The RoboCup 2013 Drop-In Player Challenges: A Testbed for Ad Hoc Teamwork

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LARG
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The University of Texas at Austin
Many of the best players in the world: Dwyane Wade, LeBron James, Carmelo Anthony, Tim Duncan and Allen Iverson.

Dream team expected to dominate

Before 2004, American teams had only lost two games in all previous Olympic tournaments, whereas in this one the American team lost three.

Big disappointment as team only got bronze medal.
RoboCup Drop-In Player Challenges

- RoboCup is an international robotics competition where autonomous robots play soccer.
- Games between teams consisting of different randomly chosen players from participants in the competition.
- No pre-coordination between teammates, teammates/opponents unknown before start of a game.
- Teams provided standard communication protocol for use during games.
- Testbed for ad hoc teamwork.
- Challenge held across three leagues at the 2013 RoboCup competition:
  - Standard Platform League (SPL)
  - 2D Simulation League
  - 3D Simulation League
Related Work

- Bowling, M., McCracken, P.: Coordination and adaptation in impromptu teams. In: AAAI, 2005

First large scale ad hoc teamwork challenge of its kind in the wild!
How To Determine Drop-In Teams

Choose drop-in players for teams using a greedy algorithm that selects players to add to teams using the following ordered preference list:

1. Played fewer games
2. Played against fewer of the opponents
3. Played with fewer of the teammates
4. Played a lower maximum number of games against any one opponent or with any one teammate
5. Played a lower maximum number of games against any one opponent
6. Played a lower maximum number of games with any one teammate
7. Random
Standard Platform League (SPL)

- Use Nao robots
- Teams of 5 vs 5 autonomous robots play soccer
- Robots can communicate over wifi
SPL Drop-In Player Challenge

- Participating teams contributed 1-2 drop-in players per 5 vs 5 game

- Games were only played for 5 minutes

- Teams provided a standard communication protocol
  - current position and variance (uncertainty) of position
  - ball’s position, variance of position, velocity, time last seen
  - boolean variables if robot has fallen or been penalized

- Drop-in players scored as combination of normalized average goal difference (AGD) and average score of human judges (AHS) between 0-10

\[
\text{score} = \text{AGD} \times \frac{10}{\text{max AGD of a drop-in player}} + \text{AHS}
\]
SPL Drop-In Player Challenge Strategy (UT Austin Villa)

- Players assigned to roles based on positions on field

- Use position information communicated by drop-in player teammates to determine who should go to ball

- When kicking will try and pass ball to teammates in good position to receive ball, but if no teammates in position then kick ball down field

- Strategy is similar to the one used for regular games
SPL Drop-In Challenge Game Video
### SPL Drop-In Player Challenge Results

Final scores and rankings for the SPL drop-in challenge (4 games played)

<table>
<thead>
<tr>
<th>Team</th>
<th>Avg Goal Diff</th>
<th>Norm Goal Diff</th>
<th>Avg Judge Score</th>
<th>Final Score</th>
<th>Rank (Goal, Judge)</th>
</tr>
</thead>
<tbody>
<tr>
<td>B-Human</td>
<td>1.17</td>
<td>10.00</td>
<td>6.67</td>
<td>16.67</td>
<td>1 (1,1)</td>
</tr>
<tr>
<td>Nao Devils</td>
<td>0.57</td>
<td>4.90</td>
<td>6.24</td>
<td>11.14</td>
<td>2 (3,2)</td>
</tr>
<tr>
<td>rUNSWift</td>
<td>0.67</td>
<td>5.71</td>
<td>5.22</td>
<td>10.94</td>
<td>3 (2,4)</td>
</tr>
<tr>
<td>UTAustinVilla</td>
<td>-0.29</td>
<td>-2.45</td>
<td>6.00</td>
<td>3.55</td>
<td>4 (4,3)</td>
</tr>
<tr>
<td>UPennalizers</td>
<td>-0.57</td>
<td>-4.90</td>
<td>4.48</td>
<td>-0.42</td>
<td>5 (5,5)</td>
</tr>
<tr>
<td>Berlin United</td>
<td>-1.29</td>
<td>-11.02</td>
<td>3.38</td>
<td>-7.64</td>
<td>6 (6,6)</td>
</tr>
</tbody>
</table>

