Hierarchical Winning Approaches to RoboCup Soccer Simulation Challenge

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Outline

1. Introduction to RoboCup 2D
2. MAXQ Based Hierarchical Online Planning
3. Concurrent Hierarchical Reinforcement Learning
4. Summary and Future Work

Overview

- MAXQ based hierarchical online planning for large MDPs
  - AAMAS (Bai et al., 2012b)
  - RoboCup Symposium (Bai et al., 2012a, 2013b)
  - ACM Transactions (Bai et al., 2015)
- Thomson sampling based MCTS for MDPs and POMDPs
  - NIPS (Bai et al., 2013a)
  - ICAPS (Bai et al., 2014b; Zhang et al., 2015)
- State and action abstractions for MDPs
  - IJCAI (Bai et al., 2016)

RoboCup Soccer Simulation 2D

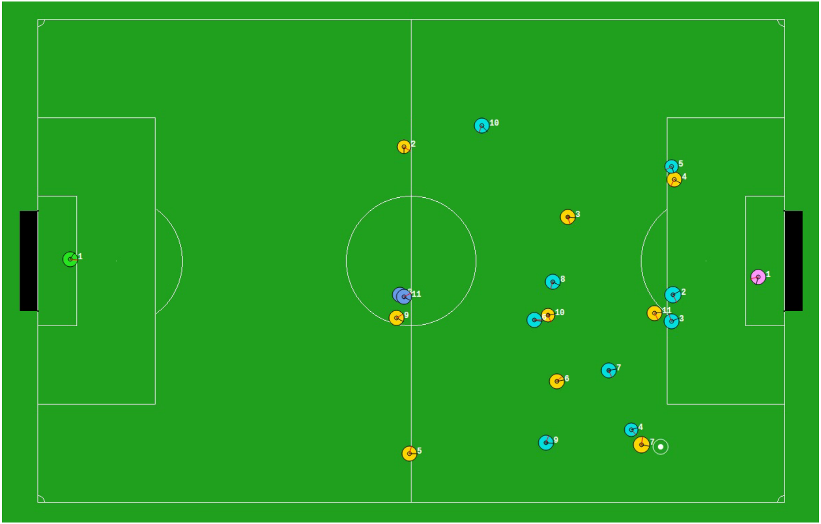
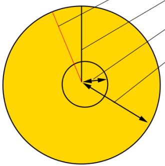


Figure 1: WrightEagle (my team) v.s. Helios

What Makes RoboCup 2D Interesting/Challenging?

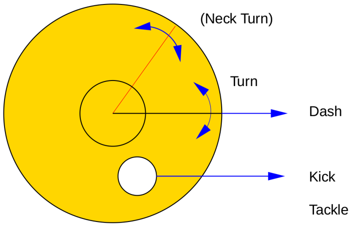
- Key Features:
  - Abstractions made by the simulator
  - High-level planning and learning
  - No need to handle low-level robotics
- Key Challenges:
  - Fully distributed multi-agent stochastic game
  - Continuous state, action and observation spaces
    * A good testbed for many real world problems

Ball and Player States



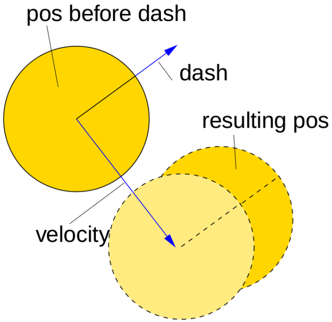
- State: $[s_b, s_1, s_2, \ldots, s_{22}]$
  - Ball State
    - Position, Velocity
  - Player State
    - Position, Velocity
    - Body Angle, Neck Angle, Stamina, ...

