

RF Signal Source Localization Using an Autonomous UAV

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Declaration

I, Arkhat Serikbekov, hereby declare that this thesis titled "RF Signal Source Search and Localization Using an Autonomous UAV with Predefined Waypoints", is the result of my own work except for quotations and citations which have been duly acknowledged.

I also declare that, to the best of my knowledge and belief, it has not been previously or concurrently submitted, in whole or in part, for any other degree or diploma at Nazarbayev University or any other national or international institution.

Arkhat Serikbekov

24.03.26

A handwritten signature in black ink, appearing to be 'Arkhat Serikbekov', written in a stylized, cursive script.

Abstract

The validation of RF signal source search and localization (SSSL) with an unmanned aerial vehicle (UAV) on predefined waypoints was the focus of this thesis project. Based on the theoretical framework established by Kwon and Guvenc (2023), a full low-cost experimental system was designed and used, which included; a HackRF One software-defined radio (SDR) 433 MHz transmitter, an RTL-SDR receiver placed on top of a custom-built FPV drone with associated Raspberry Pi companion computer, and an array of 15 waypoints spread out over (5 x 20 m). Received signal strength indicator (RSSI) readings were recorded at each waypoint along with algorithmic processing steps for peak-bin RSSI extraction, model fitting calibration method estimation, distance calculation, followed by linear least squares (LLS) localization using two anchor selection approaches: first-mid-last (FML) and closest three-points (CLS), both using dynamic reference linearization (DRL).

LLS was then verified on true numbers for distance calculation, naturally resulting in a zero localization error using FML+DRL and proving that the implementation was mathematically accurate. Hence, using measured RSSI data, at a good waypoint index, the best intermediate localization accuracy obtained was of 3.91 m. The experiment showed that outdoor RSSI dynamic range was merely 1.87 dB in the distance range of 2-10.5 m while calculated free-space path loss model proposed ~ 14.4 dB difference instead of this distance range. This lack of signal variation was explained by near-field effects, ground reflections, and the precision of hardware measurements. In case of compact grid layouts, the CLS method is exposed to collinear anchor degeneracy. Four different calibration models were compared alongside each other - showing that model sophistication matters little in noise-limited regimes. These findings provide empirical operational constraints and design principles for future UAV-based RSSI localization systems.

Keywords: UAV, RSSI, localization, software-defined radio, linear least squares, signal search

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List of Abbreviations

CHLM	Convex Hull Modified
CLS	Closest Three-Points
CON	Consecutive Three-Point
CRLB	Cramér-Rao Lower Bound
CUM	Cumulative All-Points
CW	Continuous Wave
DRL	Dynamic Reference Linearization
FFT	Fast Fourier Transform
FML	First-Mid-Last Points
FPV	First-Person View
GPS	Global Positioning System
IQ	In-Phase and Quadrature
ISM	Industrial, Scientific and Medical
LLS	Linear Least Squares
LOS	Line of Sight
MLE	Maximum Likelihood Estimation

NLOS	Non-Line of Sight
RF	Radio Frequency
RL	Reinforcement Learning
RMSE	Root Mean Square Error
RSS	Received Signal Strength
RSSI	Received Signal Strength Indicator
SDR	Software-Defined Radio
SNR	Signal-to-Noise Ratio
SRL	Static Reference Linearization
SSSL	Signal Source Search and Localization
TDOA	Time Difference of Arrival
ToA	Time of Arrival
TX	Transmitter
RX	Receiver
UAV	Unmanned Aerial Vehicle

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Chapter 1 – Introduction

1.1 Background and Motivation

Finding the sources of radio frequency (RF) signals is an extremely valuable ability that can be used in many civilian and military situations. More generally, RF signals from mobile phones, personal locator beacons, or other emergency transponders can help search-and-rescue teams find survivors who are trapped under debris or lost in remote areas. Regulatory authorities usually deal with unlicensed transmitters, interference sources, and pirate radio stations in spectrum management to protect the quality of licensed services. Because jammers are used, it's important to find enemy emitters and countermeasures, especially in electronic warfare and defense, where their timings can have a big effect on how well you understand the situation at any given time. All of these applications have the same technical problem: they need to figure out where an unknown transmitter is based on RF signal measurements taken at known locations.

Traditional RF source localization methods use static ground sensor networks, like cellular base stations or dedicated monitoring stations, that are set up on the ground in places where their locations are known. In controlled settings, these kinds of systems have worked well for localization, but they have some major problems. They need a lot of funds to build the infrastructure needed to use them, and they have difficulties because they work at fixed locations that may not allow for efficient measurement geometry. They are also vulnerable to damage during natural disasters, conflicts, and other emergencies where localization is most important [1], [2].

In the past years, unmanned aerial vehicles (UAV) have risen as an attractive platform for RF source localisation. The three-dimensional mobility of HAPs means that they can dynamically position themselves to maintain line-of-sight links with ground-based

transmitters, change their altitude and heading for optimized measurement geometry and access areas that ground based systems cannot reach [3], [4]. The miniaturization of electronics and the declining costs of UAV platforms and software-defined radio (SDR) hardware have all in combination, played a major role in the development of lightweight, economical airborne RF measurement systems that can be swiftly deployed in the field [5], [6].

Localization can be performed based on different signal observables, but the received signal strength indicator (RSSI) is highly appealing for unmanned aerial vehicles (UAVs) platforms. Angle-of-arrival methods need big antenna arrays, and time-of-arrival methods need very precise clock synchronization. In contrast, RSSI measurements can be taken with any commercial radio receiver and very little extra hardware [1], [7].

But turning RSSI measurements into accurate position estimates is a non-trivial technical feat. Signal strength is influenced by distance between transmitter and receiver and multipath propagation, shadowing, antenna orientation, as well as hardware-dependent nonlinearities [8], [9]. These contribute some uncertainty in the distance estimates (based on RSSI measurements) which then propagates through the localization algorithm into the final estimate. These problems need to be understood and quantified in order to derive reliable UAV-based localization systems.

1.2 Problem Statement

The signal source search and localization (SSSL) problem can be formulated in the following way: a stationary RF transmitter is located at an unknown position on the ground. A UAV equipped with an RF receiver flies along a predefined trajectory consisting of a sequence of waypoints. At each waypoint, the UAV collects an RSSI measurement. Using these measurements and the known waypoint positions, the objective is to estimate the two-dimensional horizontal coordinates of the transmitter.

Kwon and Guvenc [10] formalized this problem and proposed a framework in which the UAV flies a parallel track (zig-zag) pattern through a grid of waypoints, collecting RSSI measurements at each position. The RSSI values are converted to distance estimates using a log-distance path loss model, and a linear least squares (LLS) algorithm is applied to estimate the transmitter position. They proposed five different anchor selection strategies which determine which waypoints are used in the LLS computation, and evaluated these strategies through simulation using a free-space propagation model with log-normal shadowing.

Though the simulation results of [10] achieved a better localization performance, their approach have not been further validated experimentally in real hardware and outdoor environment. Simulation-based studies abstract some of the real-world propagation conditions and assume an ideal RSSI-to-distance relationship not present in practice, according to recent experimental work by Bianchi et al. [5] and Bhattacharjee et al. Often, real-world RF localization performance lags well behind theoretical models as demonstrated in [6], thus validating experimental schemes becomes crucial.

1.3 Research Objectives

This thesis aims to experimentally validate the waypoint-based SSSL approach, proposed by Kwon and Guvenc [10] in the real world, where we use real SDR hardware deployed on a UAV in an outdoor setting. The exact objectives are:

First, the implementation of an SSSL by designing a low-cost experimental platform for UAVs, using commercially available SDR components (HackRF One transmitter, RTL-SDR receiver, Raspberry Pi companion computer) and a custom-built FPV drone.

Second, for testing purpose, to implement the LLS localization algorithm with two different approaches for anchor selection (first-mid-last and closest three points) and dynamic reference linearization following the mathematical framework discussed in [10].

Third, to perform an outdoor experiment where RSSI measurements are taken at 15 known waypoints, and applied to localization of a ground-based transmitter..

Fourth, to systematically examine the localization performance with four distinct calibration models for path loss relationship and experimentally compare the results with those simulated in [10].

Fifth, to identify the practical challenges and operational limits of RSSI-based LLS localization with low-cost SDR hardware for UAV applications, hence generating empirical design guidelines for future experiments using UAVs for localization.

1.4 Contributions

This thesis makes the following main contributions:

1. An open source, low cost and replicable experiment platform for UAV based SSSL was developed and validated with commercial hardware (HackRF One, RTL-SDR, Raspberry pi and an FPV drone). The platform design, configuration parameters, measurement procedures and data processing pipeline are fully replicable by other researchers.

2. Using FML and CLS anchor selecting methods, LLS was found to be a valid method for localization, and their constraints were investigated. With high dynamic range signals, these methods could be used in real world UAV localization scenarios.

3. The operating boundary conditions for RSSI-based LLS localization were established. This experiment demonstrated that at 433 MHz with low-cost SDR hardware and distances of 2 to 10.5 m, the RSSI dynamic range is not enough for reliable distance estimation. Larger grid area where far field effects are in place, this method could produce meaningful results.

4. Four different calibration methods were compared and under low dynamic RSSI range, and it was shown which one is the most suitable.

1.5 Scope and Approach

This thesis focuses on the case of a single stationary transmitter and a single UAV with predefined waypoints. The UAV does not adapt its trajectory based on in-flight measurements; instead, it follows a fixed zig-zag path through all waypoints in the grid. This method was chosen so that it could be directly compared to the simulation framework in [10] and so that the effects of the measurement and calibration stages could be separated from those of the trajectory planning stage.

The waypoint grid is 5×20 m and has 15 spots to measure. This area is much smaller than the 300×300 m grid used in the simulation study of [10], but it is a realistic scenario for short-range localization applications and is limited by the drone's flight time and operational space. The compact grid also shows how hard it is to measure distances that are close to the line between near-field and far-field propagation areas.

Two of the five anchor selection methods from [10] are implemented in this experiment, which are first-mid-last (FML) and closest three-points (CLS). The reason for selecting these methods are because they are on opposite ends of the design spectrum. FML chooses widely spaced anchors to maximize geometric diversity, while CLS chooses the closest anchors to the target to take advantage of measurement proximity. A full picture can be obtained by comparing these two extremes and understand pros and cons of each one.

1.6 Thesis Organization

The thesis is organized in the following way:

Chapter 2 outlines the major studies on UAV-based SSSL, RSSI-based distance estimation, localization algorithms, anchor selection strategies, and SDR-based experimental platforms.

Chapter 3 describes the used system model and the methods , such as the channel model, distance estimation framework, LLS localization algorithm, anchor selection methods, and performance metrics.

Chapter 4 details the experimental setup. It discusses the hardware platform, signal configuration, calibration procedure, waypoint grid design, and data collection methodology.

Chapter 5 illustrates the results and analysis of the experiments, such as the RSSI measurements, the fitting of the calibration model, the distance estimation, the LLS localization results, and finally compares with simulation results

Chapter 6 summarizes the key contributions, defines limitations, and proposes ideas for future work.

Chapter 2 – Literature Review

2.1 UAV-Based Signal Source Search and Localization

In today's world of wireless communications, being able to locate radio frequency (RF) signals has become an important technique. Finding and accurately identifying RF sources is the basis for many uses, including search and rescue, spectrum enforcement, interference detection, and tactical military operations. For example, if there is a disaster, survivors' smartphones may still send out Wi-Fi or cellular signals even if the normal infrastructure is broken. This can help rescuers find them. It is also important to find unlicensed or malicious transmitters to protect spectrum resources and national defense. RF localization systems that work on the ground usually need stationary infrastructure, like cellular base stations or networks of distributed sensors.

Although these are effective in certain situations, they have several disadvantages including the requirement for line-of-sight connectivity, high deployment costs, and inability to function when the supporting infrastructure is damaged or unreachable [1].

Unmanned aerial vehicles (UAVs) provide a effective alternative to ground-based approaches. Their three-dimensional mobility allows them to establish line-of-sight (LOS) links with ground transmitters, dynamically adjust altitude and heading to improve measurement geometry and extend coverage to areas which are inaccessible to ground sensors [3]. UAV-based localization systems can be quickly deployed after disasters, provide autonomous surveillance in hard-to-reach areas and complement existing communication networks. The miniaturization of software-defined radios (SDRs) and small antennas also allows their integration with lightweight UAV platforms for real-time RF measurements during flight.

