Design, Demonstration, and Proof of Concept Using the Explainable Reinforcement Learning (XAI) of Soar for Combat Identification (CID)

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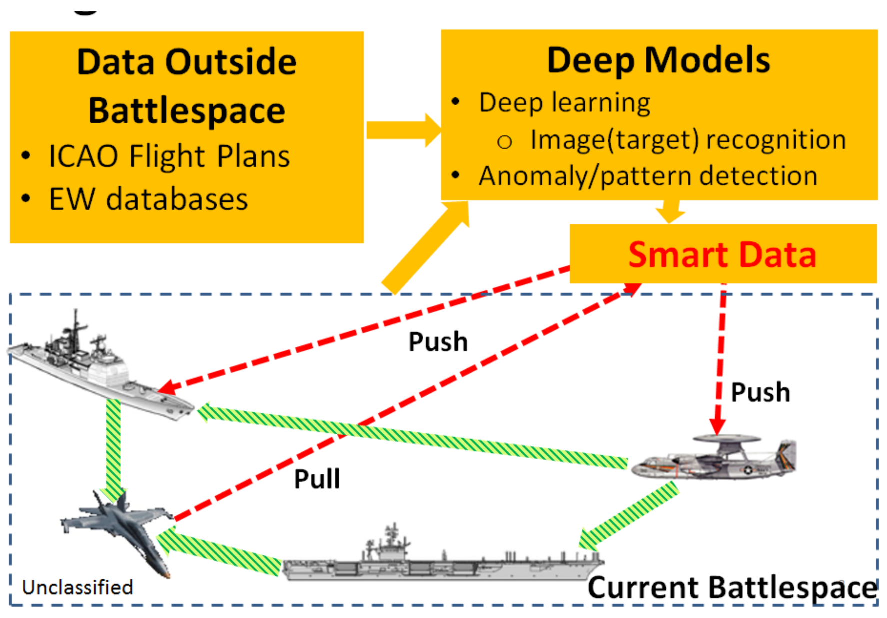
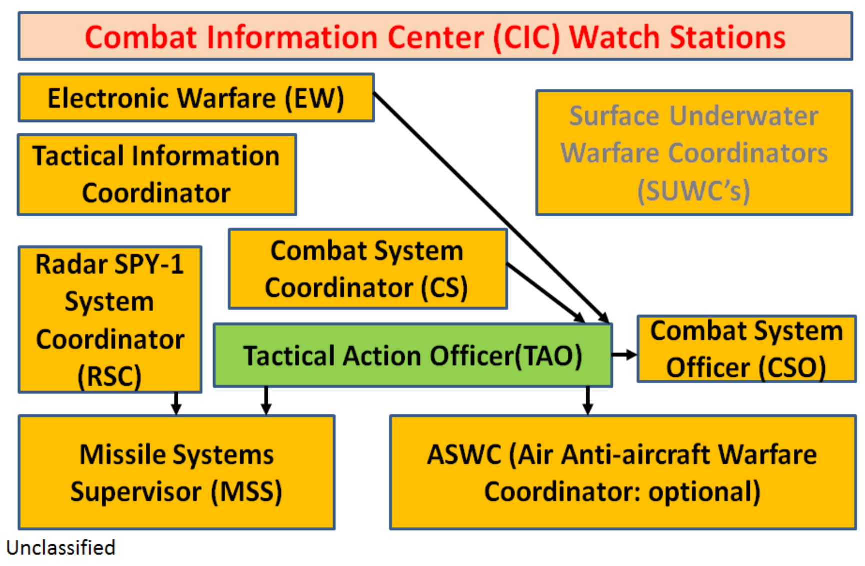
Big Picture and Challenges





Common Tactical Air Picture (CTAP)

- Collects, processes, and analyzes data from a vast network of sensors, platforms, and decision-makers
- Provides situational awareness to air warfare decision-makers

Combat Identification (CID)

- Locates and identifies critical airborne objects as friendly, hostile, or neutral with high precision