Primitive Actions



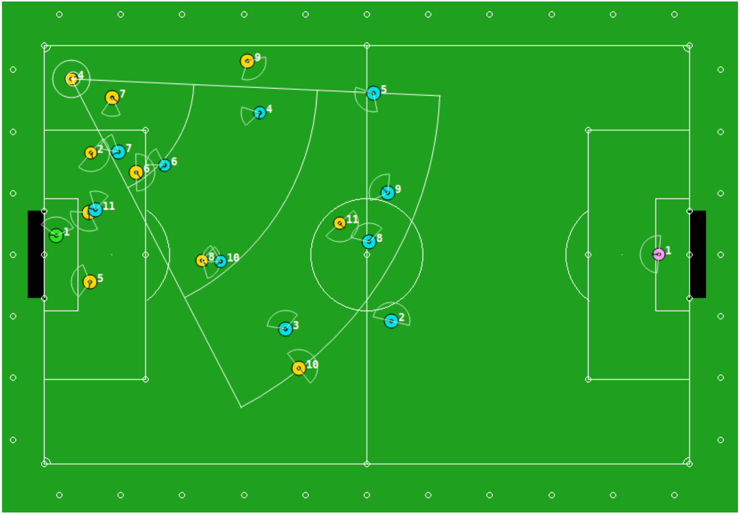
- Parameterized actions
  - $Dash(dir, power)$
  - $TurnBody(angle)$
  - $TurnNeck(angle)$
  - $Kick(dir, power)$
  - $Tackle(dir)$
  - $Catch(dir)$ [for goalie]

The Physics



- $Dash(dir, power)$
  - Moves the player
  - Exposed to noise
  - Costs some stamina
    - If stamina is too low: can not move at full speed

The Observation Model



RoboCup 2D in Action

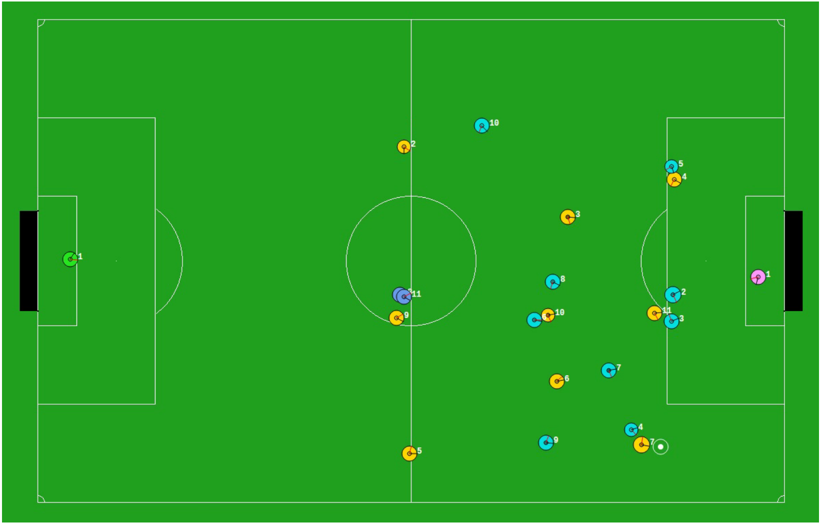


Figure 2: WrightEagle (my team) v.s. Helios

A Multi-Agent Formulation

A partially observable stochastic game (POSG) formulation:

- Agents: $1, 2, \ldots, 22$
- Joint state: $\mathbf{s} = [s_b, s_1, s_2, \ldots, s_{22}]$
- Joint action: $\mathbf{a} = [a_1, a_2, \ldots, a_{22}]$
- Observation: $\mathbf{o} = [landmarks, ball, players, \ldots]$
- Transition function: $T(\mathbf{s}' \mid \mathbf{s}, \mathbf{a}) \in [0, 1]$
- Observation function: $\Omega_i(\mathbf{o} \mid \mathbf{s}) \in [0, 1]$
- Reward function: $R_i(\mathbf{s}, \mathbf{a})$

which is practically intractable!

Converting to Single-Agent Problem

- Large number of agents involved: 22
  - Belief regression
- Assume teammates/opponents are part of the environment
  - Unpredictable/adaptive/learning
  - Stochastic policies
  - Belief states

