Transfer Learning for Space Traffic Management

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Abstract

We explore space traffic management as an application of collision-free navigation in multi-agent systems where vehicles have limited observation and communication ranges. We demonstrate using simulations that GNNs are both transferable (i.e., they can use initialized weights from analogous ground-based environments), and scalable with respect to the number of agents. We find that transfer learning can improve sample efficiency and performance compared to both the case where the model is trained directly on a space-based environment, as well as other baseline MARL approaches. Finally, we use our model to quantify the value of sharing maneuver information between satellite operators in order to improve decision-making.

1 Introduction

There are an estimated 8,800 satellites and over a million pieces of debris in the sky today [1]; by 2030, there will be an estimated 150,000 active satellites in space [2]. The sheer numbers of objects in orbit and the resulting potential collisions will likely make today’s manual approaches untenable, and make autonomous decision-making an essential characteristic of space traffic management (STM) in the future [3].

Multi-agent reinforcement learning (MARL) has shown great success in many real-world applications [4, 5], particularly for navigation and collision avoidance problems. Transfer learning has achieved extensive success by leveraging prior knowledge of past learned policies of relevant tasks [6]. Inspired by this, we investigate the effectiveness of transferring ground-based collision avoidance MARL models for STM, or more specifically, for collision avoidance of satellites in orbit. Through our experiments, we demonstrate that transfer learning from the ground to the space environment is remarkably effective: it enables better performance and improved sample complexity compared to directly training a model on the space environment. This is despite the two environments being quite different in terms of the underlying dynamics that govern them.

Additionally, we study the role that information sharing plays in satellite operator decision-making. Operators are hesitant to share information about their satellites for a number of reasons, including proprietary and security concerns [7]. While third-party screening services may scan for potential collisions between satellites belonging to different operators, these services do not have access to the high-quality state information known to the operator of a satellite. Consequently, these screening services often have a high false alarm rate, with a detrimental impact on the trust placed on their alerts by satellite operators [8]. Miscommunications between operators has resulted in numerous near-misses between satellites in orbit [9, 10]. Motivated by these observations, we use our model to quantify the value of sharing maneuver information among satellite operators for STM decision-making.
Figure 1: Schematic depiction of InforMARL, the approach that we adapt to the space environment in this paper. The meaning of each icon is shown in the legend on the left of the environment box. Each agent or satellite $i$ receives observations about other satellites and space debris within its sensing radius, denoted by the blue shaded circle. This information is passed into a GNN, which learns compact representations of the relationships between objects. The output of the GNN is denoted $x_{agg}^{(i)}$. (ii) Information aggregation: Each agent’s state and observations from a neighborhood $d$ are aggregated to obtain $X_{agg}^{(i)}$. (iii) Graph information aggregation: The vectors of all the agents are averaged to get $X_{agg}$. (iv) Finally, the concatenated vector $[o_i, X_{agg}^{(i)}]$ is input to an RL algorithm to obtain a recommended action. Figure adapted from [11].

2 Methodology

Figure 1 provides an overview of InforMARL, the approach that we adapt for space traffic management applications. The details of InforMARL can be found in [11].

In this work, we consider two different environments: (1) A space environment in which the agents (satellites) follow the Chlohesy-Wiltshire equations [12] for the relative motion of two vehicles, and (2) a ground environment in which the agents’ dynamics are governed by a double integrator physics model [13].

3 Results

In our numerical experiments, we first demonstrate the scalability of the approach using the space environment for both training and testing, while varying the number of agents. Next, we consider the effectiveness of transferring a model trained in the ground environment to the space one. Finally, we use our transfer learning-based model to evaluate the benefits of satellite operators sharing maneuver information for the purposes of space traffic management.