Kwon and Guvenc [10] formalized the problem of signal source search and localization (SSSL) using a UAV with predefined waypoints. In their work, they proposed five anchor

selection strategies for linear least squares (LLS) localization from received signal strength (RSS) measurements which are collected along a predefined UAV trajectory. Their simulation results showed that different anchor selection approaches offer distinct trade-offs in terms of accuracy, flight distance and reliability. This work serves as the theoretical foundation for the present thesis. Other studies have also explored UAV-based localization using various approaches. Demiane et al. [11] addressed the problem of trajectory optimization for localization in disaster scenarios, formulating it as a waypoint selection and path planning task which is aimed at minimizing the mission time while maintaining localization accuracy. Liu et al. [12] developed a system called HAWK, which is an aerial wireless kit, mounted on a mini-helicopter, that demonstrated practical RF localization using RSSI measurements from multiple positions. Furthermore, Vrba et al. [13] performed real-time localization of transmission sources using a coordinated formation of micro aerial vehicles, which demonstrated that multi-UAV systems can significantly improve both speed and accuracy of source localization.

Reinforcement learning (RL) has also been applied to the UAV-based SSSL problem. Wu [14] proposed a Q-learning algorithm for localizing illegal radio stations using a single UAV, where the agent learns to navigate towards the source by maximizing cumulative reward based on RSS observations. Chowdhury et al. [15] extended this RSS-based Q-learning framework to indoor UAV navigation and evaluated performance in confined environments with significant multipath propagation. More recently, Soleymani et al. [16] combined multi-agent Q-learning with particle filtering for UAV tracking within an Open-RAN architecture, achieving root mean square errors below 0.5 meters in simulation while also optimizing UAV power consumption. Their work represents one of the most recent developments in RL-based UAV localization. Additionally, a comprehensive review of UAV avionics systems by Hashim [3] provides an overview of RSSI-based, time-difference-of-arrival (TDOA), and GPS-based

localization approaches in the context of modern UAV architectures, and highlights the growing importance of low-cost localization solutions.

The trajectory design for UAV-based SSSL missions has received significant attention in the literature. Bernardini et al. [17] studied planning strategies for low-cost quadcopters in surveillance missions, establishing principles for systematic area coverage that are applicable to waypoint-based localization. Cabreira et al. [4] provided a comprehensive survey of coverage path planning algorithms for UAVs, categorizing the approaches into deterministic patterns such as parallel track (also called lawnmower pattern), spiral and expanding square, as well as adaptive methods that respond to real-time sensor inputs. The parallel track pattern which provides uniform coverage of a search area is adopted in the present work following the methodology described in [10].

2.2 RSSI-Based Distance Estimation

Among the various observables that are available for wireless localization, the received signal strength indicator (RSSI) is particularly attractive for UAV platforms because it requires no specialized hardware beyond a standard radio receiver. Unlike angle-of-arrival (AoA) methods which require antenna arrays or mechanically steered antennas that add significant payload and calibration complexity [1], or time-of-arrival (ToA) and time-difference-of-arrival (TDoA) methods which demand precise clock synchronization that is difficult to achieve in ad-hoc UAV deployments [7], RSSI measurements can be obtained from any receiver that is capable of reporting signal strength. This simplicity makes RSSI the most practical observable for lightweight and low-cost UAV localization systems.

The relationship between RSSI and the distance is described using the log-distance path loss model, which expresses received power as a function of the transmitter-receiver separation. As described by Rappaport [8], the path loss in decibels at distance d from the transmitter is given by $PL(d) = PL(d_0) + 10n \log_{10}(d/d_0) + X$, where $PL(d_0)$ is the path loss at a reference

distance d_0 , n is the path loss exponent which characterizes the propagation environment and X is a zero-mean Gaussian random variable that represents shadow fading. In free space the path loss exponent takes the theoretical value of $n = 2$, while in practical environments it can range from 1.6 in corridors with waveguide effects to as high as 6 in heavily obstructed indoor areas. For UAV air-to-ground links which typically enjoy LOS propagation, the exponent is commonly assumed to be close to 2, as it is adopted in the UAV communication models described by Zeng et al. [18].

Despite its simplicity, RSSI-based distance estimation suffers from several well-documented limitations. Sadowski and Spachos [19] investigated RSSI variability in IoT deployments and found that measurements are susceptible to multipath fading, shadowing, antenna orientation and hardware-dependent non-linearities. Zanella [9] provided a comprehensive treatment on best practices for RSS measurements and ranging, where the impacts of near-field effects, ground reflections, antenna patterns and receiver gain compression on measurement accuracy were documented. The study concluded that reliable RSSI-based ranging requires careful calibration and that the achievable accuracy depends strongly on ratio of distance-dependent signal variation to the measurement noise floor. Li [20] compared multidimensional scaling (MDS) and maximum-likelihood estimation (MLE) approaches for collaborative RSS-based localization in sensor networks and proposed hybrid MDS-MLE schemes to mitigate the effects of noisy RSSI measurements. Furthermore, Liu et al. [21] demonstrated that accounting for uncertainty in anchor node positions can significantly improve the accuracy of RSS-based localization algorithms.

The propagation environment between a UAV and ground-based transmitter introduces specific challenges which differ from conventional terrestrial or indoor settings. At low UAV altitudes, ground reflections create a two-ray propagation condition where the direct and reflected paths may constructively or destructively interfere depending on the geometry and the

frequency. This effect is particularly pronounced at sub-GHz frequencies where the wavelength is comparable to the separation between direct and reflected paths, and it can cause non-monotonic RSSI behavior which violates assumptions of the log-distance model. Ouyang et al. [22] addressed colored measurement noise in cooperative UAV navigation using RSSI and developed filtering techniques to handle the temporal correlations which are introduced by the propagation channel. Liu et al. [23] proposed piecewise convex approximation methods for UAV-assisted localization when path loss exponent is unknown and demonstrated improved robustness to calibration errors.

2.3 Localization Algorithms

Given a set of distance estimates from multiple measurement positions, the localization problem reduces to solving a system of nonlinear equations which relate the unknown source coordinates to the known receiver positions and estimated distances. Gustafsson and Gunnarsson [1] provided a comprehensive analysis of the fundamental possibilities and limitations of mobile positioning using wireless network measurements. They characterized the achievable accuracy through the Cramér-Rao lower bound (CRLB) which is derived from the Fisher information matrix. Patwari's et al. [2] survey on cooperative localization algorithms for wireless sensor networks encompasses both centralized and distributed methodologies.

Among various algorithms, linear least squares (LLS) stands out with its easy compute and closed form solution. It can be implemented in lightweight hardware during flight scenarios. The research by Guvenc et al. [24] was used in this work to define constraints for LLS-based wireless position estimation. LLS works by subtracting a reference equation from all other nonlinear distance, thereby allowing to solve linear equations through the pseudoinverse. When anchor positions are well chosen, Li [25] demonstrated that by using LLS, 3D Bluetooth indoor positioning could be achieved.

The main task in using LLS is to choose good reference points for linearization. In [7], the authors talked about how to choose a reference for linearization, which affects both the bias and the variance of the estimation. They also talked about localization and synchronization in wireless networks in great detail. The choice of reference directly impacts the conditioning of system matrix, and a badly chosen reference can magnify estimation errors dramatically. The references selection approaches discussed in the literature include linearizing around a static reference (SRL) point, such as first waypoint, or dynamic reference linearization (DRL), where closest measurement point is selected as the reference. Simulation results of Kwon and Guvenc [10]: For every anchor selection method considered, DRL outperforms SRL or achieves an equal performance.

Alternative methods include maximum likelihood estimation, minimizing the likelihood function over unknown coordinates directly to Bayesian approaches such as extended Kalman filters or particle filters. Bshara et al. performed fingerprinting- and model-based localization on WiMAX networks [26]; they concluded that, although very accurate with sufficient training data, the fingerprinting approach does not generalize as well to different environments compared to model-based approaches. The localization problem in the presence of adversaries has been studied by Ozturk and Gezici [27], where they focused on effects of eavesdroppers and jammers on source localization networks. These advanced methods may have potential accuracy improvements but usually at the price of computational complexity that is orders-of-magnitude higher which makes them unsuitable for resource-limited UAV platforms with constrained battery and computation power.

2.4 Anchor Selection and Reference Strategies

A key characteristic of LLS-based localization is that its performance critically depends on the selected position of the measurement which will be used as anchors for equations system's formation. On the other hand, using all measurements available (called cumulative

approach) results in maximum amount of information about trajectory but does also introduce increasing computational burden as UAV flies through its path. However, using only a small number of measurements reduces the computation time but may lose accuracy due to possible poor geometric diversity of selected anchors. Kwon and Guvenc [10] proposed and compared five anchor selection strategies in their work: consecutive three-point (CON), cumulative all-points (CUM), first-mid-last points (FML), convex hull modified (CHLM) and closest three-points (CLS).

The minimal computational cost comes at the expense of spatial diversity, since the three waypoints used in the CON method are just consecutive trajectory points. The CUM method employs all existing waypoints - thus giving it comprehensive coverage, but its growing matrix dimensions can increase with every new waypoint. The FML selects waypoints from the trajectory already visited in order to maximize spatial separation between anchors, by selecting the first, middle and last waypoints (up to a constant offset) leading to fixed computational cost. The CHLM, which is a geometrically motivated approach, finds the convex hull of the trajectory points and uses its vertices as anchors. Lastly, the CLS method chooses three waypoints to reduce the estimated distances to the target. This is because measurements that are closer together usually have less path loss noise, which means the distance estimates are more accurate.

The simulation results presented in [10] uncovers multiple interesting observations. Once the UAV passed the target position, CLS set the highest final localization accuracy, which was very close to zero. Yet, it needed the longest flight distance to achieve this accuracy. Although CUM had yielded the fastest convergence in flight distance, it was also computationally expensive as the matrix sizes increased. FML trade-off provides a fair compromise between reaching moderate accuracy early while maintaining computational complexity constant. CHLM was found to have good sample accuracy and solid reliability with

low complexity reflecting in overall strong performance. These trade-offs are exactly what motivates the experimental comparison performed in this thesis, which considers FML and CLS as use-case-driven methods that can be representative approaches on the accuracy-versus-efficiency axis.

Anchor selection directly impacts the localization accuracy as the geometry of selected anchors is critical. In particular, in case that anchors are collinear or nearly collinear, the matrix of a LLS system becomes ill-conditioned which causes big estimation error in the direction normal to the line of anchors. The sensitivity we identify with respect to the anchor geometry has been analyzed previously in the context of sensor network localization [12], and is particularly relevant here for either discrete grid-based waypoints, where certain placings of anchors yield degenerate configuration. Liu et al. [21] showed that adding uncertainty about the anchor position to the estimation framework can help lessen the effects of bad geometry. Liu et al. [23] showed that unknown path loss exponents make things even harder because they make the LLS estimator more sensitive to geometry.

2.5 SDR-Based Experimental Platforms

Software-defined radio (SDR) technology has become an important tool for flexible and affordable RF testing in the last few years. In contrast, hardware radios have fixed functions. SDR platforms use software to define the signal processing function, which makes it easy to change the frequency, bandwidth, modulation, and measurement. The GNU Radio framework [28] was initially proposed as an open-source platform for experimenting with radio frequency spectrum, and now it is the software infrastructure standard for SDR-based research. It allows linking of provide an extensive library of signal processing blocks in arbitrary configurations which provides researchers with the capability to implement their own receive and measurement system without having to resort to special purpose hardware.

Wei et al. [29] practically applied SDR technology to RSSI-based localization by creating a system based on reconfigurable SDR platforms for validating a bias reduction algorithm for positioning. The importance of their work is that they used real-world experiments to validate algorithmic improvements, rather than simulation alone, which set a precedent for experimental verification in the SDR localization literature. More recently, Bianchi et al. [5] presented an experimental setup for UAV-aided RSSI localization of a ground RF emitter using the Adalm Pluto SDR development board which was programmed with GNU Radio. Their system acquired RSSI measurements in both the 865 MHz Short Range Device band and 2.4 GHz ISM band, with the SDR mounted on a drone together with GPS and inertial measurement unit sensors for position logging.

Simulation and real outdoor experiments could have completely distinct performances. One example is work done by Bhattacharjee et al. [6] where they did UAV localization and tracing by using passive RF sensing. Their research showed significant discrepancy between simulation and actual localization performance, primarily attributed to multipath propagation, antenna radiation patterns, and environmental variability. This is significant when considering that all localization algorithms to date have been implemented and tested in software-based simulations.

The hardware platform used in this thesis is a HackRF One as transmitter and an RTL-SDR (v4 with R828D tuner) as receiver which are commonplace, low-cost SDR devices. HackRF one open-source half-duplex transceiver, covers 1 MHz to 6 GHz besides RTL-SDR a USB contain receiver with receive only capability between 500kHz and 1.7 GHz. The receiver logs the collected data and runs measurement software on a Raspberry Pi 4B single-board computer mounted to the UAV. Furthermore, this design illustrates that SSSL experiments can be run on commercially available off-the-shelf hardware, making the experimental setup accessible and reproducible by new research.