Future Belief Prediction

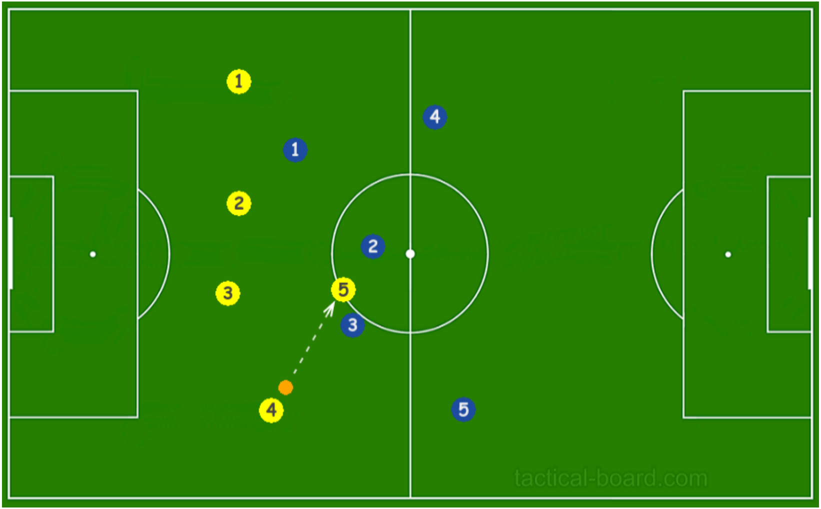


Figure 3: Player 4 planning a 10-cycle pass to player 5 at t

Future Belief Prediction (Cont'd)

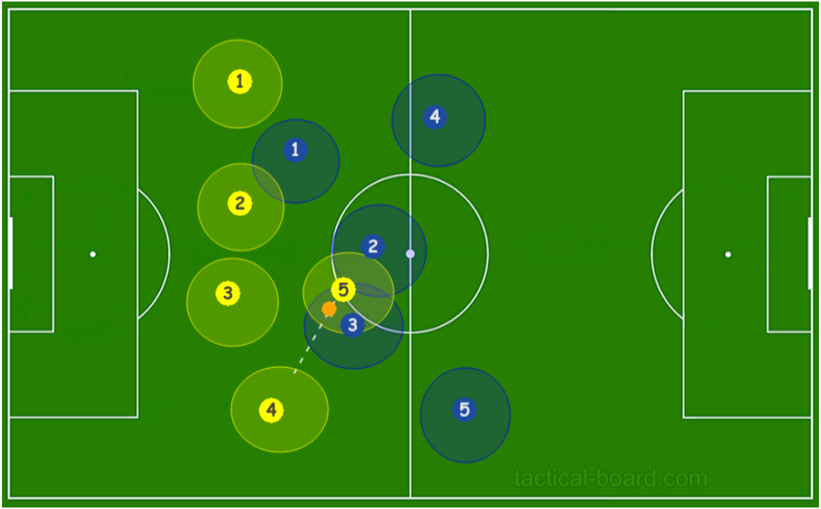


Figure 4: Predicted future state at $t + 10$

Particle Filtering based Belief Update

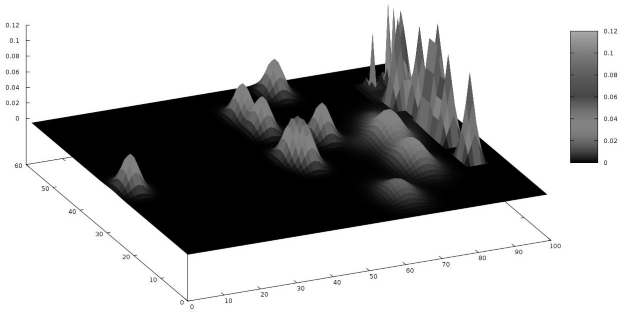


Figure 5: Belief visualization

- Particle filtering over sets for multi-object tracking
  - AAAI fall symposium (Bai et al., 2014a)

A Single-Agent Formulation

- An MDP formulation:
  - Joint belief: $\mathbf{b} = [b_b, b_1, b_2, \ldots, b_{22}]$
  - Action: $a \in \{Dash(\cdot,\cdot), Kick(\cdot,\cdot), TurnBody(\cdot), \ldots\}$
  - Transition function: $T(\mathbf{b}' \mid \mathbf{b}, a) \in [0,1]$
  - Reward function: $R(\mathbf{b}, a)$

Solving the Resulting MDP in Realtime

Exact solution is still intractable:

- The curse of dimensionality
  - Continuous high-dimensional (belief) state space
  - Continuous action space
- The curse of history
  - Long looking-ahead horizon: 6000 steps for a game
  - Sparse reward function
    - +/-1 for teammate/opponent score

Approximate Solutions

My Proposals:

- Hierarchical online planning
  - Perform a tree search from the current state within a reachable subspace consistent with a task structure
- Concurrent hierarchical reinforcement learning
  - Write a partial policy for each agent
  - Jointly learn an optimal completion for partial policies
  - An ongoing project

Hierarchical Decomposition

- Exploit hierarchical structure of a task
- Introduce macro actions/options/skills
  - In contrast with primitive actions
- Fundamental theory: Semi-MDP
  - Options: $o \in \mathcal{O}$
  - Multi-step transition function: $T(s', N \mid s, o) \in [0, 1]$
  - Hierarchical policy: $\pi(s) \in \mathcal{O}$
  - Fast planning and learning on an option basis

MAXQ Hierarchical Decomposition

- Decompose an MDP into a tree of sub-MDPs (Dietterich, 1999)
  - $M = \{M_0, M_1, \ldots, M_n\}$
  - $M_i = \langle S_i, G_i, A_i, R_i \rangle$
    1. Active states S_i
    2. Goal states G_i
    3. Available actions A_i
    4. Local reward function R_i
  - Solving M_0 solves the original MDP M
  - Hierarchical policy $\pi = \{\pi_0, \pi_1, \ldots, \pi_n\}$

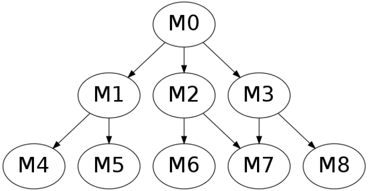


Figure 6: MAXQ hierarchy

MAXQ Hierarchical Decomposition: An Example

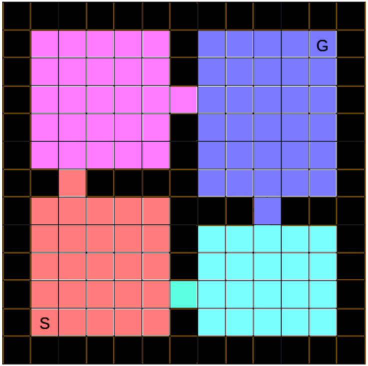


Figure 7: A 4-Room domain

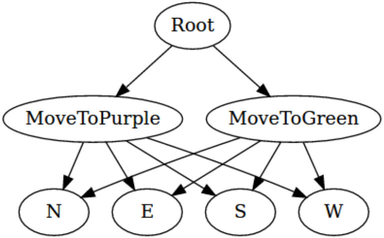


Figure 8: MAXQ task graph

MAXQ Value Function Decomposition

- Value function V^* of optimal π^* satisfies

$$V^*(i,s) = \begin{cases} R(s,i) & \text{if } M_i \text{ is primitive} \\ \max_{a \in A_i} Q^*(i,s,a) & \text{otherwise} \end{cases} \tag{1}$$

$$Q^*(i,s,a) = V^*(a,s) + \sum_{s',N} \Pr(s', N \mid s,a) V^*(i,s') \tag{2}$$

- Transition function: $\Pr(s', N \mid s, a)$
  - Marginalized: $\Pr(s' \mid s,a) = \sum_N \Pr(s', N \mid s,a)$
    - Terminating distribution

MAXQ based Online Planning: MAXQ-OP

- For non-primitive subtasks

$$V^*(i,s) \approx \max_{a \in A_i} \left\{ V^*(a,s) + \sum_{s'} \Pr(s' \mid s,a) V^*(i,s') \right\} \quad (3)$$

- Introduce search depth array d, maximal search depth array D and heuristic function $H(i,s)$

$$V(i,s,d) \approx \begin{cases} H(i,s) & \text{if } d[i] \geq D[i] \\ \max_{a \in A_i} \{V(a,s,d) + \\ \sum_{s'} \Pr(s' \mid s,a) V(i,s',d[i] \leftarrow d[i]+1)\} & \text{otherwise} \end{cases} \quad (4)$$

- Call $V(0,s,[0,0,\ldots,0])$ to find the value of s in task M_0

MAXQ-OP on Benchmark: The Taxi Problem

- States: $25 \times 5 \times 4 = 400$
  1. Taxi location: (x, y)
  2. Passenger location: R, Y, B, G and In
  3. Destination location: R, Y, B, G
- Actions: 6
  1. North, South, East, West
  2. Pickup, Putdown
- Probability 0.8 of failure