### Comparison of drop-in results vs main competition results

<table>
<thead>
<tr>
<th>Team</th>
<th>Drop-In Rank</th>
<th>Main Rank</th>
<th>Main W/T/L</th>
<th>Main Goals</th>
</tr>
</thead>
<tbody>
<tr>
<td>B-Human</td>
<td>1</td>
<td>1</td>
<td>8/0/0</td>
<td>62</td>
</tr>
<tr>
<td>Nao Devils</td>
<td>2</td>
<td>T5</td>
<td>4/1/2</td>
<td>18</td>
</tr>
<tr>
<td>rUNSWift</td>
<td>3</td>
<td>4</td>
<td>5/0/4</td>
<td>18</td>
</tr>
<tr>
<td>UTAustinVilla</td>
<td>4</td>
<td>3</td>
<td>6/0/2</td>
<td>30</td>
</tr>
<tr>
<td>UPennalizers</td>
<td>5</td>
<td>17</td>
<td>4/0/2</td>
<td>17</td>
</tr>
<tr>
<td>Berlin United</td>
<td>6</td>
<td>T9</td>
<td>1/1/3</td>
<td>3</td>
</tr>
</tbody>
</table>

### Correlation between human/judge scores and drop-in/regular soccer performance

Patrick MacAlpine (2014)
2D Simulation League

- Teams of 11 vs 11 autonomous agents play soccer
- Agents use primitives of "dash", "kick", and "turn" to interact with environment
- Agents receive noisy visual information about environment
- Agents can communicate with each other over limited bandwidth channel
2D Simulation Drop-In Player Challenge

- Games are 7 vs 7 (not 11 vs 11) to prevent implicit coordination of teams using default formations from widely used released Agent2D code base

- Full 10 minute games (two 5 minute halves)

- Teams contribute 2 drop-in players for a game

- Goalies are from released open source Agent2D team

- Teams encouraged to use Agent2D communication protocol
  - position of the ball
  - agent positions

- Score is average goal difference across all games played
Adapt to teammates by using dynamic role assignment (SCRAM) to take on roles/positions not currently assumed by other teammates

Yellow players 4 and 11 from UTAustinVilla use SCRAM role assignment
2D Simulation Drop-In Player Challenge Results (7 games played)

Average goal difference (AGD) with standard error shown in parentheses and rankings for the 2D drop-in player challenge (7 games) and also across many (4200) games.

<table>
<thead>
<tr>
<th>Team</th>
<th>AGD</th>
<th>Rank</th>
<th>AGD</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCPerspolis</td>
<td>2.40</td>
<td>1</td>
<td>3.025 (0.142)</td>
<td>1</td>
</tr>
<tr>
<td>Yushan</td>
<td>2.25</td>
<td>2</td>
<td>2.583 (0.141)</td>
<td>2</td>
</tr>
<tr>
<td>ITAndroids</td>
<td>2.00</td>
<td>3</td>
<td>1.379 (0.152)</td>
<td>5</td>
</tr>
<tr>
<td>Axiom</td>
<td>1.20</td>
<td>4</td>
<td>1.315 (0.148)</td>
<td>6</td>
</tr>
<tr>
<td>UTAustinVilla</td>
<td>0.25</td>
<td>5</td>
<td>1.659 (0.153)</td>
<td>4</td>
</tr>
<tr>
<td>HfutEngine</td>
<td>-0.20</td>
<td>6</td>
<td>-2.076 (0.152)</td>
<td>7</td>
</tr>
<tr>
<td>WrightEagle</td>
<td>-1.60</td>
<td>7</td>
<td>-6.218 (0.129)</td>
<td>9</td>
</tr>
<tr>
<td>FCPortugal</td>
<td>-2.20</td>
<td>8</td>
<td>-3.379 (0.150)</td>
<td>8</td>
</tr>
<tr>
<td>AUTMasterminds</td>
<td>-2.80</td>
<td>9</td>
<td>1.711 (0.152)</td>
<td>3</td>
</tr>
</tbody>
</table>

- Adding SCRAM dynamic role assignment to UTAustinVilla improved performance in the challenge from an average goal difference of 1.473 (+/-0.157) with static role assignments to 1.659 (+/-0.153)
2D Simulation Drop-In Player Challenge Further Analysis

Average goal difference (AGD) with standard error shown in parentheses and rankings for the 2D drop-in player challenge across many games, main competition, and playing against UTAustinVilla