2.6 Summary and Research Gap

The related works reviewed in this chapter suggest that the theoretical bases behind RSSI based localization and LLS estimation are well established, while many other simulation studies have proved potential of the UAV based SSSL approaches, there is still a lack of validation through real hardware with practical deployment. Most of the studies mentioned above use computer simulations and the few experimental works that do exist, such as Wei et al. [29], Bianchi et al. [5] and Bhattacharjee et al. [6], have reported that real-world performance differs substantially from simulation predicts.

This thesis aims to contribute to bridging the gap by designing an experimental method for SSSL using a UAV which is equipped with low-cost SDR hardware. Particularly, the study uses actual outdoor measurements compare with the FML and CLS anchor selection methods tested in simulation by Kwon and Guvenc [10]. Consequently, this thesis systematically investigates four distinct calibration models for the path loss relationship and evaluates their respective localization performances to characterize the practical limits of RSSI-based localization at short ranges with mass-market SDR hardware. The results specify the operating conditions at which a proposed waypoint-based LLS approach becomes non-viable, and provides empirical design rules that cannot be gathered by simulation alone. It is then a pragmatic validation study as well as a diagnostic study that indicates the current gap between theory and practice in the area of UAV-based RF localization.

Chapter 3 – System Model and Methodology

3.1 System Overview

This chapter presents the system model and the mathematical framework for RF signal source search and localization (SSSL). The main focus of this thesis is on the localization of a stationary RF transmitter on the surface using a single autonomous UAV flying according to a pre-planned trajectory through waypoints. Attached to the UAV is an SDR receiver that records received signal strength (RSS) measurements at each waypoint. These measurements are utilized for linear least squares (LLS) localization to estimate the position of transmitter.

The overall system operates as follows. A ground-based transmitter based on a HackRF One SDR continuously emits a 433 MHz single-tone signal. The UAV, equipped with an RTL-SDR receiver connected to a Raspberry Pi companion computer, flies through a sequence of predefined waypoints in a parallel track (zig-zag) pattern. The UAV briefly hovers at each waypoint while the receiver captures RF power measurements. Distance between each waypoint and transmitter is estimated using the received signal strength at each waypoint based on a calibrated path loss model. With distances measured from different waypoints, the LLS algorithm is used to estimate the coordinates of the transmitter.

The main challenge in this process is deciding what waypoints will be used as anchor point for the LLS computation. While more measurements become available as the UAV commences its trajectory, they do not necessarily lead to an increase in localization accuracy. Some combinations of anchors provide better geometric diversity than others, and the quality of individual distance estimates also varies due to influences from the propagation environment or measurement noise. Two anchor selection methods are considered in this thesis: first-mid-last (FML) and closest three-points (CLS), both with dynamic reference linearization (DRL). These methods are described in detail in Section 3.5.

3.2 Channel Model

The propagation channel between the UAV and the ground transmitter is modeled using the log-distance path loss model, which is widely used in wireless communication systems [8]. This model assumes that the received signal power decreases logarithmically with distance from the transmitter. Under line-of-sight (LOS) conditions, which are typical for UAV air-to-ground links, the path loss in decibels at a distance d from the transmitter can be expressed as:

$$PL(d) = PL_0 + 10\alpha \cdot \log_{10}(d/d_0) + X\sigma, \quad (3.1)$$

where PL_0 is the path loss at the reference distance d_0 , α denotes the path loss exponent, d is the distance between the transmitter and the receiver, and $X\sigma$ is a Gaussian random variable with zero mean and standard deviation σ which represents the shadow fading effect [8], [18]. In free-space propagation the path loss exponent takes the theoretical value of $\alpha = 2$. In practical environments, however, the value of α can deviate from 2 due to multipath reflections, ground effects and other environmental factors. Following the approach of Kwon and Guvenc [10], the path loss exponent is set to $\alpha = 2$ in the free-space model, while empirically fitted values are also considered from calibration measurements.

The received signal strength indicator (RSSI) at waypoint i can be related to the transmitted power and path loss as:

$$RSSI(d_i) = P_t - PL(d_i), \quad (3.2)$$

where P_t is the transmitted power in dBm and $PL(d_i)$ is the path loss at distance d_i . By rearranging (3.1) and (3.2), the distance between the transmitter and the receiver at waypoint i can be estimated from the RSSI measurement as:

$$d_i = d_0 \cdot 10^{((P_0 - RSSI_i) / (10\alpha))}, \quad (3.3)$$

where P_0 is the reference RSSI at distance d_0 , which is determined through calibration. The accuracy of this distance estimate depends on how well the path loss model represents the actual

propagation environment, the precision of the calibration parameters, and the level of measurement noise.

3.3 Distance Estimation

Using the channel model described above, each RSSI measurement at a waypoint provides an estimate of the distance between UAV position and the transmitter. The estimated distance $\hat{d}_i$ at the i -th UAV location can be written as [10], [24]:

$$\hat{d}_i = f_i(x, y, z) + n_i, \quad (3.4)$$

where n_i is the measurement noise at the i -th UAV location, and $f_i(x, y, z)$ is the true Euclidean distance between the unknown target position (x, y, z) and the i -th UAV position (x_i, y_i, z_i) . The true distance function is given by:

$$f_i(x, y, z) = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2}. \quad (3.5)$$

In this thesis, the UAV position at each waypoint is known from the predefined flight plan. The waypoint coordinates were measured and marked before the experiment, and the UAV altitude was kept approximately constant at $z \approx 2$ m during hovering. The transmitter is placed on the ground at an unknown location (x, y, z) where $z = 0$. Therefore, the localization problem reduces to estimating the two-dimensional horizontal position (x, y) of the transmitter, although the LLS formulation is kept in three dimensions for generality.

Four different calibration models are used in this thesis to convert RSSI measurements to distance estimates, in order to assess how the choice of calibration affects the localization performance. Model 1 uses the log-distance fit from indoor calibration data. Model 2 uses a signal-minus-noise metric from the same indoor calibration. Model 3 re-fits the path loss parameters using the outdoor waypoint data itself. Model 4 assumes free-space propagation with $\alpha = 2$ and uses a single reference measurement for calibration. The details of each model are presented in Chapter 4.

3.4 Linear Least Squares Localization

With distance estimates obtained at multiple UAV waypoints, the least squares (LS) algorithm can be used for estimating the target position. However, due to the high computational complexity of the nonlinear least squares approach [24], a linearized version of the algorithm is considered in this work. The linear least squares (LLS) method converts the nonlinear distance equations into a system of linear equations through a simple algebraic manipulation.

The squared distance equation at waypoint i , neglecting the noise term, can be written as [10], [24]:

$$d_i^2 = (x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2. \quad (3.6)$$

Localization of the ground target requires distance estimates measured at a minimum of three different UAV anchor positions. We define an index set $\mathfrak{v}$ of size S , where $3 \leq S \leq \tilde{N}$, that captures the unique UAV waypoint indices to be used in the localization process. Here, $\tilde{N}$ denotes the index of the current UAV position along its trajectory, and N is the index of the last waypoint. The formation of the index set $\mathfrak{v}$ depends on the anchor selection method and is described in Section 3.5.

For LLS-based localization, one of the indices in $\mathfrak{v}$ must be selected as a reference index r for the linearization. The reference selection method is discussed in Section 3.6. After selecting the reference, the reference equation corresponding to $\hat{d}_r$ is subtracted from all other equations in the set $\mathfrak{v}$. This subtraction eliminates the quadratic terms in the unknown target coordinates, producing a set of linear equations. The resulting system can be written in matrix notation as [10], [24]:

$$Av \cdot l = bv, \quad (3.7)$$

where $l = [\hat{x}, \hat{y}, \hat{z}]^T$ is the estimated target location. The matrix A_v and vector b_v are constructed as follows. For each index k in the set v , excluding the reference index r , a row is added to A_v and a corresponding entry is added to b_v :

$$A_v = 2 \cdot [xv(k) - x_r, yv(k) - y_r, zv(k) - z_r] \text{ for each } k \neq r, \quad (3.8)$$

$$bv(k) = d_r^2 - dv(k)^2 + xv(k)^2 + yv(k)^2 + zv(k)^2 - \lambda, \quad (3.9)$$

where $\lambda = x_r^2 + y_r^2 + z_r^2$ and $v(k)$ denotes the k -th index in the set v . The estimated target location l is then obtained using the LLS solution [24], [25]:

$$l = (A_v^T \cdot A_v)^{-1} \cdot A_v^T \cdot b_v. \quad (3.10)$$

The target coordinates' minimum-norm least squares estimate is given by this solution. The number and geometric distribution of anchor points, the linearization reference selection, and the quality of the distance estimates all affect the estimate's accuracy. In order to obtain a numerically stable solution, the pseudoinverse is utilized in place of the standard matrix inverse if the matrix A_v is ill-conditioned, which happens when the anchor points are almost collinear.

3.5 Anchor Selection Methods

The index set v identifies the waypoints to be used as anchors in computing the LLS. Different methods of forming v lead to different trade-offs between accuracy, computational complexity and reliability. In this work, two of the anchor selection schemes proposed by Kwon and Guvenc [10] are implemented and compared: first-mid-last (FML) and closest three-points (CLS). These two methods were selected because they represent opposite ends of the design spectrum — FML maximizes geometric diversity of the anchors, while CLS exploits the proximity to the target for better distance estimates.

3.5.1 LLS-FML (First-Mid-Last Points)

The FML method's main idea is to choose waypoints that are as far apart as possible along the UAV's path so that the anchor points are as far apart as possible from each other. The first, middle, and last waypoints make up the index set v . Mathematically, the index set is defined as [10]:

$$v = \{1, \lfloor (\tilde{N} + 1)/2 \rfloor, \tilde{N}\}, \text{ for } \tilde{N} \geq 3, \quad (3.11)$$

where $\tilde{N}$ is the current waypoint index. As the UAV moves along its path, the middle index moves and the last index moves forward, which changes the anchor triangle all the time. No matter how many waypoints have been visited, this method always costs three anchors to compute. The selected anchors have a lot of different shapes because the first and last points are as far apart as possible along the trajectory, and the middle point can be used to triangulate.

3.5.2 LLS-CLS (Closest Three-Points)

The CLS method works differently by picking the three waypoints that are closest to the target based on their estimated distances. The rationale is that closer measurements experience less path loss and typically have lower measurement noise, which should result in more accurate distance estimates. The index set is formed as [10]:

$$v = \{v\varphi(1), v\varphi(2), v\varphi(3)\}, \quad (3.12)$$

where $v\varphi$ is a reordered version of all candidate UAV locations $\{1, \dots, \tilde{N}\}$, sorted by ascending estimated distances to the target node. In other words, the CLS method always uses three UAV locations that have the closest measurement distance to the target. Once the UAV flies close to the target, the CLS method is expected to provide very accurate localization. However, it may take a long time for the UAV to reach the vicinity of the target depending on the target's location relative to the flight path. Furthermore, the CLS method is susceptible to geometric degeneracy

when the three closest waypoints happen to be collinear or nearly collinear, which can occur in grid-based waypoint layouts.

3.6 Reference Selection

The LLS algorithm requires selecting one of the anchor indices as a reference for linearization. The choice of reference affects the conditioning of the system matrix and therefore the accuracy of the position estimate. Two strategies have been proposed in the literature [10]:

Static Reference Linearization (SRL): The first index in the set $\mathbf{v}$ is always used as the reference. This method is easy to use, but if the first waypoint is far from the target, the system matrix may not be well conditioned.

Dynamic Reference Linearization (DRL): The reference is the entry in $\mathbf{v}$ with the smallest estimated distance to the target. This method changes the choice of reference point based on what is known about the target location at the time, which usually leads to a better conditioning of the system matrix because the reference point is closer to the true solution.

Kwon and Guvenc [10] showed through simulation that DRL always gives the same or better accuracy than SRL, no matter which method is used to choose anchors. This finding leads to the choice of DRL as the reference selection strategy for this thesis.

3.7 Performance Metrics

We use a number of metrics to measure the performance of each localization method. These metrics look at different parts of the localization quality and are in line with the evaluation framework used in [10].

3.7.1 RMSE vs. Waypoint Index

The root mean square error (RMSE) is computed at each waypoint index $\tilde{N}$ as the UAV progresses along its trajectory. This metric shows how the localization accuracy evolves over

time and how quickly each method converges to a accurate estimate. The RMSE at waypoint index $\tilde{N}$ is defined as:

$$RMSE_{\tilde{N}} = \sqrt{(x - \hat{x}_{\tilde{N}})^2 + (y - \hat{y}_{\tilde{N}})^2 + (z - \hat{z}_{\tilde{N}})^2}, \quad (3.13)$$

where (x, y, z) is the true transmitter position and $(\hat{x}_{\tilde{N}}, \hat{y}_{\tilde{N}}, \hat{z}_{\tilde{N}})$ is the estimated position at waypoint index $\tilde{N}$.