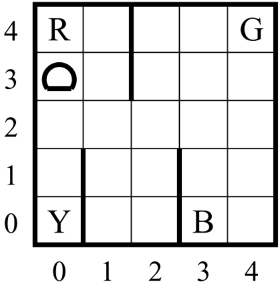


Figure 9: Taxi domain

Empirical Results in the Taxi Problem

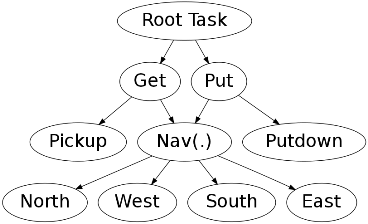


Figure 10: Task graph for Taxi

Table 1: Empirical results in Taxi

Algorithm	Avg. Reward*	Online Time (ms)
MAXQ-OP	3.93 ± 0.16	0.20 ± 0.16
LRTDP	3.71 ± 0.15	64.88 ± 3.71
AOT	3.80 ± 0.16	41.26 ± 2.37
UCT	-23.10 ± 0.84	102.20 ± 4.24

*The upper bound of Average Rewards is 4.01 ± 0.15.

Comparing to Non-Hierarchical Online Planning

- Non-hierarchical online planning algorithms
  - Use only primitive actions to grow search tree
  - Search path:

$$[s_1 \to s_2 \to s_3 \to \cdots \to s_H] \rightsquigarrow g \tag{5}$$

- MAXQ-OP algorithm
  - Use primitive and macro actions to grow search tree
  - Search path:

$$\begin{multline}[s_1 \to \cdots \to s_{H_1}] \rightsquigarrow [g_1/s'_1 \to \cdots \to s'_{H_2}] \rightsquigarrow \\ [g_2/s''_1 \to \cdots \to s''_{H3}] \cdots \rightsquigarrow g \end{multline} \tag{6}$$

- MAXQ-OP can search much deeper by exploiting the task structure

MAXQ Decomposition for RoboCup 2D

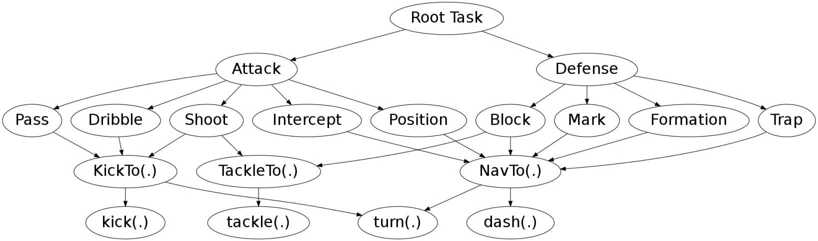


Figure 11: MAXQ based hierarchical decomposition in WrightEagle

Hierarchical Online Planning in WrightEagle

- Rule-based system:

  PlanAttack() {
  ...
  if *should_shoot* **then**
    return Shoot()
  else if *should_pass* **then**
    return Pass()
  else
    return Drrible()
  ...
  }

- Hierarchical planning:

  PlanAttack() {
  ...
  shoot $\leftarrow$ PlanShoot()
  pass $\leftarrow$ PlanPass()
  dribble $\leftarrow$ PlanDrrible()
  ...
  return $\max\{$shoot, pass, dribble, $\ldots\}$
  }

MAXQ-OP in WrightEagle

- Task hierarchy
  - Value function decomposition
- Terminating distribution approximation
  - Success and failure probabilities
- Heuristic tree search
- Local reward functions