3.1 Scalability

The first experiment, shown in Table 1, demonstrates the scalability of our algorithm when trained on $n$ agents and tested on $m$ agents. We find that in all scenarios considered, our approach can control the satellites to reach their goals within approximately 44% of the episode length. As expected, the number of collisions per agent increases when there are more satellites (i.e., the environment has become more dense). A significant finding from this work was that the reward per agent remains approximately the same even when the model is trained with $n < m$. Our approach also has robust sample complexity, with a high success rate for unseen scenarios. As the number of objects in space is expected to dramatically increase in the coming years, the scalability and sampling efficiency of our technique makes it a promising approach to space traffic management.
Table 1: Performance metrics obtained by training InforMARL on a space environment with \( n \) satellites and testing it on one with \( m \) satellites:
(a) Total reward obtained in an episode per agent, \( \text{Reward/m} \). (b) Fraction of episode taken on average by agents to reach their goal, \( T \) (lower is better). (c) Number of collisions per agent in an episode, \( \#\text{col/m} \) (lower is better). (d) Success rate, \( S\% \): percentage of episodes in which all agents are able to get to their goals (higher is better).

| \( m \) | \( n = 3 \)  | \( n = 5 \)  |
|--------|------------|------------|
| Reward/m | 61.57 | 60.52 |
| \( T \) | 0.44 | 0.44 |
| \( \#\text{col/m} \) | 0.36 | 0.78 |
| \( S\% \) | 98 | 98 |

| \( m = 5 \) | \( n = 3 \)  | \( n = 5 \)  |
|--------|------------|------------|
| Reward/m | 60.21 | 60.52 |
| \( T \) | 0.44 | 0.44 |
| \( \#\text{col/m} \) | 0.77 | 1.28 |
| \( S\% \) | 94 | 98 |

| \( m = 10 \) | \( n = 3 \)  | \( n = 5 \)  |
|--------|------------|------------|
| Reward/m | 57.78 | 57.07 |
| \( T \) | 0.43 | 0.44 |
| \( \#\text{col/m} \) | 1.41 | 1.41 |
| \( S\% \) | 96 | 91 |

3.2 Transfer learning

Figure 2 compares the effectiveness of transfer learning (denoted by InforMARL w/ Transfer Learning) relative to other MARL baseline algorithms. The transfer learning model was initialized using weights trained on a ground environment, and then trained in the space environment. Consequently in Figure 2, we offset the plot of InforMARL with transfer learning by 200,000 steps (the number of steps used to train the ground-based model). Three of the baseline methods – RMAPPO [14], VDN [15] and RMADDPG [16] – use global information, i.e., every satellite in the environment would required to share their information publicly. While this assumption can help determine a performance bound, such global information sharing is not realistic in practica. By contrast, InforMARL (both with and without transfer learning) uses only local information. Over the training period, InforMARL with transfer learning reaches a similar reward to RMAPPO [14], despite needing significantly less information. This finding indicates that the quality of the information, rather than its quantity, is an important driver of performance.

Furthermore, we see in Figure 2 that InforMARL with transfer learning outperforms the InforMARL model that was trained from scratch on the satellite environment. These results indicate that ground-based models can be used to accelerate training for space traffic applications.

3.3 Value of sharing maneuver information

Finally, we try to quantify the value of satellites sharing maneuver information (i.e., sharing their goals as well as any changes in them) with each other. To do this, we use the InforMARL model that was trained from scratch on the space environment. We test this model in a setting where the satellites no longer share their goal, \( r_i^{goal} \), and they can also change their goal to a random location midway through the episode. We consider three types of maneuver classes: (1) Fixed, where the goal remains unchanged through the episode, (2) Bounded, where the goal is randomly reset to a location that is within a bounded distance of the original goal, and (c) Random, in which the goal is randomly reset to a conflict-free location anywhere within the environment. The results are shown in Table 2.