CID goals in general are to

- Increase fidelity
- Reduce cognitive burden
- Reduce latency

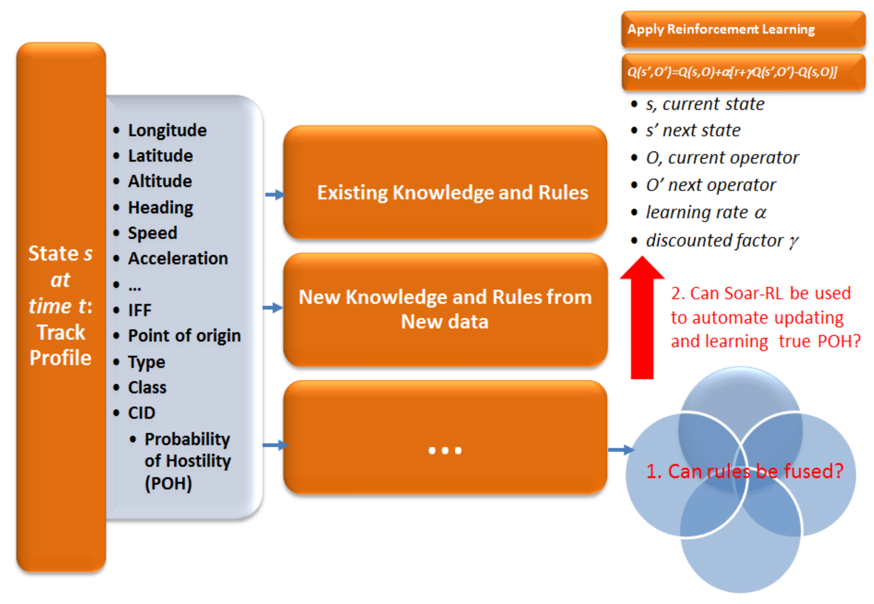
The demo shows the feasibility of applying ML/AI methods to accurately classify military aircraft or not.

The data can be extended to include

- UAS patrol patterns
- Adversarial air tracks
- Surface tracks

Method: Soar Reinforcement Learning and XAI

Soar: An open-source cognitive architecture and rule-based AI tool including reinforcement learning and long-term memory, developed by University of Michigan (Laird, 2012)



Soar-RL has advantages for CID and explainable, because

- It is rule-based
- Can include existing knowledge and rules of engagement
- Can show reasons through rules for classifications and anomalies

(Example: low altitude and slow speed flying objects are anomalous)

As shown in Equation (1),Soar-RL is implemented in a typical RL implementation involving a recursive formula that is widely accepted in the RL research and literature. Since we only consider an on-policy setting or SARSA, $Q(s_{t+1}, a) = 0$ in Equation (1). Therefore, $Q(s_{t+1}, a_{t+1})$ is updated continuously for each time point and immediate reward r.