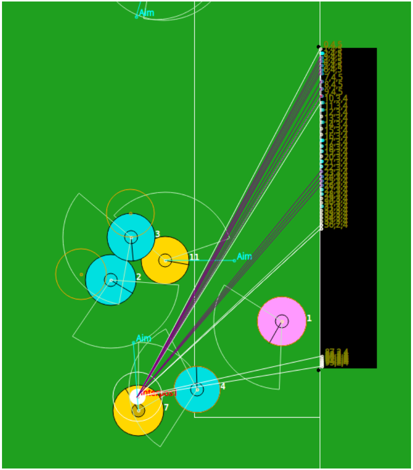


Figure 12: Search in shoot

Hierarchical Planning for Pass Behavior

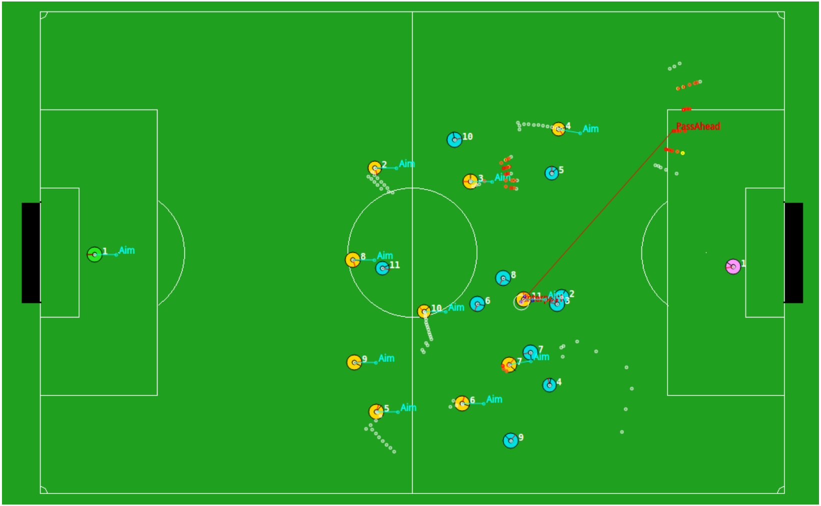


Figure 13: Hierarchical planning for pass behavior

Monte Carlo Tree Search

- Transitions as explicit distributions $\Pr(s' \mid s, a)$ are not available
- Sampling rules $s' \sim \Pr(s' \mid s, a)$ are clearly defined by the simulator
- Monte-Carlo tree search w/ state abstraction
- Low-level skills: $NavTo$, $KickTo$, ...

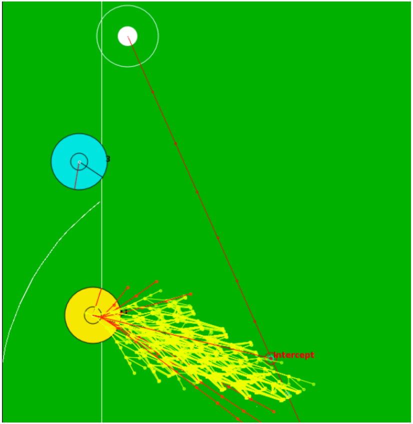


Figure 14: Search tree in *NavTo*

Terminating Distribution Estimation - An Example

- $\Pr(s_{goal} \mid s, KickTo(t)) \approx (1 - p_1) \times p_2$
  - $p_1 = \Pr(s_{caught} \mid s, KickTo(t))$
  - $p_2 = \Pr(s_{in} \mid s, KickTo(t))$

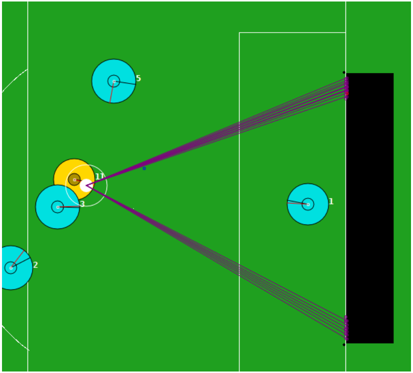


Figure 15: A shoot scenario

Terminating Distribution Estimation - An Example (Cont'd)

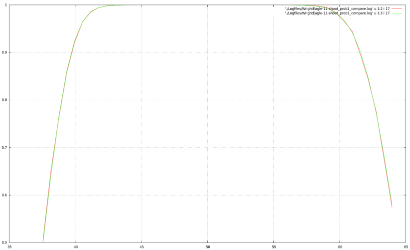


Figure 16: $\Pr(s_{in} \mid s, KickTo(t))$

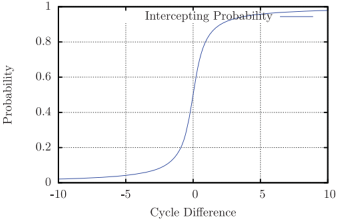


Figure 17: $\Pr(s_{caught} \mid s, KickTo(t)) \approx \max_p f(t_b(p,s) - t_g(p,s) \mid p)$

