Announced Strategy Types in Multiagent RL for Conflict-Avoidance in the National Airspace

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Abstract

The use of unmanned aerial systems (UAS) in the national airspace is of growing interest to the research community. Safety and scalability of control algorithms are key to the successful integration of autonomous systems into a human-populated airspace. In order to ensure safety while still maintaining efficient paths of travel, these algorithms must also accommodate heterogeneity of path strategies of its neighbors. We show that, using multiagent RL, we can improve the speed with which conflicts are resolved in cases with up to 80 aircraft within a section of the airspace. In addition, we show that the introduction of abstract agent strategy types to partition the state space is helpful in resolving conflicts, particularly in high congestion.

Introduction

The air traffic density in the national airspace (NAS) is increasing beyond the current capabilities of air traffic controllers. Centralized human control at each sector in the airspace works well for low plane-to-controller ratios, but with the growth commercial air traffic and the future introduction of autonomous systems in the airspace, it is clear that control algorithms must begin to handle some of the safety in the airspace. The FAA NextGen Implementation Plan promises regulation mandating that automatic dependent surveillance broadcast (ADS-B) systems be installed on all aircraft, providing a method by which air traffic control systems can easily gather information about sector congestion. More promising from a multiagent standpoint is the introduction of traffic information service broadcast (TIS-B), which provides distributed automatic ADS-B information to planes within a 15-mile radius of other planes. Using this locally-available information, we can construct conflict-avoidance in the national airspace as a distributed multiagent problem.

Q-Learning in the NAS

Conflict-avoidance in the UAS domain requires an agent to select the parameters of a diversion waypoint in a way that maintains safety while still considering the path cost of a diversion and the potential for conflict propagation in the system. In this work we use reinforcement learning agents to map plane states (relative to the plane’s nearest neighbor) to conflict-avoidance actions (waypoints) through Q-learning. A point-mass simulator is used to model agent trajectories, and agents must make a conflict-avoidance decision when the simulator detects a path conflict in some time horizon.

We call the joint state of all agents $\mathbf{s}$. Each agent $i$ has a state $s_i$, which is described in relation to its nearest neighbor, such that $s_i = \{\delta_n(i), \Theta_n(i), h_n(i), \mathcal{T}_n(i), p_i, g_i\}$, where $\delta_n(i)$ is the xy-planar distance to the nearest neighbor of $i$, $\Theta_n(i)$ is the relative heading of the nearest neighbor of $i$, $h_n(i)$ is the relative height (z-position) of the nearest neighbor of $i$, $\mathcal{T}_n(i)$ is the type of the nearest neighbor, $p_i$ is the agent’s position, and $g_i$ is the goal position of the agent. The position $p_i$ and goal position $g_i$ of the agent is not useful for the task of conflict-avoidance, so for the purpose of Q-learning we do not distinguish between states with different $p_i$ or $g_i$ values.

The type information $\mathcal{T}_n(i)$ is used to distinguish different states in Q-learning in our type-partitioned experiments, but we compare to when this is not used to distinguish types in our type-free experiments. Agents select an action $a_i = \{\tau, m, t\}$, where $\tau$ is the action type (heading change, or altitude change), $m$ is the magnitude of this change, and $t$ is the duration of the redirection. Agents use $\epsilon$-greedy action selection to choose an action $a_i$ based on their a state $s_i$, and then receive a reward $R(\mathbf{s}, \mathbf{a})$ based on the system state $\mathbf{s}$ and the action taken by the agent.

This reward captures the cost of conflicts caused after the course correction, the signal cost of taking a diversion action, and the distance cost of a particular action. We formalize our the local reward as:

$$L_i(s_i, a_i) = w_c u(1-n_c(s_i))-w_a u(n_a(a_i))-w_d d_{\text{extra}}(s_i, a_i)$$

(1)

where $L_i(s_i, a_i)$ is the local reward given by the agent's state $s_i$ and the agent's action selection $a_i$. $n_c(s_i)$ is the number of conflicts that agent $i$ is involved with, $n_a(a_i)$ is the number of deviations agent $i$ takes, $d_{\text{extra}}(s_i, a_i)$ is the amount of
extra distance that will be added by creating the diversion
waypoint, and $u$ is the unit step function. In our setup, the
values for these parameters are $w_c = 10$, $w_d = 0.1$, $w_a =
10$.

Local rewards perform well in domains without conges-
tion, but when resources cannot be shared equally to attain
optimality, global rewards can promote coordination. Our
global reward is a simple summation of the local rewards:

$$G(\vec{s}, \vec{a}) = \sum_{i=0}^{N} L_i(s_i, a_i)$$

(2)

Because global rewards can sometimes be too noisy for
agents to learn, we also test a ‘difference’ reward, which
evaluates an agent based on the effect of removing it from
the system. We derive this reward using the global reward and the
difference reward equation given in Turner et al. [?]:

$$D_j(\vec{s}, \vec{a}) = \sum_{i \in C_j} L_i(s_i, a_i)$$

(3)

where $D_j(\vec{s}, \vec{a})$ is the difference reward for agent $j$ and $C_j$
is the set of agents in projected conflict with $j$.

Agents in the system have strategy types that define gen-
erally what conflict-avoidance action they will take. There
are four different strategy types; one that always rerouted
CCW by 90°, one that always rerouted CW by 90°, one
that always changed its altitude by ±1000m, and one that
learned at a rate of $\alpha = 0.1$ and $\gamma = 0.9$ with a random
action-selection chance of $\epsilon = 0.1$. To take advantage of
this type information, an agent was pre-trained with each of
the heuristic types in an environment with 5 agents with tar-
gets and initial positions created within a 1000m$^3$ cube. The
Q-table developed by the learning agent, or stereotype, was
then used to initialize the agents in the test system.

Results and Discussion

We are interested in two things: the performance of reward
structures and scalability of reward structures with the in-
clusion of types in the state space. Figure 1 shows the im-
 pact of agent types on performance with high congestion.
Types provide good initialization for all reward structures in
the high-congestion domain. They also improve the con-
vergence of global and local rewards.

Figure 2 shows that with the difference reward, at low lev-
els of congestion the agents find optimal policies, and there
is differentiation between the performance while identifying
types and the performance without the inclusion of types.
At all levels of congestion the use of types improves the ini-
tial performance of the UAS in conflict-avoidance. However
this improvement comes at the cost of the learning speed,
through partitioning of the state space. In high congestion,
learning without types overtakes learning with types, but
converges to a similar solution. In cases of medium conges-
tion, learning without types overtakes learning with types,
which decays slightly but then converges to similar per-
formance to learning with types.

In this paper we show that discriminating by agent strat-
ty type improves performance in high congestion in the
UAS domain for global and local rewards. Under the dif-
fERENCE reward, we show that learning with types initially
outperforms learning without types, but is quickly overtaken
due to a slower learning speed. Values of learning with and
without types converge to similar performance under this
structure. Observing this, we identify a tradeoff between the
usefulness of including neighbor policies in the state space (policy
type value) and the increase in training samples from
not separating the Q-table updates by agent type. Knowing
type information is valuable in high congestion because it
provides necessary information about the local actions of the
agents. In cases with lower congestion, however, the policy
type value is lower because a more general policy is accept-
able.

Acknowledgements

This work was completed at NASA AMES Research Center.