

EFFICIENT AND LOW-COST LOCALIZATION OF RADIO
SOURCES WITH AN AUTONOMOUS DRONE

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DOCTOR OF PHILOSOPHY

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Abstract

A radio source is anything that emits radio signals. It might be a signal jammer, a cellphone, a wildlife radio-tag, or the telemetry radio of an unauthorized drone. It is often critical to find these radio sources as quickly as possible. For example, if the radio source is a GPS jammer, it must be found and stopped so nearby users can continue to use GPS signals for navigation. Traditional methods for localizing radio sources are expensive and often labor-intensive. This thesis explores the use of an autonomous drone (a small aircraft) to efficiently localize a single radio source. This thesis takes a holistic approach to the problem, making contributions to both the hardware and algorithms needed to solve it.

Because drones offer a low-cost platform to quickly localize radio sources, there has been much research into drone-based radio localization. However, previous work has limitations that this thesis attempts to address. In terms of hardware, previous approaches use sensors that are either inefficient or expensive and complex. In terms of algorithms, most work uses greedy (also called myopic or one-step) optimizations to guide the drone. While these methods can work well, they are generally suboptimal.

The first contributions of this thesis relate to hardware. Two sensing modalities are presented and evaluated for drone-based radio source localization. These modalities are simple, easily constructed, inexpensive, and leverage commercial-off-the-shelf components. Despite their simplicity, these modalities outperform sensors commonly used in prior work and are robust to radio sources with unknown or time-varying transmit power. These modalities are validated in simulation and in flight tests localizing a cellphone, a wildlife radio-tag, and another drone by its telemetry radio.

Secondly, this thesis makes contributions to the field of principled, multi-step

belief-space planning. When performing localization, the drone maintains a belief, or distribution over possible radio source locations. Its goal is to select control inputs that lead to informative sensor measurements and a highly concentrated belief, implying high confidence in its estimate of the radio source’s location. This multi-step problem is cast as a partially observable Markov decision process (POMDP). This thesis expands on recent work to incorporate belief-dependent rewards in offline POMDP solvers. In this respect, the chief contribution of this thesis is an improved lower bound that greatly reduces computation. Despite this improvement, it was found that offline solvers could not scale to handle realistic scenarios. To solve the problem in real-time, an online POMDP solver based on Monte Carlo tree search is used. In simulations, this method outperforms a greedy method in a multi-objective localization problem where the seeker drone must avoid near-collisions with a moving radio source. This method was implemented in a flight test localizing another drone by its telemetry radio.

The third set of contributions made by this thesis relate to ergodic control for information gathering, in which a sensing agent selects trajectories that are ergodic with respect to an information distribution. This thesis briefly explores the conditions under which ergodic control might be optimal. Ergodic control is shown to be the optimal information gathering strategy for a class of problems which unfortunately does not include drone-based radio localization. In another contribution, it is shown how neural networks can quickly generate information maps, a key step to generating ergodic trajectories. The resulting approximations are accurate and yield orders of magnitude reduction in computation, allowing information maps to be generated in real-time. Finally, simulations are used to evaluate ergodic control in drone-based radio source localization. While the resulting performance depends on the method used to generate ergodic trajectories, ergodic control can offer modest improvements over greedy methods in nominal conditions and greater improvements in the presence of significant unmodeled noise.

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I was fortunate to be co-advised by Per Enge before he passed away. Per was supportive and firmly believed that engineers should fearlessly tackle complex problems outside their niche specialties. For example, he encouraged me as I started fiddling with antennas and radios, which are effectively black magic to those of us who are not electrical engineers. He was convinced I would learn by doing, and he was right. Most importantly, Per was compassionate and prone to infectious laughter. He will be dearly missed by all who worked with him.

I am grateful to the Stanford GPS lab, who jokingly called me a “half-member” but treated me like one of their own. All of my (limited) knowledge about hardware, flight tests, and field experimentation is owed to them. The few trips we made to military bases for flight tests are without a doubt the most rewarding experiences

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Chapter 1

Introduction

This thesis considers the efficient localization of a single radio source by a single autonomous drone.

A *drone* is an unmanned aircraft. Common alternative terms include “aerial robot” or “unmanned aerial vehicle” (UAV). The term “drone” includes a wide range of vehicles, including multimillion dollar military aircraft, but this thesis limits its scope to consumer drones, such as those produced by the company DJI. While this work exclusively uses a multicopter drone, many of the techniques in this thesis could be extended to other aircraft types. The drone in this work is also autonomous, meaning it plans and executes its flight without input from a pilot on the ground.