3.7.2 Long-Term RMSE

The long-term RMSE is the localization error at the final waypoint of the UAV trajectory ($\tilde{N} = N$). This metric represents the best accuracy that each method can achieve after the UAV has completed its entire flight path and all possible measurements have been collected.

3.7.3 Flight Distance to Threshold

To evaluate how quickly each method reaches a acceptable level of accuracy, a minimally acceptable localization RMSE threshold θ is defined. A ground target is considered to be localized if the localization error falls below and does not again exceed θ . The flight distance at which this condition is first satisfied is recorded as the required minimum flight distance. In [10], the threshold was set to $\theta = 20$ m for a 300×300 m search area. In this thesis, due to the smaller grid size (5×20 m), a threshold of $\theta = 5$ m is used as a more appropriate benchmark.

3.7.4 Reliability

If the RMSE of an algorithm fluctuates significantly as the UAV moves through its trajectory, the algorithm is considered less reliable even if it eventually reaches the threshold. Following the definition in [10], the reliability γ is computed as:

$$\gamma = \sum(\rho_i)/(N - 1), \text{ where } \rho_i = 1 \text{ if } RMSE_i \geq RMSE_{i-1} + \beta, \quad (3.14)$$

where ρ_i is a marker bit at the i -th index of the UAV trajectory, β is the acceptable RMSE gap which is set to 1 m in this work, and RMSE_i is the RMSE value at the i -th index. A lower value of γ indicates higher reliability, meaning that the RMSE decreases more consistently as the UAV progresses. The reliability metric provides an auxiliary means to compare algorithms beyond their final accuracy.

3.8 Summary

This chapter has presented the complete mathematical framework for RSSI-based localization of a ground transmitter using a UAV with predefined waypoints. The log-distance path loss model provides the link between RSSI measurements and distance estimates. The LLS algorithm converts these distance estimates into a position estimate through a linearized system of equations. Two anchor selection methods, FML and CLS, offer different strategies for choosing which waypoints to include in the computation, and the DRL reference selection adapts the linearization to minimize estimation error. The performance of each combination is evaluated using RMSE, flight distance, and reliability metrics. In the next chapter, the experimental setup and the specific hardware and software configurations which are used to collect the measurement data are described.

Chapter 4 – Experimental Setup

4.1 Overview

This chapter describes the hardware platform, software configuration, calibration procedure, waypoint grid design, and data collection methodology which were used to conduct the outdoor SSSL experiment. The experimental setup was designed to provide a practical, low-cost implementation of the waypoint-based localization framework described in Chapter 3, using commercially available SDR hardware and a consumer-grade drone. A complete end-to-end experimental pipeline was successfully developed and deployed, from signal generation and airborne measurement to data logging and post-processing.

4.2 Hardware Platform

The experimental platform consists of a ground-based transmitter, an airborne receiver system mounted on a UAV, and a ground station laptop for post-processing. The hardware components and their specifications are summarized in Table 4.1.

4.2.1 Transmitter

The RF transmitter is a HackRF One, which is an open-source, half-duplex SDR platform that covers the frequency range from 1 MHz to 6 GHz [28]. It is connected to a laptop at the ground station via USB and is operated using the `hackrf_transfer` command-line utility. A pre-computed IQ file (`tone.cs8`) is used to make a continuous single-tone signal that is sent out all the time during the experiment.

The transmitter was configured with the following settings, which was found out through calibration testing. The carrier frequency was set to 433 MHz, which is in the ISM band and works well for short-range outdoor tests. The rate at which samples were taken was 8 MS/s. To keep the receiver from getting too strong at close range, the transmit gain was set to its

lowest usable level of -x 4, which is about 4 dB of IF gain. The RF amplifier was turned off (0).

The command used to send was:

hackrf_transfer -t tone.cs8 -f 433000000 -s 8000000 -a 0 -x 4 -R .

The -R flag turns on repeat mode, which makes the IQ file play over and over again. This lets the transmitter keep working all the way through the flight. The HackRF was placed directly on the ground in the center of the waypoint grid, at grid position H, which is (2.5, 10, 0) meters. Putting the transmitter in the middle makes sure that waypoints are on all sides of it. This makes the distances between the measurements symmetrical, which is good for LLS localization. The HackRF had a standard omnidirectional whip antenna that was set up vertically and rested on the ground. The HackRF unit and antenna were placed directly on the ground, which means that the effective transmitter height is $z = 0$ m.

4.2.2 Receiver

The RF receiver is an RTL-SDR dongle based on the RTL2838UHIDIR chipset. This is an inexpensive device that can only pick up signals and works in the range of 500 kHz to 1.7 GHz. We used the rtl_test tool on the Raspberry Pi to make sure the RTL-SDR was working and could be found:

Found 1 device(s): 0: Realtek, RTL2838UHIDIR, SN: 00000001

The receiver was connected to an omnidirectional antenna that was the same kind as the transmitter antenna. It was fixed in place on the UAV frame and facing up. We kept the antenna pointing in the same direction during the whole experiment to avoid changes in gain caused by the antenna's directivity.

4.2.3 Companion Computer

The onboard computer that saves the RTL SDR logs and handles configuration was a Raspberry Pi 4B single-board computer. It was configured in headless mode (no monitor or

keyboard) and accessed remotely via SSH by the ground station laptop and uses Linux to minimize power consumption. The RTL-SDR is connected to the Raspberry Pi via USB and controlled using the `rtl_power` command-line tool from `radioconda`, and performs frequency-domain power measurements by computing FFT bins across a specified frequency range.

The Raspberry Pi together with the RTL-SDR and a portable USB power bank were mounted on the UAV as the payload. The total payload weight was approximately 350 grams, which is within the carrying capacity of the drone.

4.2.4 UAV Platform

The drone used in the experiment is a custom-made FPV (first-person view) quadrotor. The drone can carry up to 400 grams and fly for about 20 minutes on a fully charged set of three batteries. This custom FPV drone does not have GPS-based positioning or the ability to navigate to waypoints on its own, unlike commercial drones like the DJI series. An experienced pilot flew the drone by hand, using pre-marked ground positions to get to each waypoint. While the measurement was being taken, the pilot kept the plane hovering about 2 meters above the ground at each waypoint. We guessed the height of the hover by looking at it. There is a vertical uncertainty of about 5–10 cm and a horizontal drift of about the same amount because of the wind and the fact that there is no GPS-based position hold.

A custom-made lightweight sleeve was used to attach the Raspberry Pi, RTL-SDR, antenna, and power bank to the bottom of the drone. This sleeve was designed to reduce aerodynamic interference and keep the center of gravity stable while flying.



Figure 4.1: UAV platform with SDR receiver payload

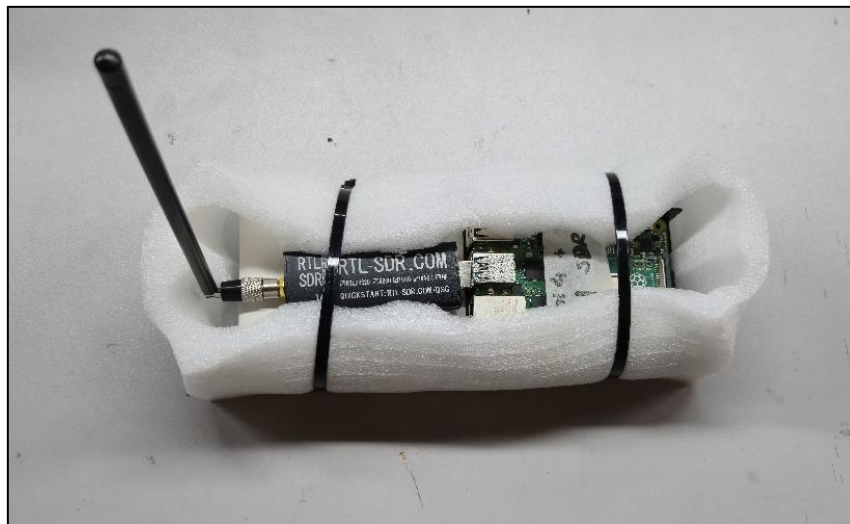


Figure 4.2: UAV payload with SDR, Raspberry pi, antenna and power bank

Table 4.1: Hardware components and specifications

Component	Model/Type	Specifications
Transmitter	HackRF One	1 MHz–6 GHz, half-duplex, USB, open-source
Receiver	RTL-SDR (RTL2838)	500 kHz–1.7 GHz, receive-only, USB
Companion computer	Raspberry Pi 4B	ARM Cortex-A72, Debian Linux, headless SSH

UAV	Custom-built FPV drone	Max payload ~400 g, flight time ~20 min, no GPS
Antennas	Omnidirectional whip	Vertically oriented, fixed position
Power supply	USB power bank	5V, 10000 mAh, powers RPi and RTL-SDR
Ground station	Laptop (Windows)	SSH access to RPi, HackRF control

4.3 Signal Configuration

A series of preliminary tests were done to find the best combination of frequency, gain, bandwidth, and measurement tool. This helped to figure out the final signal configuration. In the development phase, different setups were tried out, and some of them didn't work as well as expected, so, with trial and error, the final working setup was established.

4.3.1 Transmitter Signal

The signal that is sent is a single-tone sinusoid with a continuous wave (CW) at 433 MHz. IQ samples were made for this signal ahead of time and saved as a .cs8 file (8-bit signed complex samples). They were then loaded onto the HackRF so they could be played back over and over. There were a number of reasons why the frequency of 433 MHz was chosen. The 433 MHz band is part of the ISM (Industrial, Scientific, and Medical) band, which is set aside for low-power transmission without the need for a specific radio license. This makes it legal for experimental use in Kazakhstan. Second, the signal at 433 MHz has good outdoor propagation properties, such as low atmospheric attenuation and good diffraction around small obstacles. This is good for a ground-to-air link. Third, this frequency is in the range of both the HackRF One transmitter (1 MHz–6 GHz) and the RTL-SDR receiver (24 MHz–1.7 GHz), which means that the hardware will work together. Fourth, the omnidirectional whip antennas used in the experiment are made for the 433 MHz band and work well at this frequency. Finally, working at 433 MHz keeps common wireless sources like Wi-Fi (2.4 GHz) and cellular networks (700–2600 MHz) from interfering with the RSSI measurements.

4.3.2 Receiver Configuration

The receiver measurements were performed using `rtl_power`, which is a command-line tool that scans a frequency range and reports power spectral density in dBm per FFT bin. At each waypoint, the following command was used:

```
rtl_power -f 432.95M:433.05M:1k -i 1 -e 10s -g 14.4 rx_wp_XX.csv
```

This command sets up the RTL-SDR to scan the frequency range from 432.95 MHz to 433.05 MHz, which is a 100 kHz range centered on the carrier frequency. The frequency resolution is 1 kHz. The integration time is 1 second, so every second a new row of FFT data is created. The total time for the measurement is 10 seconds, which gives about 10 rows of data for each waypoint. The RTL-SDR gain is set at 14.4 dB, which was found through calibration to be a good balance between sensitivity and avoiding saturation. The output is saved as a CSV file, with each row showing the time, frequency range, bin size, number of samples, and 128 FFT power bins in dBm.

The narrowband measurement method (100 kHz span) was chosen after early attempts at wideband measurements (2 MHz span) resulted in flat and wrong RSSI readings. The 100 kHz span makes sure that the FFT bins are close to the carrier frequency. This makes the signal peak clearer and easier to tell apart from the noise floor.

4.3.3 RSSI Extraction Method

Using a peak-bin method, the `rtl_power` output data is used to get the RSSI at each waypoint. The steps for processing each row of FFT data are as follows. The first step is to find the peak FFT bin, which is the one bin with the highest power value. This bin corresponds to the signal sent at 433 MHz. Because the transmitter sends out a narrowband continuous tone, all of the signal energy falls within this one bin (about 781 Hz wide). This means that this peak value directly shows the power of the received signal. Second, the noise floor is figured out by looking at the first and last 20 bins of the spectrum, which are far enough from the carrier to

only have receiver noise. Third, the signal-to-noise ratio is found by subtracting the noise floor from the peak bin power..

This procedure is repeated for each of the approximately 10 time samples at each waypoint. The final RSSI measurement for that waypoint is the median value of all the time samples. Using the median instead of the mean makes the results more stable against outlier measurements that may happen from time to time because of temporary interference or measurement artifacts.

