], a[i]> \text{ for } i=0 \text{ to } t-1\)
“Few Zeroes” [Kalyanakrishnan & Stone, ’07]

Experience replay [Lin, ‘92], Fitted Q Iteration [Ernst et al., ‘05]

Other ways to scale up

- Advice/demonstration/TAMER, state/temporal abstraction
- Transfer learning, adaptive/hierarchical representations
Outline

- Build complete solutions to relevant challenge tasks
  - Drives research on component algorithms, theory
- Learning Agents
- Multiagent reasoning
Multiagent Reasoning

Once there is one, there will soon be many
To coexist, agents need to interact
Example: autonomous vehicles
- DARPA “Grand Challenge” was a great first step
- “Urban Challenge” continues in the right direction
- Traffic lights and stop signs still best? [Dresner & Stone, ’04]
Autonomous Bidding Agents

- Usual assumption: rational agents
- In practice, must prepare for the unexpected
  - Other agents created by others
  - Teammate/opponent modeling
  - Especially in competition scenarios
Trading Agent Competitions

**ATTac**: champion travel agent [Stone et al., ’02]

- Learns model of auction closing prices from past data
- Novel algorithm for conditional density estimation

**TacTex**: champion SCM agent [Pardoe & Stone, ’06]

- Adapts procurement strategy based on recent data
- Predictive planning and scheduling algorithms

Common multiagent tradeoff: learn detailed static model vs. adapt minimally on-line
Outline

- Build complete solutions to relevant challenge tasks
  - Drives research on component algorithms, theory
- Learning Agents
- Multiagent reasoning
- Implications
A Goal of AI

Robust, fully autonomous agents in the real world

What happens when we achieve this goal?

- Question: Would you rather live 100 years ago? Or 100 years in the future?
- Not clear — world changing in many ways for the worse

AI can be a part of the solution

© 2010 Peter Stone
Summary

Robust, fully autonomous agents in the real world

- Build complete solutions to relevant challenge tasks
  - Good problems drive research

Combine algorithmic research, problem-oriented approaches
Summary

Robust, fully autonomous agents in the real world

- Build complete solutions to relevant challenge tasks
  - Good problems drive research

Combine algorithmic research, problem-oriented approaches

- Current challenges need learning, multiagent reasoning
This presentation is provided as part of the Hot Science - Cool Talks Outreach Series, and is supported by the Environmental Science Institute, the Jackson School of Geosciences, and the College of Natural Sciences at The University of Texas at Austin.

Additional support provided in part by a grant from the Motorola Foundation.
Dr. Peter Stone

Peter Stone is the founder and director of the Learning Agents Research Group within the Artificial Intelligence Laboratory in the Department of Computer Science at The University of Texas at Austin. His main research interest in AI is understanding how we can best create complete intelligent agents. He considers adaptation, interaction, and embodiment to be essential capabilities of such agents.