A *radio source* is something that radiates in the electromagnetic spectrum. It can be something meant to radiate, such as a radio or transmitter, or something that accidentally radiates, such as faulty electrical equipment. A variety of radio sources are used in this work, including an amateur radio, a wildlife radio-tag, and a cell phone. These sources range in frequency from about 200 MHz to 2.4 GHz, covering parts of the VHF and UHF bands. While the techniques in this thesis are designed for this frequency range, many of them can be extended to other frequencies.

To *localize* roughly means “to locate”. Whereas locating implies finding an exact location, localizing implies confining to a small area. When the drone starts localizing a hidden radio source, there is a large area in which the source might reside. This space of possible source locations is reduced with successive measurements; efficient

localization reduces this space quickly and confines possible source locations to a small area.

In the context of robotics, localization often means localizing the robot itself. However, this thesis assumes the drone knows its position and orientation. This assumption is reasonable as most drones are equipped with GPS receivers, magnetometers, and other sensors. Any uncertainty in the drone’s own position is ignored as it is much smaller than uncertainty in the radio source’s position. It is possible the radio source interferes with GPS signals, forcing the drone to operate in a GPS-denied environment. However, the drone can use alternative positioning techniques, such as other satellite navigation systems or optical flow of the terrain. While these methods might not be as reliable as GPS, they are acceptable for a small, inexpensive drone. The specific methods of localization in GPS-denied environments is beyond the scope of this work.

The contributions of this thesis aim to make drone-based radio localization efficient in time, cost, and human effort. Because a practical solution is desired, many flight tests are flown to evaluate and validate the proposed techniques.

1.1 Motivation

This work was originally funded by the Federal Aviation Administration (FAA) through the Stanford GPS Lab. The FAA’s interest in rapidly localizing radio sources comes from their desire to protect aviation and the national airspace [1]. As aviation relies more heavily on GPS for precise navigation, it becomes vulnerable to disruptions of GPS. Therefore, early work aimed to rapidly localize anything radiating at the GPS frequencies and interfering with navigation solutions.

GPS is prone to interference because its signals are weak once they reach Earth. Each GPS satellite flies at an altitude of 20 000 km and radiates with 27 W of power. By the time these signals reach Earth, they are received with about 1×10^{-16} W [2]. For comparison, a cell phone radiates with about 0.1 W. Because GPS signals are so weak, they can be jammed, or overwhelmed, by any radiation in the GPS frequency band, denying navigation solutions.

This jamming is often accidental. In 1999, a camera on Stanford's campus unintentionally jammed GPS in a 1 km radius, even affecting helicopters flying to Stanford Hospital [3]. The camera transmitted pictures of a construction site to construction headquarters. The camera's designers mistakenly thought transmissions at 1570 MHz would not interfere with the GPS L1 frequency (1575.45 MHz). Using a golf cart and directional antenna, the Stanford GPS Lab found the camera and, terminating it with extreme prejudice, restored GPS to campus. In another incident from 2001, boats in Moss Landing Harbor reported a GPS outage. An investigation revealed that defective amplifiers on television antennas were accidentally radiating in the GPS frequency band [4].

Not all GPS jamming is accidental, as some criminals actively jam it for nefarious purposes. Car thieves jam GPS to circumvent anti-theft devices that report the car's position, and some truck drivers do so to avoid GPS-based road tolling [5], [6]. A stationary jammer detection device on a three-lane highway reported 45 jamming events over 115 hours of operation [7]. Exacerbating the jamming problem, the contemporary concern for privacy has led to the proliferation of personal privacy devices [3], [8]–[10]. These small GPS jammers often affect other users and are illegal to sell or operate in many countries. Drivers with these devices have disrupted FAA GPS-based systems as they drive or park near Newark Liberty International Airport [11]. The ability to rapidly localize sources of GPS interference could mitigate the risk GPS jamming poses to aviation.

GPS interference is not the only threat to aviation, as manned aircraft are threatened by the rising popularity of consumer drones. In a three-month span in 2017, the FAA recorded 634 sightings of unmanned aircraft operating near airplanes, helicopters, and airports [12]. In 2017 the UK experienced 92 "Airprox" events in which drones compromised the safety of manned aircraft [13]. The FAA has had to warn drone pilots not to fly near wildfires, as it forces firefighting aircraft to land [14]. While it is often illegal to fly near airports, aircraft, and emergency operations, some drone pilots are unaware of the laws or ignore them.

Dangerous and illegal drone operations could be mitigated with rapid radio localization. Trespassing drones could be localized by their telemetry signals, or the drone

pilot's transmitter could be localized. Although a technically competent adversary could avoid detection by programming an autonomous path and maintaining radio silence, radio localization is useful in many scenarios and is a tool that should be available to enforcement personnel.