Heuristic Evaluation

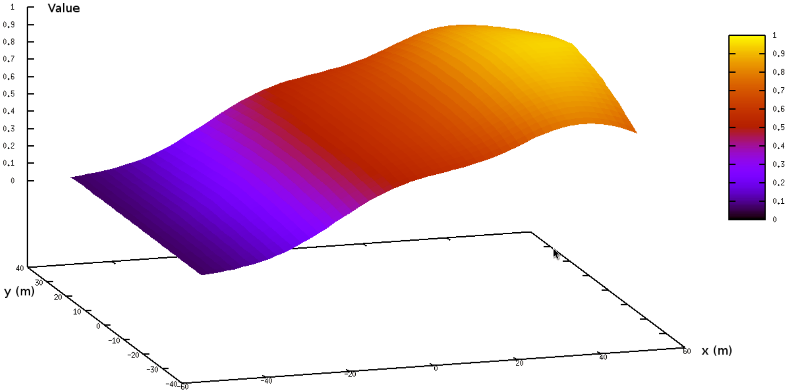


Figure 18: A heuristic function based on ball position

The Idea of Virtual Agent

- The state is augmented with a virtual agent index which is transferred among teammates
  - The teammate controlling the ball
- Search tree is grown from the perspective of the virtual agent
  - Player 5 is doing decision-making
    - A search tree with player 5 as the virtual agent at the root node
    - Player 5 passes the ball to player 7
    - Player 7 becomes the virtual agent for the subtree thereof

Achievements

WrightEagle team (from Univ. of Sci. & Tech. of China):

- Started work on RoboCup 2D since 2006
- Became the main contributor since 2009
- Won 5 world champions: 2009, 2011, 2013, 2014 and 2015
- Published on NIPS, AAMAS, ICAPS, RoboCup, etc.
- More information:
  - `https://en.wikipedia.org/wiki/RoboCup_2D_Soccer_Simulation_League`
  - `http://www.wrighteagle.org/2d/`

Hierarchical Reinforcement Learning

- Hierarchical planning:

  PlanAttack() {
  ...
  shoot $\leftarrow$ PlanShoot()
  pass $\leftarrow$ PlanPass()
  dribble $\leftarrow$ PlanDrrible()
  ...
  return $\max\{$shoot, pass,
  dribble, ...$\}$
  }

Hierarchical abstract machines (HAMs) (Parr & Russell, 1998):

- Write a partial program for an agent
- Leave some undetermined choice points
- Use reinforcement learning to learn an optimal completion

Partial Program

Partial program: an incomplete policy $\pi(s)$ with (many) unspecified choice states

- A hierarchical finite state machine with choice states
- Equivalently, a piece of code with choice macros

Partial Program - an Example

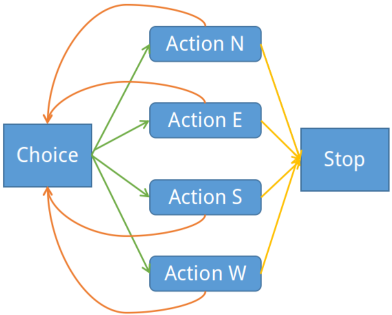


Figure 19: An FSM

Navigate(State s) {
while *!atDestination(s)* **do**
  a ← Choose({N, E, S, W})
  Action(a)
  s ← GetState()
}

Hierarchical Abstract Machines

- A hierarchy of partial programs
- High-level programs can call low-level programs
- Each program has its own:
  - Machine state
  - Call stack
  - Internal memory

M_1(State s) {
while *!terminated(M_1, s)* **do**
  m ← $Choose_1(\{M_2, M_3\})$
  Call(m)
}

M_2(State s) {
while *!terminated(M_2, s)* **do**
  a ← $Choose_2(\{a_1, a_2\})$
  Action(a); s ← GetState()
}

Hierarchical Reinforcement Learning with HAMs

An agent executing a partial program:

- An MDP over joint space of environment and machine states
- An SMDP over choice points
  - Choice point: a joint state with machine state as a choice state
  - $Q(s, m, c) \leftarrow R(s, m, c, s', m', \tau) + \gamma^{\tau} Q(s', m', c')$

Deterministic Transitions Among Choice Points

Deterministic transitions:

