Reinforcement learning for autonomous and novel behavior in OneSAF

Potential for new TTPs, technology evaluation, and Requirements definitions

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Reinforcement Learning (RL) can enhance OneSAF by adding autonomy to simulation entities

Autonomous entities create potential for:

- Generating new battlefield strategies with minimal human bias
- Helping warfighters learn in a much more creative, stimulating, and instructive environment
- Expanding how the military engages in future conflicts
- Allowing experimentation and evaluation of new technologies
- Informing Requirements definitions for the future force
One Semi-automated Forces (OneSAF)

A simulation tool for modeling real-world representations of combat and non-combat operations

- Used for design, experimentation, analysis, and training, including human-in-the-loop scenarios
- Physics-based (realistic) environment
- Uses behavior models to control entities
- Behaviors are rule-based and customizable

Goal: add RL capability to enhance entity behaviors

https://ict.usc.edu/prototypes/onesaf/#gallery-1
Advantages of RL over rule-based models

- **Complexity**: Complex situations require more rules than humans can derive
- **Adaptation**: Decisions are made even if situation is new
- **Novelty**: Thorough exploration allows new solutions to be found
**RL is a type of Machine Learning (ML)**

<table>
<thead>
<tr>
<th>Supervised Learning (SL)</th>
<th>Unsupervised Learning (UL)</th>
<th>Reinforcement Learning (RL)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Data Constraints</strong></td>
<td><strong>Existing Dataset</strong></td>
<td><strong>Create Data via Exploration</strong></td>
</tr>
<tr>
<td><strong>Training Data</strong></td>
<td><strong>Labeled (tagged)</strong></td>
<td><strong>Unlabeled</strong></td>
</tr>
<tr>
<td><strong>Common Objectives</strong></td>
<td><strong>Classification, Regression</strong></td>
<td><strong>Labeling, Segmentation, Clustering</strong></td>
</tr>
</tbody>
</table>

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[Diagram showing classification, regression, decision/action sequences]
RL Is an Exploratory Learning Approach

Learns from potentially infinite examples in environment (complex problem)

Result is a policy for decision making that optimizes expected reward

https://deepmind.com/blog/article/generally-capable-agents-emerge-from-open-ended-play

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Reinforcement Learning: Applications

- Manufacturing: Robotics, computer chip design
- Warehouse process efficiency
- Data center cooling and control (Google)
- Autonomous navigation of vehicles
- Healthcare Treatment Policy
- Trading and Bidding strategies

High level competitive games (DoTA:2, Starcraft2)
- OpenAI’s ‘Five’ beats human world-champion team in 5v5 match
- AlphaGo/lee/Zero defeat world’s top players
RL in Aircraft Autonomy: Air combat

Complex flight behavior (AI is pilot)

F-16 drone wins ‘Human vs Artificial Intelligence’ aerial dogfight
https://ukdefencejournal.org.uk/f-16-drone-wins-human-
RL-SAF: RL for OneSAF

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RL Model (TD3) -> RL Algorithm -> API

mongodb

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**RL-SAF API (beyond RL)**

- Controls OneSAF via Python
- Communicates with OneSAF via REST endpoints
- Can run sequences of tasks with or without user interaction
  - Examples
    - Load a scenario via scene file/template
    - Move and orient entities via magic commands
    - Initialize, run, and reset a scenario
    - Get/Set entity and simulation properties
- Independent of RL algorithm
RL Algorithm and TD3

- Makes use of OneSAF commands to move and fire
  - More efficient learning for shorter training runs
- Uses OpenAI Gym framework and TD3 algorithm
  - TD3 works well for continuous action spaces (infinite solutions)
- Observation space (available to RL actor/model)
  - RL actor: speed, heading, distance to destination, heading to destination, health, distance to nearby buildings, whether fire command is queued, simulation time
  - Enemy: speed, heading, distance, bearing, health
- Action space (available to RL actor/model)
  - RL actor: forward distance, forward direction, fire
- Reward (sum of components)
  - Time/speed, distance to destination, health, enemy health, out of bounds penalty
Simulation scenario:
- RL Actor (blue) starts in random locations
- Goal is to kill enemy (red) and occupy town (pink cross)
- Enemy follows patrol loop through town
- Both actors may fire at any time

(First animation will show a different scenario)

Results: What to look for in next few slides
- Movement and navigation
- Firing ability
- Novel solutions: improvement over rule-based behavior models
Movement/Navigation: smooth and efficient

Firing ability: Blue does not engage Red

Novel behavior: Blue avoids road to hide from Red

(Alternate scenario)
- **Movement/Navigation:** Blue navigates in urban environment
- **Firing ability:** Blue does not fire even when conditions are right
- **Novel behavior:** Blue avoids damage while attempting to occupy town
- **Movement/Navigation:**
  Finds center of town and high point for firing

- **Firing ability:**
  Blue acquires Red then fires from safe distance (compensates for poor firing performance)

- **Novel behavior:**
  Fires from distance, potentially taking advantage of Red’s firing accuracy at long range
● **Movement/Navigation:**
  Blue moves along tree line behind buildings

● **Firing ability:**
  Blue should fire earlier

● **Novel behavior:**
  Blue hides and waits for Red to stop patrolling, then fires
## Current RL model state

<table>
<thead>
<tr>
<th>Topic</th>
<th>Result</th>
<th>Explanation / Details</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Movement and navigation</strong></td>
<td>⭐⭐⭐⭐</td>
<td>● Fast and efficient</td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Easily avoids obstacles/threats</td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Goes to destination</td>
</tr>
<tr>
<td><strong>Firing ability</strong></td>
<td>⭐⭐⭐</td>
<td>● Effective when conditions are optimal</td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Rarely fires immediately</td>
</tr>
<tr>
<td><strong>Novel solutions</strong></td>
<td>⭐⭐⭐⭐</td>
<td>● Learned to achieve goal in realistic situation (loss of firing capability)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Hides to avoid enemy</td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Waits for enemy to stop, then fires</td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Acquires enemy, then moves far away to fire</td>
</tr>
<tr>
<td><strong>Improvement over rule-based behavior models</strong></td>
<td>⭐⭐⭐⭐</td>
<td>● Uses best capabilities</td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Adapts to situation</td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Learns enemy behavior (without human input)</td>
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</tbody>
</table>

**Easy learning**
- Abundant feedback (every simulation step)

**Difficult learning**
- Delayed firing chain feedback (need more observations)
- Infrequent enemy engagement (need more directed training)

**Few constraints and strong adaptation**
- Essentially no rules (find a way to win)
- Lack of firing capability is partial driver

**Few constraints**
- Essentially no rules (find a way to win)
- Rule-based firing is currently better, but with improvements, RL firing should excel
**RL-SAF enhances OneSAF by adding autonomy to simulation entities**

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High-level explanation of reinforcement learning: [https://quansight.com/post/exploring-reinforcement-learning](https://quansight.com/post/exploring-reinforcement-learning)

Practical RL Short Course (deeper dive and model building): [https://github.com/Quansight/Practical-RL](https://github.com/Quansight/Practical-RL)