<table>
<thead>
<tr>
<th>Team</th>
<th>Drop-In Rank</th>
<th>Main Rank</th>
<th>Against UTAustinVilla Rank</th>
<th>AGD</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCPerspolis</td>
<td>1</td>
<td>5</td>
<td>4</td>
<td>3.127 (0.059)</td>
</tr>
<tr>
<td>Yushan</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>4.034 (0.065)</td>
</tr>
<tr>
<td>AUTMasterminds</td>
<td>3</td>
<td>4</td>
<td>2</td>
<td>5.111 (0.117)</td>
</tr>
<tr>
<td>UTAustinVilla</td>
<td>4</td>
<td>8</td>
<td>8</td>
<td>0.000 (self)</td>
</tr>
<tr>
<td>ITAndroids</td>
<td>5</td>
<td>7</td>
<td>7</td>
<td>0.505 (0.063)</td>
</tr>
<tr>
<td>Axiom</td>
<td>6</td>
<td>3</td>
<td>5</td>
<td>1.803 (0.074)</td>
</tr>
<tr>
<td>HfutEngine</td>
<td>7</td>
<td>9</td>
<td>9</td>
<td>-6.027 (0.184)</td>
</tr>
<tr>
<td>FCPortugal</td>
<td>8</td>
<td>6</td>
<td>6*</td>
<td></td>
</tr>
<tr>
<td>WrightEagle</td>
<td>9</td>
<td>1</td>
<td>1</td>
<td>6.176 (0.287)</td>
</tr>
</tbody>
</table>

- Top half of drop-in player challenge teams had an average rank of 4.25 against UTAustinVilla.
- Bottom half had an average rank of 6.75.
3D Simulation League

- Teams of 11 vs 11 autonomous agents play soccer
- Realistic physics using Open Dynamics Engine (ODE)
- Agents modeled after Aldebaran Nao robot
- Agents receives noisy visual information about environment
- Agents can communicate with each other over limited bandwidth channel
3D Simulation Drop-In Player Challenge

- Games are 10 vs 10 (no goalies)

- Full 10 minute games (two 5 minute halves)

- Teams contribute 2 drop-in players for a game

- Teams are provided a standard communication protocol
  - position of the ball
  - time ball last seen
  - position of the agent
  - if agent has fallen

- Score is average goal difference across all games played
3D Simulation Drop-In Player Challenge Strategy (UT Austin Villa)

- Attempt to beam (teleport) in to take kickoff
- Go to ball if closest player otherwise stay behind ball in support role
- Evaluate communicated information from teammates to determine if they’re trustworthy

Blue player 2 and 3 from UTAustinVilla
3D Simulation Drop-In Player Challenge Results (4 games played)

Average goal difference (AGD) with standard error shown in parentheses and rankings for the 3D drop-in player challenge (4 games) and also across many (630) games

<table>
<thead>
<tr>
<th>Team</th>
<th>AGD</th>
<th>Rank</th>
<th>AGD (SE)</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>BoldHearts</td>
<td>1.50</td>
<td>1</td>
<td>0.178 (0.068)</td>
<td>4</td>
</tr>
<tr>
<td>FCPortugal</td>
<td>0.75</td>
<td>T2</td>
<td>1.159 (0.060)</td>
<td>1</td>
</tr>
<tr>
<td>Bahia3D</td>
<td>0.75</td>
<td>T2</td>
<td>-0.378 (0.068)</td>
<td>7</td>
</tr>
<tr>
<td>Apollo3D</td>
<td>0.75</td>
<td>T2</td>
<td>0.159 (0.068)</td>
<td>5</td>
</tr>
<tr>
<td>magmaOffenburg</td>
<td>0.25</td>
<td>5</td>
<td>0.254 (0.068)</td>
<td>3</td>
</tr>
<tr>
<td>RoboCanes</td>
<td>-0.50</td>
<td>6</td>
<td>-0.286 (0.068)</td>
<td>6</td>
</tr>
<tr>
<td>UTAustinVilla</td>
<td>-0.75</td>
<td>T7</td>
<td>0.784 (0.065)</td>
<td>2</td>
</tr>
<tr>
<td>SEUJolly</td>
<td>-0.75</td>
<td>T7</td>
<td>-0.613 (0.066)</td>
<td>9</td>
</tr>
<tr>
<td>Photon</td>
<td>-0.75</td>
<td>T7</td>
<td>-0.425 (0.068)</td>
<td>8</td>
</tr>
<tr>
<td>L3MSIM</td>
<td>-1.25</td>
<td>10</td>
<td>-0.832 (0.065)</td>
<td>10</td>
</tr>
</tbody>
</table>

