Automomous Control of Aircraft for Communications and Electronic Warfare: The Promises of Recent Artifical Intelligence Literature

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Abstract

We pose an unsolved problem in autonomous control of aircraft for communications and jamming (electronic warfare) and review the literature relevant to this problem. Some work offers approximately optimal solutions to related problems in different domains—promising applicability to the important scenarios considered here. Other work covers methods that we may find useful in extending these relevant solutions.

The problem we address lies within the fields of adversarial Multi-Agent Reinforcement Learning (MARL) and active sensing. In our problem, two opposing factions (labeled "blue" and "red") compete to win a zero-sum/purely adversarial game. The blue side tries to maintain communication links between ground-based assets with a fleet of "comms;" whereas the red side tries to jam this network with a fleet of "jammers." An Unmanned Aerial Vehicle (UAV) becomes a comm or a jammer when fitted for one of these purposes.

Each faction lacks access to the state of the opposing side, and must infer this state probabilisticly through positioning its fleet for best sensory performance and localization (active sensing). Moreover, the ground troops of each side, when also positioned appropriately, have the possibility of shooting down any of their adversary's UAVs. The blue side must simultaneously achieve its objective of keeping units on the ground in communication and the red side must simultaneously try to jam this communication. Despite best efforts, different units/UAVs can fall in and out of communication with their respective headquarters, making each of the blue and red factions a multi-agent collection, fully cooperating among itself, but with different information, to fight its adversary having opposing goals.

Our contribution poses this problem while pointing to literature for possible ideas for moving the field forward. We discuss the use of a heirarchy of simpler-than-reality mini-games for efficiently investigating and building upon solutions leading to a successful implementation for the full adversarial problem in real-world combat.

1 Introduction

If unfortunate circumstances compel our leaders to order our armed forces to take a city from an adversary, the command headquarters on the ground would benefit from constant two-way communication with all its other units during the conflict.

In the fog that accompanies such struggles, our forces cannot rely on our enemy's network of cell towers to keep in touch. Instead, two way radios, linked by a network of "comms" (UAVs for communication) will hopefully allow our friendlies to stay connected.

While vastly better than cell phones, such a network has it own set of challenges. Indeed, our adversaries clearly prefer to keep us out of communication. To pursue this preference, they may send up jammers (UAVs for blocking communication). Thus begins a delicate dance of each side positioning its fleet to best find the other's birds and in so doing best keep or block communications.

We study the question of how each side can control its fleet by autonomously ordering and carrying out flight and communications- electronics operation instructions (CEOI) to optimally achieve its objectives. We are interested in the strategies for both sides, because to defeat our enemy, we must understand the intelligent countermeasures they may take. Moreover, in a real war, our side—as well as theirs—may choose to fly both comms and jammers, requiring strategies for both roles.

Much recent literature has tackled the problem of optimal search and rescue. Other work has considered different scenarios requiring similar tools—notably cyber-security and precision farming. CITE 3. Search and rescue clearly relates to the problem at hand because, as with rescue, each of our sides benefits from successfully inferring the positions of targets. But there is a difference between search and rescue and electronic warfare. People being rescued presumably want to be found and will presumably cooperate with this effort. In electronic warfare, on the other hand, participants always aim to keep their locations hidden from the other side. As a result, while search and rescue can succeed with a purely active sensing and optimal control solution, in our scenario, we need to learn to counter an opponent's strategy. To this end, we propose to apply artificial intelligence: specifically, adversarial multi-agent reinforcement learning. This paper reviews the literature relevant to this approach to electronic warfare.

2 Optimal and suboptimal filtering

The filtering problem takes measurements of a stochastic system—possibly transformed measurements and possibly with noise—and produces estimates of the state of the system.

Readers will find the optimal solution to this problem in the first pages of any textbook CITE on nonlinear filtering: a recursion consisting of alternating applications of the Chapman-Kolmogorov Equation and Bayes Rule.

Unfortunately, solving each of these equations demands an integration which remains impossible to perform exactly (ie without discretizatiom) in all but two cases. In all other cases, a researcher must settle for an approximation—a suboptimal (but hopefully still *approximately* optimal) filter. Readers will find that the rest of the nonlinear filtering textbooks (the rest beyond the first few pages devoted to the optimal exposition) develop these suboptimal approximations.

We list the two truely optimal solutions to the filtering equation as (1) the Kalman filter, and (2) the hidden Markov filter. The Kalman filter applies with a linear model of the process, a quadratic objective function measuring optimality, and Gaussian noise corruption (both the process noise and the measurement noise). On the other hand, a hidden Markov filter applies with a finite-state model of the process. These restrictions unacceptably constrain usable models for our application area, and therefore we will focus on approximately optimal alternatives.

Several specific approximations merit mention. An extended Kalman filter linearizes the state space around each sample point allowing the calculations behind the Kalman filter to proceed. The approximation works well when the optimal distributions for state remain close to Gaussian. If they do not, the Extended Kalman Filter can perform poorly. A second approximation, a grid-based filter, approximates the state space with a finite grid of points allowing the calculations behind a hidden (finite) Markov filter to proceed. A grid-based filter works well for the lowest dimensional state spaces, but becomes intractable when the dimensions become even slightly higher. In preliminary investigations of the main problem that motivated this review [reseach paper in prepapration], one and two targets worked well (each adding two dimensions to the state), whereas three targets did not.

Papers and textbooks call the last class of approximations that deserves our attention "particle filters." In short, the idea approximates evolving distributions with a finite swarm of Monte Carlo sample points called particles. These methods possess great generality and flexibility, but many researchers find particle methods more difficult to understand, and to successfully implement, than their simpler and more straightforward cousins. Note that there exist many different ways to implement particle filters, each with its own benefits and limitations. We will discuss these methods further in the next section, as several papers concerning Active Sensing use particle filters.

3 Active sensing

4 Reinforcement Learning

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