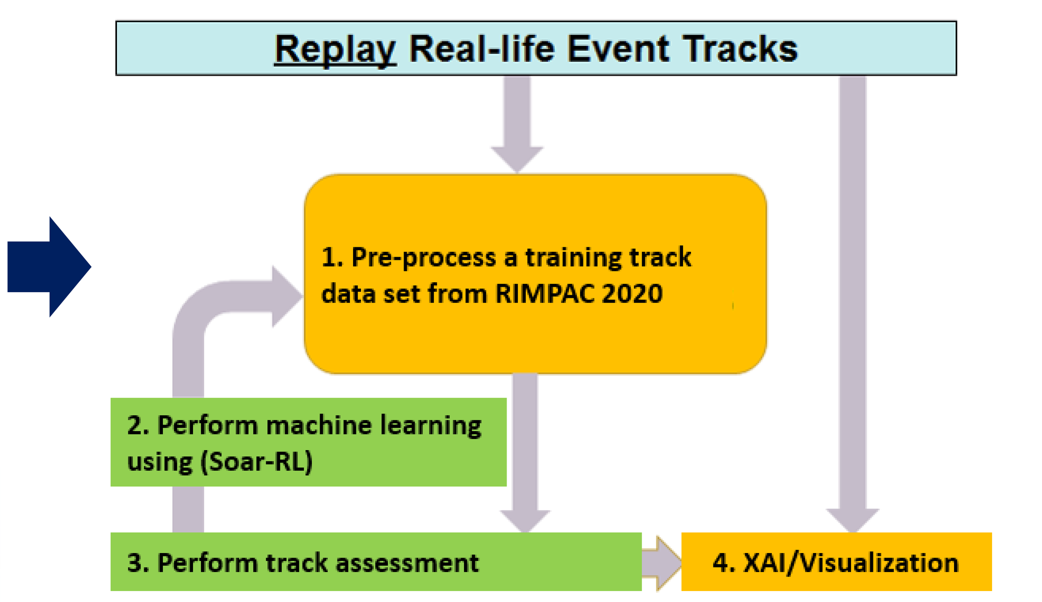
$$Q(s_{t+1}, a_{t+1}) = Q(s_t, a_t) + \alpha[r + \gamma \max_{a\in A} Q(s_{t+1}, a) - Q(s_t, a_t)] \qquad (1)$$

(https://soar.eecs.umich.edu/downloads/Documentation/SoarManual.pdf: page 145)

Tactical Server and Kinematic AI Model Concept

- At-Sea RIMPAC 2020 Exercise Aegis ship tracks collected and tested on the NPS kinematic AI Model
- Multination Exercise in 8/2020 (Source: https://news.usni.org/2020/08/17/scaled-back-at-sea-rimpac-2020-exercise-kicks-off-near-Hawaii)
- **Goal**: Assess airborne objects using kinematic attributes

Demo from Real-life Event Data



For each track, compute kinematics features developed from the ADS-B model (Zhao, etc. 2019, NAML)

- Average altitude up to time *t*
- Average altitude change up to time *t*
- Average absolute altitude change up to time *t*
- Average speed up to time *t*
- Average speed change up to time *t*
- Average absolute speed change up to time *t*
- Average heading change up to time *t*
- Average absolute heading change up to time *t*
- Total altitude change up to time *t*
- Total altitude absolute change up to time *t*
- Total heading change up to time *t*
- Total absolute heading change up to time *t*
- Total speed change to up to time *t*
- Total absolute speed change up to time *t*
- Total track duration up to time *t*

Results

1. Applied an unclassified prototype to the SIPR level RIMPAC data in a few weeks

Demonstrating a Tactical AI for Combat ID

Step 1-4: Generate the ML/AI models from a training data set

Step 1: Compute track features	Edit
Step 2: Pre-condition data	Edit
Step 3: Soar-RL Training	Edit
Step 4: Apply Soar prediction	Edit
Step 5: Fuse all predicted scores	Edit

Step 6: Display an original new test track i (live feed or re-replay from an event, for example)

Step 7: Apply the ML/AI Models to the test track i	Edit

Step 8: Display augmented fields, ML/AI decisions, and scores for the test track i using Google Earth