- $(s, [M_1, Choose_1], M_2) \rightarrow (s, [M_1, M_2, Choose_2])$
- $\tau = 0$
- $r = 0$
- $Q(s, m, c) = V(s, m') = \max_{c'} Q(s, m', c')$

M_1(State s) {
while *!terminated(M_1, s)* **do**
  m ← $Choose_1$({M_2, M_3})
  Call(m)
}

M_2(State s) {
while *!terminated(M_2, s)* **do**
  a ← $Choose_2$({a_1, a_2})
  Action(a); s ← GetState()
}

Concurrent Hierarchical Learning with HAMs

- Each agent has its own partial program
- Running and learning concurrently
  - $Q(\mathbf{s}, \mathbf{m}, \mathbf{c}) \leftarrow R(\mathbf{s}, \mathbf{m}, \mathbf{c}, \mathbf{s}', \mathbf{m}', \tau) + \gamma^\tau Q(\mathbf{s}', \mathbf{m}', \mathbf{c}')$
  - Share machine state and value functions
  - Make joint choices when available

Synchronization Semantics

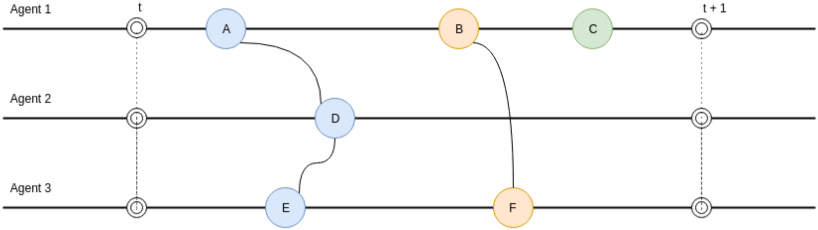


Figure 20: Synchronization for concurrent learning

RoboCup Keepaway Task

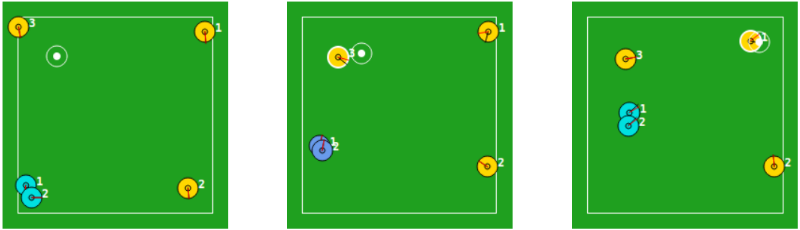


Figure 21: A 3 vs 2 RoboCup keepaway task

- Keepers: maintain possession of the ball
- Takers: gain possession of the ball
- Assume fully communication with shared memory

HAMs for RoboCup Keepaway

Partial program for keepers:

- If fastest to intercept, intercept
- If kickable, call hold or pass
- Otherwise, call stay or move

Unspecified choice states:

- Choose({Hold, Pass})
  - Choose({PassTo1, PassTo2}), Choose({PassSpeed...})
- Choose(Stay, Move)
  - Choose({MoveToDir...}), Choose({MoveSpeed...})

Function Approximation

- State: 15 dimensional feature vectors
  - $\mathbf{s} = [f_1, f_2, \ldots, f_{15}]$
  - Distances and angles
- Tile coding (encode $\mathbf{s} \times \mathbf{m}$ into a huge binary vector)
  - $\mathbf{s} \times \mathbf{m} = [1000101010..0101]_{50,000} = [t_1, t_2, \ldots, t_{480}]$
- Linear SARSA learning with binary features
  - $Q(\mathbf{s}, \mathbf{m}, \mathbf{c}) \approx w_{\mathbf{c}}[t_1] + w_{\mathbf{c}}[t_2] + \cdots + w_{\mathbf{c}}[t_{480}]$

Demonstration: Learned Policy

- Learned policy at early stage
- Converged policy

Summary

- RoboCup soccer simulation 2D
  - A belief-MDP formulation
- A hierarchical planning approach
  - MAXQ-OP online planning
- A hierarchical learning approach
  - Concurrent reinforcement learning with HAMs

Future Work

- Hierarchical Monte Carlo planning
- Reward decomposition and reward shaping
- Coordination graph for joint choices
- Game theoretical planning/learning

Thank you!

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