Rapid localization of radio sources is useful in many applications beyond protection of the national airspace. An important example is localization of radio-tagged wildlife [15]. Ecologists tag animals with radio beacons and track their movements to learn about their motion. This effort is critical to helping animals and conservation efforts. Another application is localization of avalanche beacons, where quickly localizing victims drastically improves the survival rate [16].

Existing localization techniques are expensive in time, cost, and human effort. For example, ecologists laboriously localize radio-tagged wildlife by hiking over rough terrain and manually rotating a directional antenna. A flying solution allows rough terrain to be bypassed while reducing radio reflections from obstacles on the ground [17], [18]. The FAA has proposed using small manned aircraft to localize sources of GPS interference [19]. However, a manned solution is expensive.

A drone could localize radio sources efficiently and with low cost. A low-cost, consumer drone could overfly rough terrain and ground clutter while costing much less than a manned aircraft. Drone autonomy could reduce the operational burden on researchers.

It is impossible to foresee the countless applications of drone-based radio localization that might arise in the future; a solution that is simple, low-cost, and light-weight is somewhat future-proofed. For example, the U.S. Marine Corps recently stated that infantry squads will soon include a drone operator with a small drone [20]. A low-cost, light-weight localization system could be applied to this platform or unanticipated future applications.

1.2 Related Work

Drone-based radio localization consists of many subproblems, each of which have their own, extensive literature. Detailed background for each area is presented in the

individual chapters, but this section provides a brief, holistic overview of attempts to use drones for localizing radio sources.

Perhaps the earliest work in using drones to localize radio sources was described by Gabe Hoffmann at Stanford University in 2008 [21]. This work’s main contribution was a greedy, information-theoretic trajectory planner for drones localizing a stationary radio source [16]. This method is generally suboptimal but computationally efficient, so it has been used in much subsequent research [15], [22]–[25]. However, Hoffmann’s flight tests were limited to a small search area ($9\text{ m} \times 9\text{ m}$) and a sensor that only worked for a specific avalanche beacon [21]. More general sensors, capable of finding other radio sources, were only simulated and not realized in hardware.

Between 2008 and 2010, significant work was done in the context of radio-tagged wildlife [18], [26], [27]. This work proposed mounting directional antennas on fixed-wing drones and using a measurement model based on signal strength. Predicting signal strength requires the radio source’s transmit power, which is unknown for sources like GPS jammers. Further, signal propagation is complicated and depends on many factors, resulting in much unmodeled noise. Therefore, this modality was limited to simulations and ground tests.

Rotating a directional antenna can yield bearing estimates to a radio source without knowing the transmit power. In 2013, this method was applied to a drone that constantly rotates to keep itself airborne (inspired by maple seeds) [28]. However, this kind of drone is uncommon and difficult to control. In 2014, this constantly-rotate-for-bearing modality was applied to a conventional quadcopter, but constantly rotating the drone complicates control loops and severely limits translational speed and range [29].

In 2014, the Stanford GPS Lab began work on a drone to localize GPS jammers, with the aim of eliminating the drawbacks in previous work. We equipped a DJI S-1000 octocopter with a directional antenna. Instead of constantly rotating, the drone only rotates once to make a bearing estimate, fly normally to a new location, and rotate again for a new bearing estimate. In 2015, we demonstrated this rotate-for-bearing modality and localized a WiFi router [22]; in 2016, we localized GPS jammers in exercises hosted by the Department of Homeland Security [23]. This modality was

simultaneously developed and deployed to localize wildlife radio-tags [15], [30], [31].

This early work at the Stanford GPS lab forked into two branches. One branch has continued to focus specifically on GPS jammer localization, leading to research into beam-steering and navigation in GPS-denied environments [32]. A critical limitation of the rotate-for-bearing modality is the long time required to make a single bearing estimate [15], [31]. Beam-steering addresses this limitation and allows for near-instantaneous bearing estimates to be made by measuring the phase differences measured by an antenna array. However, beam-steering is complex and antenna arrays can be heavy, which could impede adoption in other application areas.

The research in this thesis represents the second branch, which is focused on extending early work to other applications, such as localizing radio-tagged wildlife. Therefore, simplicity and low-cost are major goals of this work. The limitations of the rotate-for-bearing modality are addressed, including the slow measurement rate. This work also devotes significant attention to evaluating and improving the algorithms used to localize radio sources.

1.3 Contributions

This thesis presents both hardware and algorithmic solutions to challenges in drone-based localization of radio sources. These contributions covers three main areas: hardware, planning, and ergodic control.

Hardware

Hardware contributions focus on the how the drone pulls useful information from the radio waves transmitted by the radio source:

1. Two sensing modalities for drone-based radio localization are presented and evaluated; these modalities are simple and efficient, leading to fast localization.
2. It is shown how these modalities can be realized with low cost and simple electrical components.