Enhanced Multiagent Reinforcement Learning for Flight Planning of Aerial Vehicles

Weichang Wang[1] Yongming Liu[2] Lei Ying [3]
ECEE, Electrical Engineering, Arizona State University[1]
School for Engineering of Matter, Transport and Energy, Arizona State University[2]
Electrical Engineering and Computer Science Department, University of Michigan, Ann Arbor[3]

Motivations

- The increase of air traffic volume makes the flight planning problem much more complicated.
- Changing environment requires reacting policy
- Efficient Exploration: less data, faster training

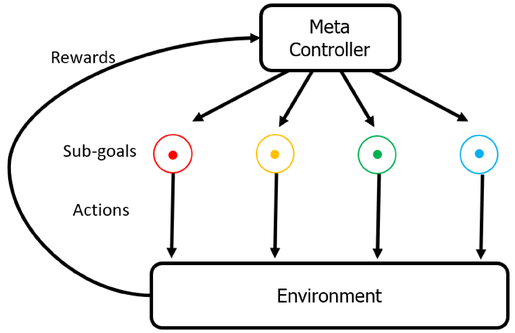
Methodology:

- Hierarchical Training:
  - Meta Controller: assign a task for the vehicles

$$\max_{\pi_g} \mathbb{E}\left[\sum_{t'=t}^{\infty} \gamma^{t'-t} f_{t'}(s,g) | s, \pi_g\right]$$

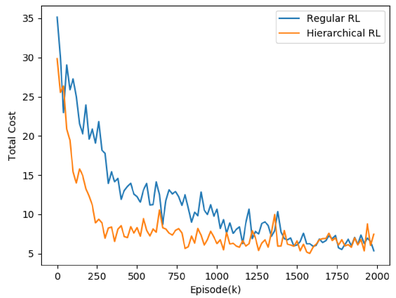
  - Sub Controller: finish assigned task

$$\max_{\pi_{a|g}} \mathbb{E}\left[\sum_{t'=t}^{\infty} \gamma^{t'-t} r_{t'}(s,a|g) \ | s, g, \pi_{a|g}\right]$$



Efficient Exploration in Maze:

- Main Problem: Reach destination
- Sub task: Approach next way point



Efficient Exploration, Faster Training

Algorithm 1: Hierarchical Tabular Q Learning

Input: Initialized tabular $Q_{sub}(s,a|g)$ and $Q_{meta}(s,g)$
foreach *Episode* do
  $s \leftarrow$ Start Points, $g \leftarrow epsGreedy(s, \varepsilon_1, Q_{meta})$;
  while *Not Arrived* do
    $R = 0, S_{meta} = s, T = 0$;
    while $s \neq g, d$ *or* $U(0,1) < \beta$ do
      $a \leftarrow epsGreedy(s, \varepsilon_2, Q_{sub,g})$;
      Execute Action a;
      Obtain reward r, next state s' from environment;
      $R \leftarrow R + \gamma^T R$;
      $f \leftarrow -dist(s,g) - \alpha_1 \mathbb{1}\{\text{collision}\}$;
      $Library_g \leftarrow (s, a, f, s')$;
      $s \leftarrow s'$;
      Update $Q_{sub}(s,a|g)$ from $Library_g$
    end
    $S_{meta} \leftarrow s$;
    $g \leftarrow epsGreedy(s, \varepsilon_1, Q_{meta})$;
    $Library_{meta} \leftarrow (S_{meta}, g, R, T, s)$;
    Update $Q_{meta}(s,a|g)$ from $Library_{meta}$;
  end
end

Mean-Field Multiagent Reinforcement Learning in Continuous State Space

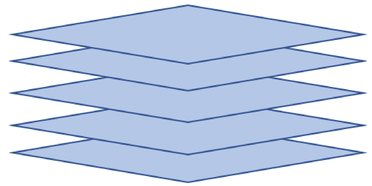
Motivations

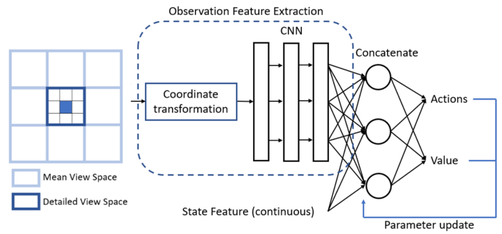
- Discrete space is not able to handle the complex movement of aerial vehicles
- Make the designed flight plan easily implemented.
- Improve the accuracy of the flight plan.

- Advantage:
  - Distributed Algorithms, Centralized Learning with Decentralized Execution
  - Low Complexity
  - Safe Trajectories
- Multi-Resolution Mean-Field
  - Detailed observation on the intruders in close area to the agent, to avoid collision.
  - Mean-field observation only require average number of intruders in further area, to avoid potential congestion.

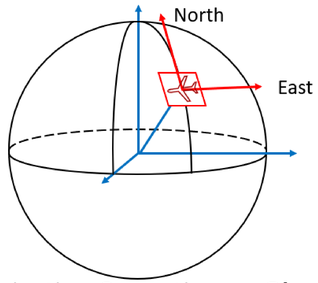
- Implementation in GNATS System
  - Provide a training process for predefined flights
  - Works in cruise phase
  - The longitude and latitude of intruders are corrected on Local tangent plane.
  - The positions updated and decisions made every minute.
  - Control of aircraft: {left-left turn, left turn, remain, right turn, right-right turn}

- Input: Four Layer Matrix
  - 1st layer: mark the number of intruders in the view space
  - 2nd layer: intruder's distance towards destination
  - 3rd layer: intruder's heading direction in the view space
  - 4th layer: intruder's speed in the view space
  - 5th layer: mean view space





Network Structure of MFCA in GNATS



Planar Projection Correction on Observation

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