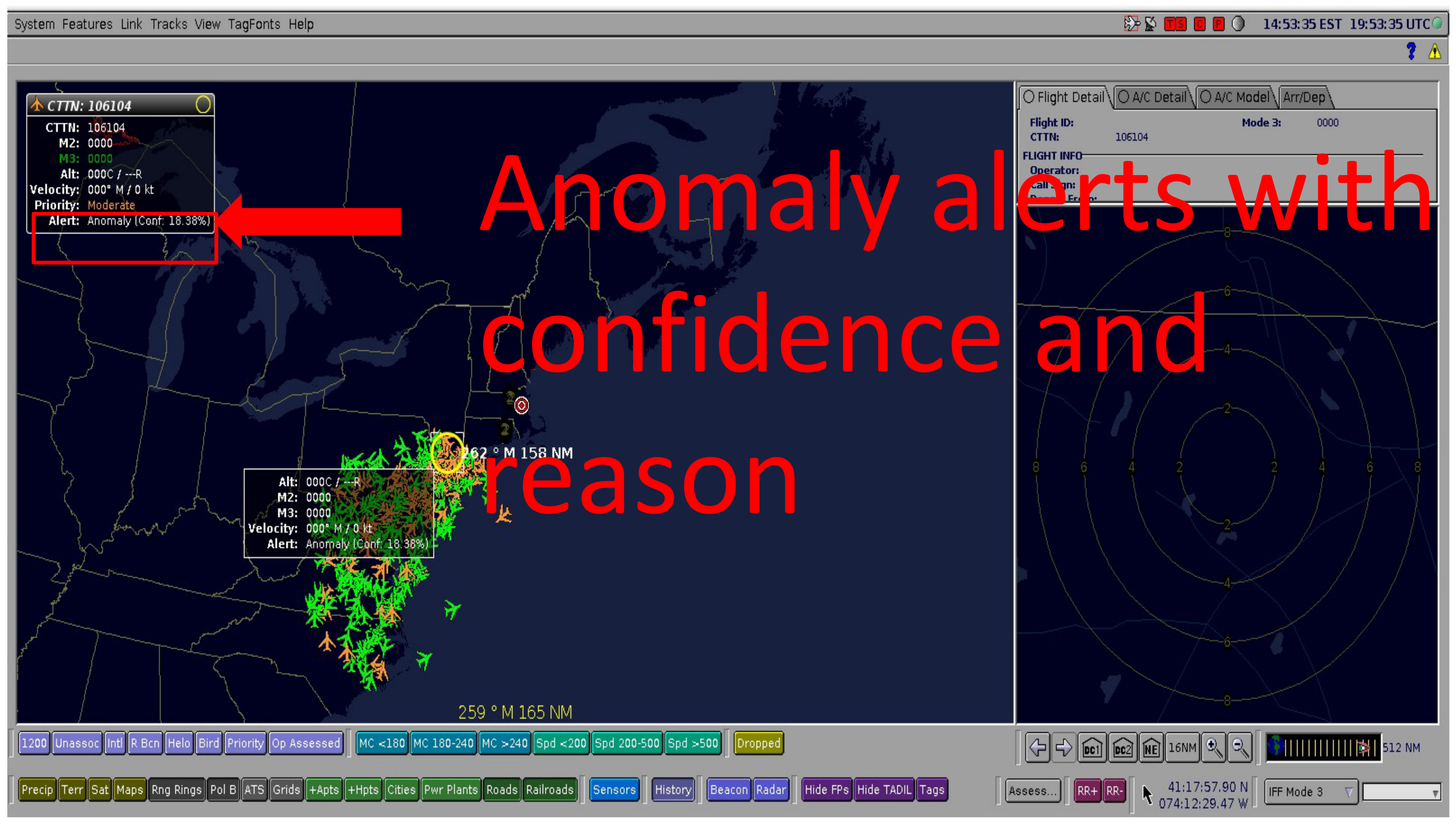
Step 9: Soar-RL Adapt	Edit
Step 10: Google Earth Visualization for Adaptation	Edit

Step 11: Anomaly Detection and Lexical Link Analysis

Step 12: Show Raytheon-MITLL TDF	Edit

2. Demonstrated Soar-RL and XAI using real data in a tactical environment, performed a few shot machine learning and anomaly detection

3. Integrated with the Tactical Display Framework and showed alerts and reasons for anomalies



(A view of an unclassified ADS-D data sample, not RIMPAC data)

Conclusions, Acknowledgements, and Disclaimer

- **Conclusion**
  - Demonstrated an integrated tactical server of kinematics AI model for real exercise data
  - Showed the potential of the Kinematic AI Model with the Soar-RL and XAI for improving the current CID and CTAP to help warfighters and reduce their cognitive load
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- **Disclaimer**: The views presented are those of the authors and do not necessarily represent the views of the U.S. Government, Department of Defense (DoD), or their Components

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