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

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May 20, 2021

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 knowledge and access to the state of the opposing side, but benefits from inferring this state probabilisticly through positioning its fleet for best sensory performance and localization (active sensing). This maneuvering should take into account the real possibility of any UAV getting shot down by its adversary's ground troops if appropriately positioned. That said, the objective of each side should remain foremost. The blue side aims to simultaneously keep all units in communication while the red side aims to simultaneously 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, despite 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 towards 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.

Recent literature has tackled the problem of near-optimal search and rescue [1] and other related search and localization paradigms [2, 3, 4]. Other work has considered different applications requiring similar tools—notably cyber-security [5] and precision farming [6]. Search and rescue, for example, clearly relates to the problem at hand because, as with rescue, each side in our conflict clearly benefits from successfully inferring the positions of targets on the other side. 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, targets aim to conceal their true locations from their adversaries. 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 victory.

2 Optimal and sub-optimal 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 many textbooks on nonlinear filtering [7, 8, 9, 10]. The solution implements a recursion consisting of alternating applications of the Chapman-Kolmogorov Equation and Bayes Rule.

Unfortunately, solving each of these equations demands an integration remaining provably intractable in most cases—indeed in all but two cases that researches have already identified. In all other cases, a researcher must settle for an approximation—a sub-optimal (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 sub-optimal approximations. All of the methods discussed in this section can be found in many such textbooks on filtering, so we will not give historical pointers to the literature.

First, we list the two truly optimal solutions to the filtering equation as (1) the Kalman filter, and (2) the finite hidden Markov filter. The Kalman filter uses a linear model of the process, a quadratic objective function measuring optimality, and Gaussian noise corruption (LQG problem) (Gaussian in both the process noise and the measurement noise). On the other hand, a finite hidden Markov filter uses 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 probability distributions for state remain close to Gaussian. If they do not remain approximately Gaussian, the Extended Kalman Filter can perform poorly, leading to poor state estimates and impoverished inference.

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 computationally intractable when the dimensions become even slightly higher. In preliminary investigations the electronic warfare problem that motivated this review [Carver, research paper in preparation], one and two targets worked well (each adding two dimensions, longitude and latitude, to the state), whereas three simultaneous targets remained expensive beyond reach. In this work, we aimed to find jammers ("targets") without bearing information from observing successful or unsuccessful radio connections to friendlies.

The field calls the last class of filtering 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 and its extensions

This section spans several disciplines, including reinforement learning, deep reinfocement learning, distributional reinforcement learning, Bayesian reinforcement learning, and multi-agent reinforcement learning.

Let us start by defining the terms above. Reinforcement learning (RL) extends machine learning to sequential problems where an agent or agents learn to interact with an environment to maximize cumulative reward. Deep RL uses neural networks to represent the functions learned by the agent(s). Classically, RL implementations deal with inevitable uncertainty in represented quantities and maintaining point estimates for these quantities. Distributional RL departs from this tradition by maintaining probability distributions for the uncertain quantities. If the actor(s) perform Bayesian inference on these distributions (as they generally do), the actor implements Bayesian RL. Finally multi-agent RL extends RL to environments that include other interacting agents cooperating or competing for reward.

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