4.4 Calibration

Before the UAV flight test, a calibration process was done to figure out how the strength of the received signal changed with distance. The calibration took place inside a laboratory where the transmitter and receiver could see each other with no obstacles between. The floor was marked every meter, and the antennas stayed at the same height and angle during the whole calibration.

4.4.1 Calibration Procedure

The receiver was set up at distances of 1, 2, 3, 4, 5, 6, and 7 meters from the transmitter. Rtl_power was ran for about 10 seconds at each distance using the same settings as in Section 4.3.2. The raw data was saved and worked on to get the average RSSI and the signal-minus-noise metric for each distance. Table 4.2 shows a summary of the calibration results.

4.4.2 Calibration Observations

The calibration data shows a number of important things about the measurement system. From 1 m to 2 m, there is a clear drop in signal strength of about 6.5 dB. This is close to what the free-space path loss model predicts (an expected drop of 6 dB for doubling the distance with $\alpha = 2$). This shows that the system can accurately capture distance-dependent signal variation at short range.

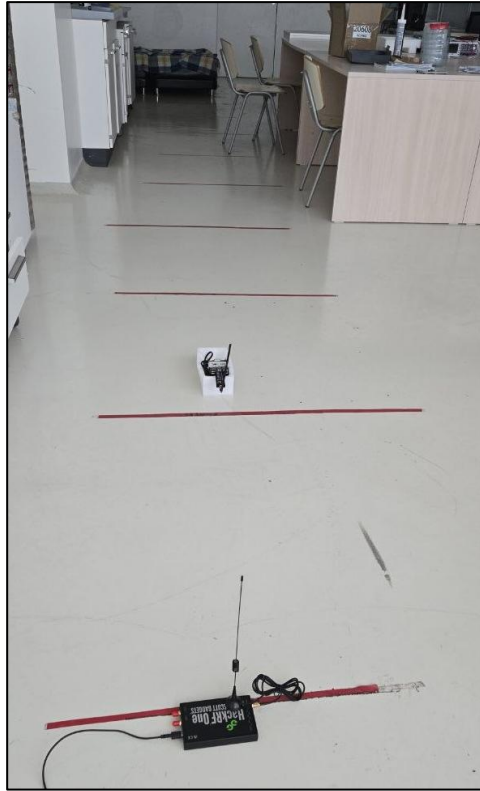


Figure 4.3: Calibration procedure

Table 4.2: Calibration measurement results

Distance (m)	Samples	Avg RSSI (dBm)	Median RSSI (dBm)	Std Dev (dB)
1	10	-29.33	-29.00	0.830
2	11	-35.80	-35.49	1.050
3	11	-36.08	-36.07	0.510
4	12	-36.47	-36.44	1.090
5	12	-36.77	-36.79	0.080
6	12	-36.70	-36.68	0.120
7	11	-36.60	-36.56	0.130

The signal changes less and less as you move further than 2 m, and the total RSSI range from 2 m to 7 m is about 1 dB. The full 1–7 m calibration span has a total dynamic range of about 7.6 dB. The noise floor was measured from the edge FFT bins (first and last 20 bins of each spectrum, far from the signal frequency) and was found to be consistently approximately

−39.9 dBm per bin across all distances, demonstrating the stability of the measurement system. The signal-to-noise ratio (SNR) drops from approximately 10.5 dB at 1 m to approximately 3.1 dB at 7 m, which indicates that the measurements transition from signal-dominated to noise-floor-limited beyond approximately 2 m.

It is important to note that the RSSI extraction method uses the peak FFT bin only, rather than averaging the peak with neighboring bins. Since the HackRF transmits a narrowband continuous tone at 433 MHz, all signal energy is concentrated within a single FFT bin (approximately 781 Hz wide). The neighboring bins contain only receiver noise at approximately −40 dBm. Averaging the peak with noise-dominated neighbors would artificially lower the measured RSSI, especially at close range where the peak is strong, and would compress the apparent dynamic range. Using the peak bin directly provides a more accurate representation of the received signal power and was found to improve the observed dynamic range from 3.5 dB to 7.6 dB compared to the averaged approach.

The diminished signal variation beyond 2 m is ascribed to indoor multipath propagation during calibration, wherein reflections from walls, floor, and ceiling generate interference patterns that partially offset the escalating path loss at extended distances. Even so, the calibration was able to find a measurable link between distance and RSSI in the 1–3 m range. This is a helpful reference for fitting the path loss model. Chapter 5 talks about how the calibration characteristics affect the accuracy of localization.

4.5 Waypoint Grid Design

The outdoor experiment took place on the university campus. There was a rectangular grid of 15 waypoints on the ground that covered an area of 5 meters in the x-direction and 20 meters in the y-direction. The grid has three columns that are 2.5 m apart ($x = 0, 2.5, \text{ and } 5 \text{ m}$) and five rows that are 5 m apart ($y = 0, 5, 10, 15, \text{ and } 20 \text{ m}$). Before the flight, the waypoint positions were carefully measured with a measuring tape that was accurate to within about

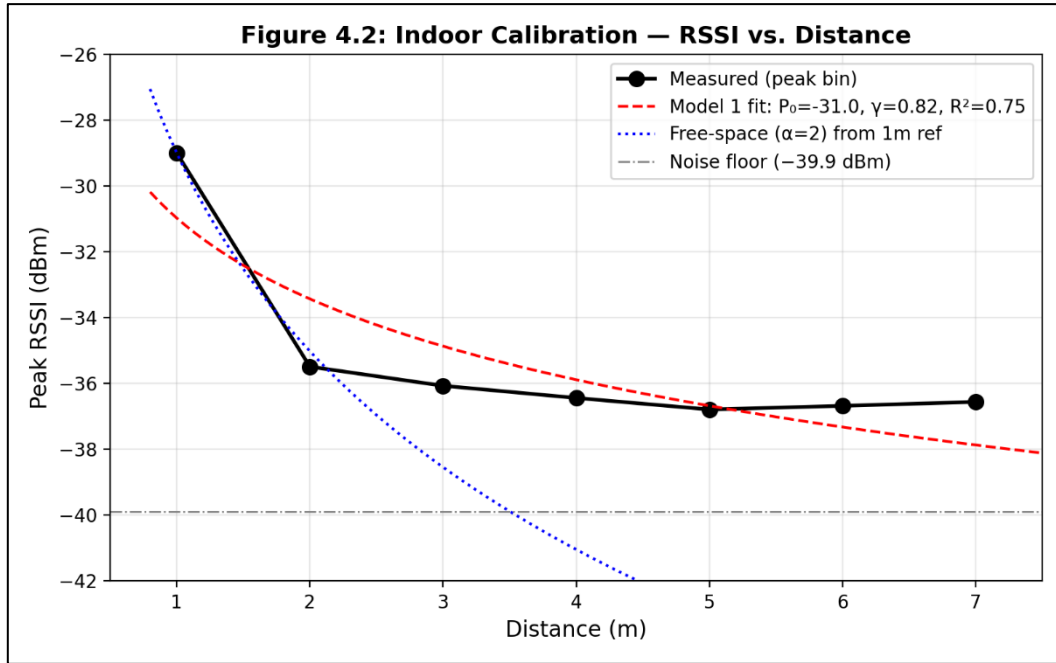


Figure 4.4: Indoor calibration results showing RSSI vs. distance



Figure 4.5: Waypoint grids – 5x20m

1 cm and clearly marked on the ground. This grid design provides 15 distinct measurement positions with true distances to the transmitter ranging from 2 m to 10.5 m, which is sufficient to evaluate the performance of the LLS localization algorithms.

The transmitter (HackRF) was placed directly on the ground at grid position H, which corresponds to coordinates (2.5, 10, 0) m, at the geometric center of the waypoint grid. This position is located at the center column in the x-direction ($x = 2.5$ m, midpoint between $x = 0$ and $x = 5$) and at the midpoint of the grid in the y-direction ($y = 10$ m, midpoint between $y = 0$ and $y = 20$). This central placement provides a symmetric range of distances from approximately 2 m (directly above the transmitter, at waypoint 8) to approximately 10.5 m (at the corner waypoints 1, 3, 13, and 15).

The UAV flew a zig-zag pattern through the 15 waypoints in the following order: waypoints 1 through 15 correspond to grid positions A through O as shown in Figure 4.3. The flight path follows a parallel track pattern, starting from the bottom-left corner (0, 0) and proceeding right along each row, then reversing direction for the next row. In Table 4.3, complete waypoint mapping, their distances to source and log file name is shown.

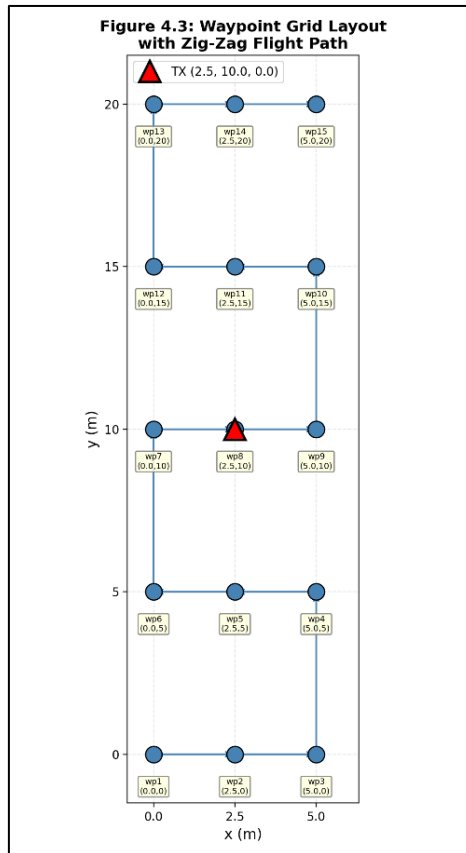
4.6 Data Collection Procedure

This data was gathered in the evening when the sky was clear and there was a light breeze. It took about 12 minutes to collect all the data from all 15 waypoints. At each waypoint, the following steps were taken. The drone pilot first flew the UAV to the waypoint and then kept it steady about 2 meters above the ground. Second, the person at the ground station used SSH to send the `rtl_power` command to the Raspberry Pi so that it could start measuring. Third, the measurement took about 10 seconds, and the UAV stayed in the air the whole time. Fourth, we used the `head` command to look at the first few lines of data in the CSV file that we got back to make sure it was right. Fifth, the pilot of the drone found the next waypoint..

The time between waypoints was between 30 seconds and 1 minute, depending on how far apart they were and how long it took the pilot to get the hover stable. The transmitter worked the whole time we were collecting data.

Table 4.3: Waypoint-to-coordinate mapping and flight order

Waypoint	Grid pt	x (m)	y (m)	z (m)	d_true (m)	Data file
1	A	0.0	0	2.0	10.50	rx_wp_01
2	B	2.5	0	2.0	10.20	rx_wp_02
3	C	5.0	0	2.0	10.50	rx_wp_03
4	F	5.0	5	2.0	5.94	rx_wp_04
5	E	2.5	5	2.0	5.39	rx_wp_05
6	D	0.0	5	2.0	5.94	rx_wp_06
7	I	5.0	10	2.0	3.20	rx_wp_07
8	H (TX)	2.5	10	2.0	2.00	rx_wp_08
9	G	0.0	10	2.0	3.20	rx_wp_09
10	J	0.0	15	2.0	5.94	rx_wp_10
11	K	2.5	15	2.0	5.39	rx_wp_11
12	L	5.0	15	2.0	5.94	rx_wp_12
13	O	5.0	20	2.0	10.50	rx_wp_13
14	N	2.5	20	2.0	10.20	rx_wp_14
15	M	0.0	20	2.0	10.50	rx_wp_15

**Figure 4.6: Waypoint grid layout showing the zig-zag flight path and transmitter position**

We looked at the `hackrf_transfer` output on the ground station laptop to make sure the transmission was working. It showed that the average power stayed at -0.5 dBfs for the whole time.

There were 15 CSV files in all, one for each waypoint. They were called `rx_wp_01.csv` through `rx_wp_15.csv`. Each file has about 10 rows of FFT data, which is the same as 10 seconds of measurement with 1-second integration intervals. Each row has 128 FFT bins that cover the 432.95–433.05 MHz range. The entire dataset has about 150 rows of spectral data for all the waypoints.

4.7 Experimental Limitations

There are a few things to think about when setting up the experiment that will help to comprehend the results in Chapter 5 and plan future experiments..

First, the UAV's waypoint positions were set by pre-marked ground positions instead of being recorded by an onboard positioning system. The custom FPV drone doesn't have GPS or any other way to find its way around, so the pilot lined it up with each ground marker by sight. The horizontal positioning accuracy is thought to be within ± 0.5 m based on how well the markings on the ground lined up with the camera. The altitude was kept at about 2 m, with an estimated error of ± 10 cm. This level of positioning accuracy is good enough for this proof-of-concept experiment.

