UT^2: Human-like Behavior via Neuroevolution of Combat Behavior and Replay of Human Traces

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Our Approach: UT^2

- Human traces to get unstuck and navigate
  - Filter data to get general-purpose traces
  - Future goal: generalize to new levels
- Evolve skilled combat behavior
  - Restrictions/filters maintain humanness
- Probabilistic judging based on experience
  - Also assume that humans judge well
Index and replay nearest traces

- Get unstuck
  - Mix of scripted responses and human traces
  - Human traces used when scripted response fails

- Explore levels
  - Want to explore like humans
  - Synthetic data: lone human wandering levels
  - Allow collisions since humans bump into walls with no problem
  - Resort to A* when retracing does not work
Use of Evolution

Evolved neural network in Battle Controller defines combat behavior
Battle Controller Outputs

• 6 movement outputs
  – Advance
  – Retreat
  – Strafe left
  – Strafe right
  – Move to nearest item
  – Stand still

• Additional output
  – Jump?
Battle Controller Inputs

- Pie slice sensors for enemies
- Ray traces for walls/level geometry
- Opponent movement sensors
- Other misc. sensors for current weapon properties, nearby item properties, etc.
Evolving Battle Controller

• Used NSGA-II with 3 objectives
  – Damage dealt
  – Damage received (negative)
  – Geometry collisions (negative)

• Evolved in DM-1on1-Albatross
  – Small level to encourage combat
  – One native bot opponent

• High score favored in selection of final network

• Final combat behavior highly constrained
Playing the judging game
Judging

• When to judge
  – More likely after more interaction
  – More likely as time runs out
  – Judge if successful judgment witnessed

• How to judge
  – Assume equal # humans and bots
  – Mostly judge probabilistically
  – Assume target is human if it judged correctly
## Humanness results

<table>
<thead>
<tr>
<th>Most human bots</th>
<th>Most human humans</th>
<th>Most human epic bots</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>bot name</strong></td>
<td><strong>player name</strong></td>
<td><strong>skill level</strong></td>
</tr>
<tr>
<td><strong>humanness %</strong></td>
<td><strong>humanness %</strong></td>
<td><strong>humanness %</strong></td>
</tr>
<tr>
<td>UT^2</td>
<td>Craig Speelman</td>
<td>1</td>
</tr>
<tr>
<td>21.0526 %</td>
<td></td>
<td>33.3333 %</td>
</tr>
<tr>
<td>HumanLikeBot</td>
<td>Chris Holme</td>
<td>4</td>
</tr>
<tr>
<td>17.6471 %</td>
<td></td>
<td>28.5714 %</td>
</tr>
<tr>
<td>ICE-WCCI2012</td>
<td>John Weise</td>
<td>2</td>
</tr>
<tr>
<td>7.6923 %</td>
<td></td>
<td>11.1111 %</td>
</tr>
<tr>
<td></td>
<td>Samaneh Rastegari</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>9.0909 %</td>
<td>0.0000 %</td>
</tr>
</tbody>
</table>

## Judging results

### Best bot judges

<table>
<thead>
<tr>
<th>bot name</th>
<th>accuracy %</th>
</tr>
</thead>
<tbody>
<tr>
<td>UT^2</td>
<td>53.8462 %</td>
</tr>
<tr>
<td>HumanLikeBot</td>
<td>51.2195 %</td>
</tr>
<tr>
<td>ICE-WCCI2012</td>
<td>40.0000 %</td>
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</tbody>
</table>

### Best human judges

<table>
<thead>
<tr>
<th>human name</th>
<th>accuracy %</th>
</tr>
</thead>
<tbody>
<tr>
<td>John Weise</td>
<td>63.4146 %</td>
</tr>
<tr>
<td>Chris Holme</td>
<td>61.9048 %</td>
</tr>
<tr>
<td>Samaneh Rastegari</td>
<td>56.8182 %</td>
</tr>
<tr>
<td>Craig Speelman</td>
<td>50.0000 %</td>
</tr>
</tbody>
</table>
Where do we stand?

Bots vs Humans, 2008–2011

2012
Best human
Best built in bot
Best entry (UT^2)

% judged human

bots  builtins  humans
Discussion

• Bot humanness is still low!
• Native bots are still most human!
• Humans are not very human either!
• Does judging change the game?
• Does the API hinder our progress?
• More detailed judgment analysis…
Questions?

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