The fixed+shared case corresponds to the performance of the baseline InforMARL model, which assumed that the goals were fixed and shared. Comparing the fixed+shared and fixed+hidden cases,
Table 2: Comparison of the impact of maneuver information sharing on rewards, for different maneuver classes (fixed, bounded and random), which may be shared or hidden. The following metrics are compared: (a) Total reward obtained in an episode per agent per step, Reward/step; (b) fraction of episode taken by the agents to reach their goal, \(T\) (lower is better); (c) number of collisions per agent in an episode, \(#\ col/m\) (lower is better), and (d) percentage of episodes in which all agents get to their goals, \(S\%\) (higher is better). The results are averaged over 100 test episodes.

| Maneuver class | Maneuver sharing | \(m=3\) | \(m=5\) |
|---------------|-----------------|----------|----------|
|               | Rew/\(m/step\) | \(T\) | # col/\(m\) | \(S\%\) | Rew/\(m/step\) | \(T\) | # col/\(m\) | \(S\%\) |
| Fixed         | Shared          | 2.47     | 0.44     | 0.36     | 98     | 2.41     | 0.44     | 0.78     | 94     |
|               | Hidden          | 2.33     | 0.45     | 0.63     | 92     | 2.19     | 0.46     | 1.2      | 84     |
| Bounded       | Shared          | 2.30     | 0.46     | 0.71     | 98     | 2.26     | 0.45     | 1.22     | 96     |
|               | Hidden          | 1.24     | 0.56     | 0.76     | 87     | 1.22     | 0.57     | 1.06     | 75     |
| Random        | Shared          | 1.09     | 0.61     | 0.76     | 52     | 0.87     | 0.61     | 1.41     | 35     |
|               | Hidden          | 1.21     | 0.59     | 0.80     | 48     | 1.11     | 0.59     | 1.46     | 30     |

we see that the value of maneuver sharing here is low, because a satellite’s fixed goal can be inferred from its state.

The random scenarios have poor performance relative to the fixed ones. Here, the satellites also require additional time to reach the new goal location, which decreases the reward per step. Maneuver sharing has limited benefits here; future work could investigate better information sharing mechanisms for such scenarios. When the distance between the original and new goals is bounded, we find that sharing has a significant positive impact (e.g., in terms of the reward per time-step or the success rate). In the context of STM decision-making, this shows that maneuver sharing can improve the ability of a satellite operator to respond to the planned movements of other satellites.

4 Related Work

Few studies have explicitly considered the impact of information sharing on collision avoidance and overall safety in space traffic management. The Federal Communications Commission and Department of Commerce solicited feedback from operators about space traffic management data sharing [7, 17]; in response, commercial operators expressed a desire to limit the exchange of proprietary information that could give their competitors insight into the capabilities, health, and life of their satellites. It was also suggested that some operators may not have high-quality data to share. In contrast to prior work in the field that has used RL for spacecraft trajectory optimization, guidance, and control [18, 19, 20, 21], we focus on multi-agent decision making among satellite operators to improve the safety and efficiency of space traffic operations.

5 Conclusions and Future Work

We demonstrated that transfer learning from a ground-based environment to a space-based one can improve both sample complexity and performance, despite the significant differences in the underlying dynamics that govern the agents in the two environments. We also find that InforMARL, our GNN-based approach, is scalable in a space-based environment, satisfying a critical need for space traffic management as the skies become more dense with satellites and debris. Finally, we found that sharing maneuvers or goals among satellite operators can improve the safety and efficiency of space traffic operations. Future work will include designing incentives for information-sharing, and accounting for perturbation effects, and communication delays and dropouts.

Acknowledgements

The authors would like to thank the MIT SuperCloud [22] and the Lincoln Laboratory Supercomputing Center for providing high performance computing resources that have contributed to the research results reported within this paper. The NASA University Leadership initiative (grant #80NSSC20M0163) provided funds to assist the authors with their research, but this article solely
reflects the opinions and conclusions of its authors and not any NASA entity. This research was sponsored in part by the United States AFRL and the United States Air Force Artificial Intelligence Accelerator and was accomplished under Cooperative Agreement Number FA8750-19-2-1000. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the United States Air Force or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notion herein. Sydney Dolan was supported by the National Science Foundation Graduate Research Fellowship under Grant No. 1650114.
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A Baseline Implementation Sources

We modified the codebases from the official implementations for the MAPPO baselines. We also adapted the codebase for MADDPG and VDN for our experiments which was benchmarked on other standard environments. The links for all these implementations are listed below.