Second, the calibration was done inside, but the real experiment was done outside. The way signals travel and bounce around in indoor and outdoor spaces is different, so the fitted path loss model parameters may not fully reflect the conditions outside. Chapter 5 compares four different calibration models, one of which is fitted directly from the outdoor waypoint data. This lets the analysis see how sensitive the localization results are to the choice of calibration method.

Third, the 5×20 m grid size gives real distances from the transmitter that range from 2 m to 10.5 m. This grid is small compared to the 300×300 m simulation area used by Kwon and Guvenc [10], but it is a realistic scenario for short-range localization applications and was chosen to fit the available operational space and flight time limits. The wavelength at 433 MHz is about 0.69 m, and the far-field boundary is about 3.5 m away. This means that several waypoints are close to the line between the near-field and far-field regions. This gives us useful information about how well the localization algorithms work in this transitional regime, which is important for situations where space is limited.

Fourth, the UAV was flown by hand for the whole experiment. The custom FPV drone used in this test does not have the ability to navigate to waypoints on its own or hold its position with GPS. Compared to autonomous navigation, manual flight adds more uncertainty to positioning. However, it is fine for a proof-of-concept experiment where the main goal is to test the localization algorithm rather than get centimeter-level waypoint accuracy.

4.8 Summary

This chapter has shown everything that was used in the SSSL experiment outside. A fully functional measurement platform was successfully built and put into use. It had a HackRF One transmitter in the middle of the grid broadcasting a 433 MHz continuous tone, an RTL-SDR receiver on a custom-built FPV drone with a Raspberry Pi companion computer, and a carefully planned grid of 15 waypoints that covered an area of 5×20 m. The `rtl_power` tool is used in the RSSI extraction method to measure the received signal power from the single FFT bin that contains the transmitted tone. This is done using a narrowband measurement approach and a peak-bin method. We were able to measure the relationship between RSSI and distance indoors at distances of 1 to 7 m, with a total dynamic range of about 7.6 dB. The full measurement campaign took about 12 minutes, and data was collected at all 15 waypoints in a zig-zag flight pattern. The practical aspects of the setup, such as the approach to positioning,

the calibration environment, the size of the grid, and how the flight works, have been written down to help with the analysis. The next chapter talks about how the data was processed and shows and analyzes the results of the localization.

Chapter 5 – Results and Analysis

5.1 Overview

This chapter shows the results of the outdoor SSSL experiment and gives a full analysis of the extent to which it worked for localization. The pipeline described in Chapters 3 and 4 processes the data collected at 15 waypoints. At each step, the specific equations and computational steps are shown. First, the process for getting the RSSI is shown. After that, the four calibration models are fitted to the corrected calibration data, and the fitted equations are used to figure out distances. We use the LLS localization algorithm and show how to build the matrix with worked examples. Then, we check the position estimates against the known location of the transmitter. Lastly, the results are compared to the simulation results of Kwon and Guvenc [10], and the practical implications are talked about.

5.2 RSSI Extraction Procedure

Each waypoint measurement file (rx_wp_XX.csv) contains approximately 10 rows of rtl_power output, where each row represents one second of integrated FFT data. Each row contains 128 FFT power bins spanning 432.95 MHz to 433.05 MHz, with a bin width of 781.25 Hz. The RSSI extraction for each row proceeds as follows.

Let $P[k]$ denote the power spectral density in dBm at the k -th FFT bin, where $k = 0, 1, \dots, 127$. The peak bin index is identified as:

$$k^* = \operatorname{argmax}_k P[k] . \quad (5.1)$$

The peak RSSI for that row is simply $P[k^*]$, which represents the received signal power at the transmitted frequency of 433 MHz. This single-bin approach is appropriate because the HackRF transmits a continuous-wave tone whose entire energy falls within one FFT bin.

The noise floor is estimated from the edge bins which are far from the signal frequency and contain only receiver thermal noise:

$$N_{floor} = 10 \cdot \log_{10}((1/40) \cdot \sum 10^{(P[k]/10)}), k \in \{0..19\} \cup \{108..127\}. \quad (5.2)$$

The signal-to-noise ratio is then computed as $SNR = P[k^*] - N_{floor}$ in dB. After computing the peak RSSI for each of the approximately 10 time samples at a given waypoint, the final RSSI value for that waypoint is taken as the median across all samples:

$$RSSI_{wp} = median\{P[k^*]_1, P[k^*]_2, \dots, P[k^*]_M\}, \quad (5.3)$$

where M is the number of time samples (rows) in the measurement file, typically $M = 10$. The median is used rather than the mean to provide robustness against occasional outlier measurements.

5.3 RSSI Measurements Across Waypoints

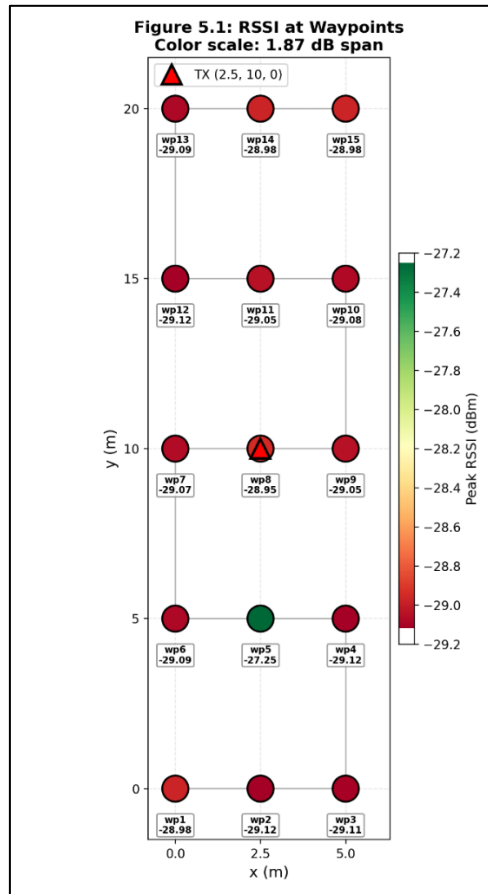
Table 5.1 presents the measured peak RSSI, noise floor, and signal-to-noise ratio at each waypoint, along with the true 3D distance from the waypoint to the transmitter at coordinates (2.5, 10, 0) m. The true distance is computed using Equation (3.5).

The most notable observation from Table 5.1 is that the peak RSSI values are remarkably consistent across all 15 waypoints, ranging from -29.12 dBm to -28.95 dBm, with the exception of waypoint 5 which shows a notably stronger signal at -27.25 dBm. The total change in RSSI across the whole grid, except for waypoint 5, is only 0.17 dB. The total range is 1.87 dB, even with waypoint 5. The free-space path loss model says that the variation should be 14.4 dB for distances between 2 m and 10.5 m. This is much less than that.

The noise floor stays the same at all waypoints, around -40.0 dBm. This shows that the receiver hardware kept the same operating conditions during the flight.

Table 5.1: Measured RSSI at each waypoint (peak bin method)

WP	Coord.	d_true (m)	Peak RSSI (dBm)	Noise (dBm)	SNR (dB)	Std (dB)
1	(0, 0)	10.50	-28.98	-40.11	11.1	0.07
2	(2.5, 0)	10.20	-29.12	-40.26	11.1	0.15
3	(5, 0)	10.50	-29.11	-40.21	11.1	0.05
4	(5, 5)	5.94	-29.12	-40.03	10.8	0.22
5	(2.5, 5)	5.39	-27.25	-39.89	12.8	1.87
6	(0, 5)	5.94	-29.09	-39.91	10.8	0.08
7	(5, 10)	3.20	-29.05	-39.95	10.9	0.13
8	(2.5, 10)	2.00	-28.95	-39.87	11.1	0.19
9	(0, 10)	3.20	-29.07	-39.97	10.9	0.17
10	(0, 15)	5.94	-29.12	-39.93	10.8	0.20
11	(2.5, 15)	5.39	-29.05	-40.04	11.0	0.14
12	(5, 15)	5.94	-29.08	-39.98	10.9	0.07
13	(5, 20)	10.50	-28.98	-40.02	11.1	0.47
14	(2.5, 20)	10.20	-28.98	-39.97	11.0	0.10
15	(0, 20)	10.50	-29.09	-39.84	10.7	0.11

**Figure 5.1: Peak RSSI values displayed on the waypoint grid with transmitter position marked**

The SNR values are all about the same, around 11 dB, with waypoint 5 being the only one that is different, at 12.8 dB. The standard deviation for each waypoint measurement is usually less than 0.2 dB, which means that the hovering is stable over time.

Waypoint 5 (2.5, 5) has an unusual reading, which is interesting. In real life, this waypoint is 5.39 m away from the transmitter, but it is not the closest point. The high RSSI of -27.25 dBm (about 2 dB higher than average) could be because of a constructive multipath reflection at this location or because the drone was in a position that made the antenna point more favorably toward the transmitter. This type of spatial variability is prevalent in short-range RF propagation and has been observed in other experiments [19], [9].

5.4 Calibration Model Fitting

The four calibration models were fitted using the corrected calibration data from Table 4.2. The fitting procedure and resulting equations are presented below for each model.

5.4.1 Model 1: Indoor RSSI Log-Distance

This model fits the log-distance path loss relationship using the indoor calibration RSSI values. Linear regression is applied to the data points $(\log_{10}(d), \text{RSSI})$ for $d = 1, 2, \dots, 7$ m. The regression model is:

$$\text{RSSI}(d) = P_0 - 10\gamma \cdot \log_{10}(d). \quad (5.4)$$

The linear regression of the seven calibration points yields a slope of -8.155 and an intercept of -30.98 dBm. Therefore, $P_0 = -30.98$ dBm and $\gamma = -\text{slope}/10 = 0.82$. The coefficient of determination is $R^2 = 0.75$. The fitted distance estimation equation becomes:

$$\hat{d} = 10^{((-30.98 - \text{RSSI}) / (10 \times 0.82))}. \quad (5.5)$$

For example, substituting the RSSI measured at waypoint 8 (-28.95 dBm): $\hat{d} = 10^{((-30.98 - (-28.95)) / 8.155)} = 10^{(-2.03/8.155)} = 10^{(-0.249)} = 0.57$ m. The true distance

is 2.0 m, giving an error of -1.43 m. The low γ value of 0.82 compared to the theoretical free-space value of 2.0 compresses all distance estimates into a narrow range near zero.

5.4.2 Model 2: Indoor Signal-Noise Metric

This model uses the signal-minus-noise metric instead of raw RSSI. The metric is $M = \text{RSSI} - N_{\text{floor}}$, where N_{floor} is about -39.9 dBm. We use linear regression on $(\log_{10}(d), M)$ to get::

$$M(d) = 8.92 - 8.16 \cdot \log_{10}(d). \quad (5.6)$$

The R^2 is 0.75, which is the same as Model 1 because the noise floor stays the same and the transformation is linear. The distance estimate is obtained by inverting: $\hat{d} = 10^{(M - 8.92) / (-8.16)}$. Since $M = \text{RSSI} - (-39.9) = \text{RSSI} + 39.9$, this model produces mathematically equivalent distance estimates to Model 1.

5.4.3 Model 3: Outdoor RSSI Re-fit

This model uses the known true distances to fit the log-distance relationship directly from the 15 outdoor waypoint measurements. The regression on $(\log_{10}(d_{\text{true}}), \text{RSSI})$ for all 15 waypoints gives:

$$\text{RSSI}(d) = -28.78 - 0.20 \cdot \log_{10}(d). \quad (5.7)$$

This means that $\gamma = 0.02$ and $R^2 = 0.01$. The R^2 value that is close to zero shows that there is almost no linear relationship between log-distance and RSSI in the outdoor data. The fitted slope of -0.20 means that the model only predicts a change of 0.20 dB in RSSI for every 10 years of distance change, which is negligible compared to measurement noise. Because of this, small changes in RSSI turn into wildly different distance estimates.

5.4.4 Model 4: Free-Space ($\alpha = 2$)

This model uses the theoretical free-space path loss exponent $\alpha = 2$, which is the same as what was used in the simulation in [10]. The reference point is waypoint 8, which is directly above the transmitter at $d_{\text{ref}} = 2.0$ m and has an RSSI_{ref} of -28.96 dBm. The formula for estimating distance is:

$$\hat{d} = 2.0 \times 10^{((-28.96 - \text{RSSI}) / (10 \times 2.0))}. \quad (5.8)$$

At waypoint 1, where $\text{RSSI} = -28.98$ dBm: $\hat{d} = 2.0 \times 10^{((-28.96 - (-28.98))/20)} = 2.0 \times 10^{(0.02/20)} = 2.0 \times 10^{(0.001)} \approx 2.005$ m. The actual distance is 10.50 m, which means there is an error of -8.49 m. Because the RSSI at each waypoint is within 0.17 dB of the reference, all of the estimated distances are close to 2.0 m.