Evaluations across only a few games are very noisy
3D Simulation Drop-In Player Challenge Strategy Analysis

Average goal difference (AGD) with standard error shown in parentheses and rankings for the 3D drop-in player challenge across many (630) games

<table>
<thead>
<tr>
<th>Agent</th>
<th>AGD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dribble</td>
<td>1.370 (0.064)</td>
</tr>
<tr>
<td>UT Austin Villa</td>
<td>0.784 (0.065)</td>
</tr>
<tr>
<td>NoKickoff</td>
<td>0.676 (0.065)</td>
</tr>
<tr>
<td>DynamicRoles</td>
<td>0.568 (0.071)</td>
</tr>
</tbody>
</table>

Dribble  Agent only dribbles and never kicks.
DynamicRoles Uses dynamic role assignment.
NoKickoff  No teleporting next to ball to take the kickoff.

Dynamic role assignment useful in domains where agents have equal skills (2D) but not as much when there is a large disparity in skill levels (3D)
3D Simulation Drop-In Player Further Analysis

Average goal difference (AGD) with standard error shown in parentheses and rankings for the 3D drop-in player challenge over many games, main competition, and playing against UTAustinVilla

<table>
<thead>
<tr>
<th>Team</th>
<th>Drop-In</th>
<th>Main</th>
<th>Against UTAustinVilla</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rank</td>
<td>Rank</td>
<td>Rank</td>
</tr>
<tr>
<td>FCPortugal</td>
<td>1</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>UTAustinVilla</td>
<td>2</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>magmaOffenburg</td>
<td>3</td>
<td>T5</td>
<td>5</td>
</tr>
<tr>
<td>BoldHearts</td>
<td>4</td>
<td>T5</td>
<td>6</td>
</tr>
<tr>
<td>Apollo3D</td>
<td>5</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>RoboCanes</td>
<td>6</td>
<td>T5</td>
<td>7</td>
</tr>
<tr>
<td>Bahia3D</td>
<td>7</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Photon</td>
<td>8</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td>SEUJolly</td>
<td>9</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>L3MSIM</td>
<td>10</td>
<td>9</td>
<td>9</td>
</tr>
</tbody>
</table>

Top half of drop-in player challenge teams had an average rank of 3.4 against UTAustinVilla, bottom half had an average rank of 7.6
Summary

Drop-In Player challenges provide a good testbed and template for ad hoc teamwork.
Summary

- Drop-In Player challenges provide a good *testbed and template for ad hoc teamwork*

- Considerable *noise makes it hard to evaluate agents after only a few games*
Summary

- Drop-In Player challenges provide a good testbed and template for ad hoc teamwork

- Considerable noise makes it hard to evaluate agents after only a few games

- There is a strong correlation between teams’ performances in the drop-in player challenge and regular soccer
Open Questions

- How to get more meaningful results in only a few games?
  - Use a scoring metric with more granularity and less noise
  - Award teams for successful passes, ball possession, and shots on goal
  - How do best measure/evaluate/score ad hoc teamwork?
    - Assign credit to individuals instead of having the same reward for the entire team
    - Subjective vs quantitative scores
    - Normalize scores based on agents individual abilities
Open Questions

How to get more meaningful results in only a few games?

- Use a scoring metric with more granularity and less noise
- Award teams for successful passes, ball possession, and shots on goal
Open Questions

- **How to get more meaningful results in only a few games?**
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  - Award teams for successful passes, ball possession, and shots on goal

- **How do best measure/evaluate/score ad hoc teamwork?**
Open Questions

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  - Use a scoring metric with more granularity and less noise
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- How do best measure/evaluate/score ad hoc teamwork?
  - Assign credit to individuals instead of having the same reward for the entire team
  - Subjective vs quantitative scores
  - Normalize scores based on agents' individual abilities
2014 RoboCup Drop-In Player Challenges

- **Standard Platform League (SPL)**
  - Mandatory participation
  - Attempting to standardize human judge scoring

- **2D Simulation**
  - Interest in holding the challenge again but no decision on this has been made yet

- **3D Simulation**
  - Challenge will be held again with similar rules to 2013
  - Teams will be encouraged to write about and document strategies
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- 3D Simulation
  - Challenge will be held again with similar rules to 2013
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Hope that these challenges provide a template for adhoc teamwork research test beds in other domains
More Information

More information and videos at:
http://tinyurl.com/arms14dropin
Email: patmac@cs.utexas.edu

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