- MAPPO: [https://github.com/marlbenchmark/on-policy](https://github.com/marlbenchmark/on-policy)
- MADDPG, VDN: [https://github.com/marlbenchmark/off-policy](https://github.com/marlbenchmark/off-policy)

B Hyperparameters

We performed a hyperparameter search for these algorithms by varying the learning-rates, network size and a few algorithm specific parameters. We observed that the hyperparameters used in the original implementation gave the best performance, and used those same values for our experiments as well.

Table 3 lists the hyperparameters specific to the InforMARL implementation. Here, “entity embedding layer dim” and “entity hidden dim” refer to the embedding layer input and output dimension respectively which is used to process the entity-type variable in the graph. “add self loop” refers to whether a self-loop should be added while constructing the agent-entity graph. “gnn layer hidden dim” is the output dimension of each layer in the graph transformer. “num gnn heads” and “num gnn layers” are the number of heads in the attention layer and number of attention layers used in the graph transformer. “gnn activation” is the activation function used after each layer in the GNN module.

| Hyperparameters             | Value  |
|----------------------------|--------|
| entity embedding layer dim | 3      |
| entity hidden dim          | 16     |
| num embedding layer        | 1      |
| add self loop              | False  |
| gnn layer hidden dim       | 16     |
| num gnn heads              | 3      |
| num gnn layers             | 2      |
| gnn activation             | ReLU   |

Table 3: Hyperparameters used in InforMARL

Tables 4, 5, 6 list the hyperparameters common for the InforMARL, MAPPO, MADDPG, and VDN implementations. For MADDPG, MAPPO, VDN and InforMARL, “batch size” refers to the number of environment steps collected before updating the policy via gradient descent. “mini batch” refers to the number of mini-batches a batch of data is split into. “gain” refers to the weight initialization gain of the last network layer for the actor network. “num envs” refers to the number of parallel roll out threads used to collect state-transition tuples.

C Computational Environment

Our models were trained on a server with 40 Intel Xeon Gold 6248 @ 2.50 GHz processor cores and 2 NVIDIA Volta V100 graphics cards. Our code uses PyTorch [23] version 1.11.0, CUDA version 11.3, and PyTorch Geometric Library [24] version 2.0.4.
| Common Hyperparameters          | Value                        |
|--------------------------------|------------------------------|
| recurrent data chunk length    | 10                           |
| gradient clip norm             | 10.0                         |
| gae lambda                     | 0.95                         |
| gamma                          | 0.99                         |
| value loss                     | huber loss                   |
| huber delta                    | 10.0                         |
| batch size                     | num envs × buffer length × num agents |
| mini batch size                | batch size / mini-batch      |
| gain                           | 0.01                         |
| network initialization         | Orthogonal                   |
| optimizer                      | Adam                         |
| optimizer epsilon              | 1e-5                         |
| weight decay                   | 0                            |
| use reward normalization       | True                         |
| use feature normalization      | True                         |

Table 4: Common Hyperparameters used in MAPPO and InforMARL

| Common Hyperparameters          | Value                        |
|--------------------------------|------------------------------|
| gradient clip norm             | 10.0                         |
| random episodes                | 5                            |
| epsilon                        | 1.0 → 0.05                   |
| epsilon anneal time            | 50000 timesteps              |
| train interval                 | 1 episode                    |
| gamma                          | 0.99                         |
| critic loss                    | mse loss                      |
| buffer size                    | 5000 episodes                |
| batch size                     | 32 episodes                  |
| optimizer                      | Adam                         |
| optimizer eps                  | 1e-5                         |
| weight decay                   | 0                            |
| network initialization         | Orthogonal                   |
| use reward normalization       | True                         |
| use feature normalization      | True                         |

Table 5: Common Hyperparameters used in MADDPG, VDN

| Common Hyperparameters          | Value |
|--------------------------------|-------|
| num envs                       | 128   |
| buffer length                  | 25    |
| num GRU layers                 | 1     |
| RNN hidden state dim           | 64    |
| fc layer hidden dim            | 64    |
| num fc                         | 2     |
| num fc after                   | 1     |

Table 6: Common Hyperparameters used in MAPPO, MADDPG, VDN and InforMARL