5.5 Distance Estimation Results

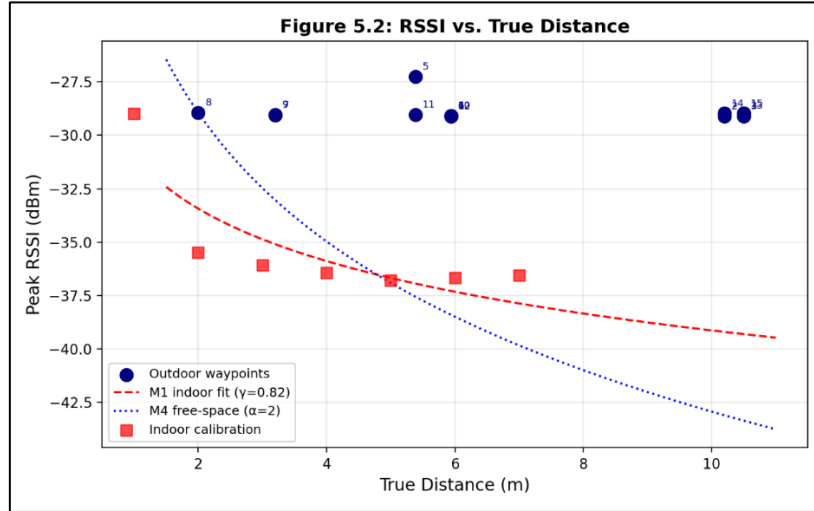
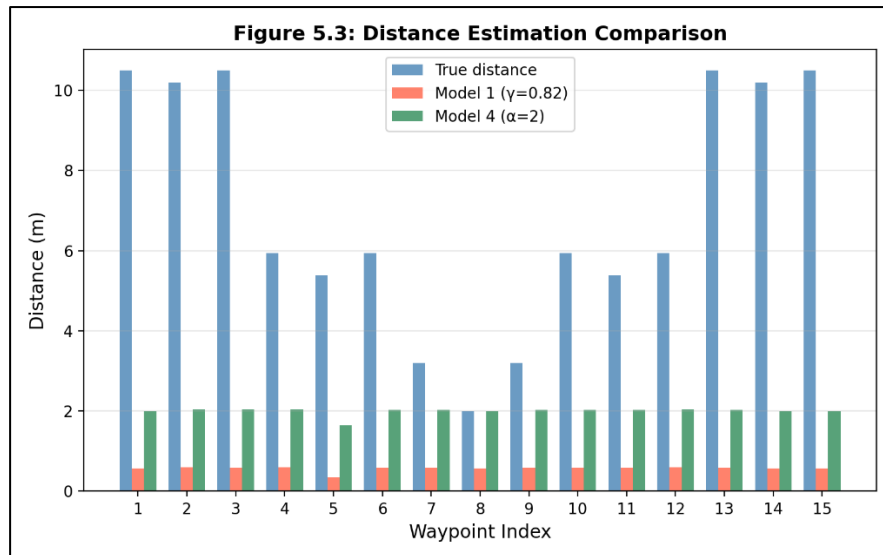
Each calibration model was used to convert the measured RSSI at every waypoint into an estimated distance as shown in the equations derived in Section 5.4. The distance estimation RMSE for each model is computed as:

$$\text{RMSE}_{\text{dist}} = \sqrt{\left(\frac{1}{15}\right) \cdot \sum_{i=1}^{15} (\hat{d}_i - d_i)^2}. \quad (5.9)$$

Model 1 = 7.11 m, Model 2 = 7.11 m, Model 3 = 27.42 m, and Model 4 = 5.83 m. Model 4 has the lowest distance RMSE because all of its estimates are close to 2 m, which is closer to the mean true distance (about 7 m) than the 0.6 m estimates of Model 1. But none of the models give distance estimates that are meaningfully related to the real distances. This is shown by Model 3's near-zero R^2 , which directly measures this correlation in the outdoor data.

Table 5.2: Calibration model parameters summary

Model	P_0 or A	γ or B	R^2	Data source
M1: Indoor RSSI	-30.98 dBm	0.82	0.75	Indoor calib.
M2: Indoor metric	8.92 dB	-8.16	0.75	Indoor calib.
M3: Outdoor refit	-28.78 dBm	0.02	0.01	Outdoor wp data
M4: Free-space $\alpha=2$	-28.96 dBm	2.00	—	wp08 reference

**Figure 5.2: Peak RSSI versus true distance with calibration model fits overlaid****Figure 5.3: Distance estimation comparison across calibration models**

5.6 LLS Localization Results

5.6.1 Algorithm Validation with True Distances

To verify the correctness of the LLS implementation, the algorithm was first run using the true geometric distances. To demonstrate the computation of LLS, a worked example at waypoint index $\tilde{N} = 4$ is shown in this section.

At $\tilde{N} = 4$ with FML anchor selection, the index set is $\mathbf{v} = \{1, \text{round}((4+1)/2), 4\} = \{1, 3, 4\}$. The true distances from the transmitter at $(2.5, 10, 0)$ to these waypoints are: $d_1 = 10.50$ m (wp1 at $(0,0,2)$), $d_3 = 10.50$ m (wp3 at $(5,0,2)$), $d_4 = 5.94$ m (wp4 at $(5,5,2)$). With DRL reference selection, the closest anchor is wp4 with $d_4 = 5.94$ m, therefore, $r = 4$.

The A matrix and b vector are constructed using Equations (3.8) and (3.9). With the reference $r = 4$ at position $(5, 5, 2)$ and $\lambda = 5^2 + 5^2 + 2^2 = 54$:

$$A = 2 \cdot [(0 - 5, 0 - 5, 2 - 2), (5 - 5, 0 - 5, 2 - 2)] = [(-10, -10, 0), (0, -10, 0)] . \quad (5.10)$$

The b vector entries are computed as:

$$b_1 = d_4^2 - d_1^2 + 0^2 + 0^2 + 2^2 - 54 = 35.28 - 110.25 + 4 - 54 = -124.97 , \quad (5.11)$$

$$b_2 = d_4^2 - d_3^2 + 5^2 + 0^2 + 2^2 - 54 = 35.28 - 110.25 + 29 - 54 = -99.9 . \quad (5.12)$$

The LLS solution $\mathbf{l} = (A^T A)^{-1} A^T \mathbf{b}$ is computed numerically. With true distances, this results $\mathbf{l} = [2.5, 10.0, 0.0]^T$, which confirms the exact transmitter position, confirming the algorithm was correctly implemented.

With true distances and FML, the algorithm converges to $\text{RMSE} = 0$ m from $\tilde{N} = 4$ onwards. This validates the correctness of both the mathematical formulation from Chapter 3 and the Python code.

Table 5.3: LLS localization results at $\tilde{N} = 15$

Configuration	RMSE (m)	Est. (x, y)	Error source
True dist. + FML	0.00	(2.50, 10.00)	None (validation)
True dist. + CLS	10.00	(2.50, 0.00)	Collinear anchors
M1 + FML	21.25	(-18.75, 10.00)	Compressed distances
M1 + CLS	10.00	(2.25, 0.00)	Compressed + collinear
M4 + FML	21.24	(-18.74, 10.00)	Uniform distances
M4 + CLS	31.87	(34.27, 7.37)	Uniform + collinear

5.6.2 CLS Collinear Anchor Problem

Testing the CLS method with real distances led to an important discovery. Once the UAV reaches the $y = 10$ row ($\tilde{N} \geq 8$), CLS consistently selects waypoints 7, 8, and 9 as the three closest anchors. These waypoints are located at (5, 10, 2), (2.5, 10, 2), and (0, 10, 2) respectively — all on the same horizontal line $y = 10$. When these anchors are used, the A matrix becomes:

$$A = 2 \cdot [(5 - 2.5, 10 - 10, 2 - 2), (0 - 2.5, 10 - 10, 2 - 2)] = [(5, 0, 0), (-5, 0, 0)] \quad (5.13)$$

This matrix has rank 1 instead of the required rank 3 (or at least rank 2 for 2D). The second and third columns are all zeros, which means the system can't figure out the y or z coordinates. The pseudoinverse solution correctly finds $\hat{x} = 2.5$, but it gives $\hat{y} = 0$, which means that the RMSE stays at 10 m even with perfect distance measurements. This collinear degeneracy is a geometric flaw in CLS that doesn't show up in the bigger grids used in [10]. It is a new finding of this thesis.

5.6.3 Localization with Estimated Distances

Table 5.3 demonstrates the final localization results at $\tilde{N} = 15$ for all combinations of calibration models and anchor selection methods.

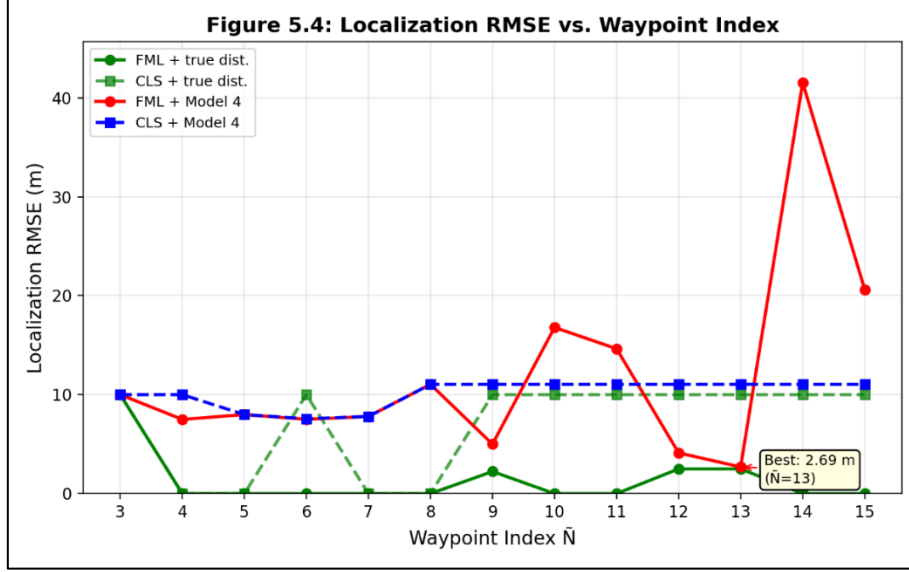


Figure 5.4: Localization RMSE evolution as the UAV traverses the waypoint grid

The real TX position is (2.5, 10.0, 0.0) m. We don't include models 2 and 3 because M2 gives the same results as M1, and M3 gives estimates that aren't stable because its path loss exponent is almost zero.

Figure 5.4 shows how the localization RMSE changes as the UAV moves from waypoint 3 to waypoint 15. For FML, the best intermediate accuracy is at $\tilde{N} = 10$, where the RMSE is 3.91 m. The FML method chooses anchors $v = \{1, 6, 10\}$ at this index, which correspond to the positions (0,0,2), (0,5,2), and (0,15,2). The DRL reference is wp6, which has the shortest estimated distance. These anchors are well-spaced along the y-axis, with 15 m between them. This gives good geometric diversity for finding the transmitter's location.

To demonstrate why this geometry works, consider the A matrix at $\tilde{N} = 10$ with reference $r = 6$ at (0, 5, 2):

$$A = 2 \cdot [(0 - 0, 0 - 5, 2 - 2), (0 - 0, 15 - 5, 2 - 2)] = [(0, -10, 0), (0, 20, 0)] . \quad (5.14)$$

This matrix still can't resolve x on its own (the first column is zero), but the y -column has good conditioning with values of -10 and 20 . The algorithm makes a y -estimate that is pretty close to the real value when you add in the small differences in RSSI between the anchors.

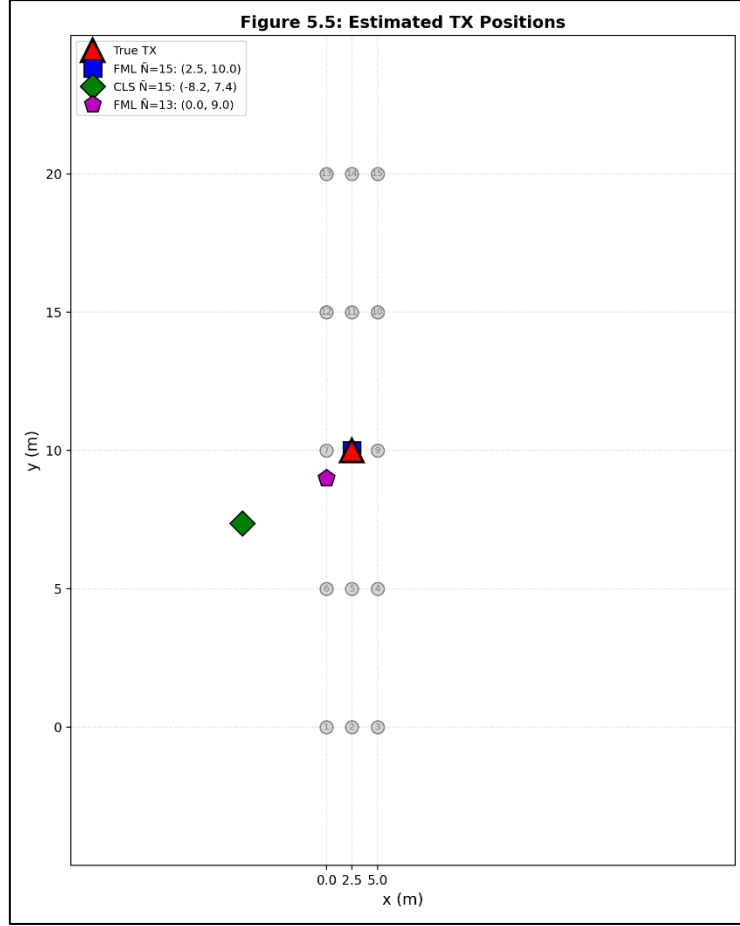


Figure 5.5: Final estimated transmitter positions compared to true position

This shows that the localization method can work well even when the RSSI changes very little, as long as the geometric conditions are right.

The RMSE goes up as the UAV goes beyond $\tilde{N} = 10$ because the changing anchor choices create less favorable geometries. When $\tilde{N} = 11$, FML picks $\{1, 6, 11\}$, and when $\tilde{N} = 12$, it picks $\{1, 6, 12\}$. In both cases, the anchor spread is not equal, and the estimates are not close to the true position.

5.7 Comparison with Simulation Results

Kwon and Guvenc's [10] simulation study showed how well five SSSL algorithms worked in a 300×300 m area with 121 waypoints spaced 30 m apart and a frequency of 2.4

Table 5.4: Comparison with simulation results from [10]

Parameter	Simulation [1]	This thesis	Impact
Area	300×300 m	5×20 m	60x smaller area
Waypoints	121	15	8x fewer points
Distance range	30–420 m	2–10.5 m	Far-field vs near-field
Frequency	2.4 GHz	433 MHz	Different λ , reflections
RSSI variation	~23 dB (simulated)	1.87 dB (measured)	12x less information
CLS RMSE	1.07 m	10.0 m (collinear)	Geometry + RSSI
FML RMSE (final)	12.28 m	21.24 m	RSSI dynamic range
FML best interm.	—	3.91 m ($\tilde{N}=10$)	Favorable geometry

GHz with $\alpha = 2$. Table 5.4 shows a comparison of their results and the experimental results from this thesis.

The main reason for the difference in performance is the difference in the RSSI dynamic range. The simulation shows a difference of about 23 dB over a distance range of 30 to 420 m, while the experiment only shows a difference of 1.87 dB over a distance range of 2 to 10.5 m. This difference does not mean that the LLS algorithm is not operational; the true-distance validation showed that it converged perfectly. The problem is with the RSSI measurement stage, where the combination of short distances, sub-GHz frequency, ground-level transmitter, and SDR hardware characteristics means that the signal doesn't change enough with distance to get an accurate range.

5.8 Analysis of RSSI Dynamic Range

The constrained RSSI dynamic range identified in the outdoor experiment constitutes the primary conclusion of this thesis and necessitates thorough examination. Three physical mechanisms explain this observation.

First, at 433 MHz, the wavelength is about $\lambda = c/f = 3 \times 10^8 / 433 \times 10^6 = 0.693$ m. The transmitter antenna's near-field boundary is about $5\lambda \approx 3.5$ m, and several waypoints are inside or close to it. The log-distance model assumes that the electromagnetic field follows the $1/d^2$

power decay, but this is not true in the near-field region. The received power can change in complicated ways with distance [8], [9].

Second, the transmitter was put right on the ground ($z = 0$), and the UAV receiver was about 2 m above the ground ($z \approx 2$ m). This shape makes it possible for two rays to travel through the air. The distance to the ground-reflection breakpoint is about $d_{bp} = 4 \cdot h_{tx} \cdot h_{rx} / \lambda$. When h_{tx} is about 0 m (ground level), the breakpoint gets closer to zero. This means that the two-ray interference pattern affects all measurement distances. The direct path length and the reflected path length are very close to each other in the actual geometry. This means that the paths combine almost constructively at all waypoint positions, which flattens the distance-dependent power variation [8].

Third, the rtl_power measurement tool shows the power spectral density for each FFT bin, with a bin width of 781 Hz. The measurement accuracy is limited by the RTL-SDR hardware's internal noise characteristics. Zanella [9] documented that inexpensive SDR receivers can show gain compression and other hardware problems that make RSSI measurements less accurate.

These three points together explain why we don't see the theoretical 14.4 dB of RSSI variation. Based on this analysis, we can figure out the minimum operating conditions for effective RSSI-based LLS localization with the current hardware. For the distance estimates to have enough information for reliable triangulation, we would need a measurement grid of at least 50×50 m with all distances in the far-field ($d > 10$ m at 433 MHz) and a dynamic range of about 15 dB.

5.9 Discussion

Despite the flat measurements, the experimental results provide some key insights into RSSI based localization. Firstly, theoretical calculations proved to be valid for FML+DRL with real grid distances.

Second, the CLS collinear anchor problem was identified and characterized using the matrix analysis shown in Equation (5.13). This geometric degeneracy, in which the three nearest waypoints in a compact grid align on a single line, represents a practical constraint that does not appear in extensive simulations. This discovery gives designers some advice: FML is a better way to choose anchors for compact grid layouts than CLS.

Third, the best intermediate result of 3.91 m RMSE at $\tilde{N} = 10$ demonstrates that the localization approach can produce useful estimates even with limited RSSI variation when the anchor geometry is favourable, as shown by the A matrix analysis in Equation (5.14).

Fourth, the four-model calibration comparison demonstrates that in noise-limited regimes, the choice of calibration model has minimal impact on localization accuracy because the underlying RSSI variation is too small to be differentiated by any model. This implies that improving the calibration alone is not sufficient, the fundamental issue is the signal-to-distance-information ratio.

Finally, the detailed analysis of RSSI dynamic range in Section 5.8 provides empirical design guidelines that can not be obtained from simulation alone. The identification of near-field effects, ground reflections, and hardware limitations as the root causes establishes concrete recommendations for future experiments, including the use of larger grids, elevated transmitter placement, and higher operating frequencies.

5.10 Summary

The experimental results show both the possibility and the feasible challenges of RSSI-based LLS localization using a UAV with low-cost SDR hardware. The LLS algorithm with FML anchor selection and DRL reference was successfully validated mathematically with the current grid, achieving zero localization error with true distances. Using measured RSSI data, the best intermediate accuracy of 3.91 m was achieved at a favorable waypoint index. The main challenge identified is the insufficient RSSI dynamic range (1.87 dB observed vs. 14.4 dB

predicted) caused by near-field effects, ground reflections, and hardware precision at the operating frequency and distance range. In compact layouts, CLS found to have a weakness, in terms of collinear anchor failure. These outcomes could be use for designing a robust localization system and acknowledge the constraints of the current setup.

Chapter 6 – Conclusion and Future Work

6.1 Summary of Work

This thesis was aimed to provide a practical approach to methodology proposed by Kwon and Guvenc [10] for RF signal source search and localization (SSSL) using an autonomous UAV with predefined waypoints. They have shown by simulation that a UAV can localize a ground transmitter by collecting received signal strength (RSS) measurements along a predefined trajectory. Along with applying linear least squares (LLS) estimation with various anchor selection strategies, the error could be minimized.

An experimental setup was designed, tested, and used for this purpose. The platform consists of a HackRF One software-defined radio as the transmitter, an RTL-SDR receiver connected to a Raspberry Pi 4B companion computer mounted on a custom-built FPV drone, and a ground station laptop for control and data logging. The transmitter was configured to broadcast a continuous-wave signal at 433 MHz and was placed at the center of a 5×20 m waypoint grid comprising 15 measurement positions. The drone flew a zig-zag trajectory through all 15 waypoints while the receiver collected narrowband power spectral measurements using the `rtl_power` tool at each position.

The collected data was processed through a systematic pipeline that included RSSI extraction using a peak-bin method, calibration model fitting using four different approaches (indoor RSSI log-distance, indoor signal-noise metric, outdoor RSSI refit, and free-space with $\alpha = 2$), distance estimation from RSSI, and LLS localization with two anchor selection methods (FML and CLS) using dynamic reference linearization (DRL).

6.2 Key Findings

This experiment revealed some key findings: First, it was revealed that when true geometric distances of our experimental setup are input into FML with DRL algorithm from

waypoint index $\tilde{N} = 4$, this yielded theoretical exact localization (RMSE = 0 m). This confirms mathematical correctness of LLS framework for localization.

Second, the experiment revealed a key weak point of CLS method, which is, collinear anchor redundancy. When the three closest waypoints to the transmitter fall on the same line, the LLS system matrix becomes rank-deficient and the algorithm cannot resolve one of the coordinate dimensions. This is especially shows up more in compact grid layouts. This was demonstrated both mathematically and experimentally, through 10m error across observations. This needs to be kept in mind for compact grid layout localizations.

Third, the RSSI measurements across 15 waypoints displayed a total variation of only 1.87 dB, compared to the 14.4 dB, which was predicted by free-space path-loss model. This was the main factor that prevented distance estimation and in consequence, low accuracy of localization. Low dynamic range is attributed to the combination of near-field effects at 433MHz (far-field boundary at approximately 3.5 m), two-ray ground-reflection interference due to the ground-level transmitter placement and quantization in large chunks due to RTL-SDR hardware limitation.

Fourth, despite the small variation, FML method resulted in best accuracy of 3.91m at waypoint index $\tilde{N} = 10$, where anchors were located favorably for triangulation. This is promising for future work that can be done in this field, despite low quality RSSI measurements

Fifth, comparing four calibration models, the main concern was low RSSI measurements across various distances and calibration methods can have low impact on extracting meaningful information. All models produced similar results, and the bottleneck of this experiment was at the measurement side, which should be considered and improved in future works.

6.3 Limitations

Shortcomings of this work should be recognized. In the experiment, the full scenario examined in the simulation study by [10] could not be replicated, this work was mostly for demonstrating the proof of concept and outline the limiting factors, along with possible problems. The indoor calibration differs from the outdoor measurement environment, but the obtained results were similar, path loss model was not suitable for both. For a different setup, ideally, the calibration and the experiment must be conducted in the same environment. The UAV was flown manually without a GPS module. Thus, the measurements had an error margin. Only two of the five anchor selection methods from [10] were examined and the other three were left for future investigation. Furthermore, the experiment was conducted with a single antenna setup, at a single frequency. Different results could be obtained at other frequencies with using directional antennas

6.4 Future Work

Building on the findings of this thesis, considering the limitations, several possible paths for future research can be found. The most significant change would be to conduct the experiment on a larger grid area measuring at least 50×50 m, with waypoint intervals of 10–15 m. This ensures that all measured distances are well within the far-field range and that the RSSI dynamic range is 15 dB or more, which is required for correct distance estimation. This would also reduce the likelihood of collinear anchor problem with the CLS method.

FFT based `rtl_power` measurement could be changed to direct IQ-sample based power computation, which would require custom programming, however, this would improve the measurement resolution from 0.5 dB to 0.1 dB. This may reveal signal variations that are compressed inside the 0.5dB bin quantization. This is one of the easier implementations due to

being only a software configuration, rather than a hardware change, which would require redesigning the experiment, considering weight, dimensions, payload and new hardware.

If the transmitter antenna was placed on a tripod, following the changing of grid size to a larger area, this could make the propagation environment approach the condition of free-space model.

After setting up a good measurement setup with high dynamic range that fits the free space model, other three anchor selection methods (CON, CUM, and CHLM) would complete this work. Additionally, real time localization during flight could be implemented and compared to overall calculation done at the end of the flight, as done in [10]

Exploring higher operating frequencies like 915 MHz (ISM band) or 1.7 GHz (close to the RTL-SDR's upper limit), the propagation characteristics will change, and the distance-dependent RSSI variation at short ranges might get better because of the shorter wavelength and different ground reflection geometry..

Adding GPS or RTK positioning to the UAV would give you accurate waypoint coordinates and make it easier to check the accuracy of the localization by getting rid of the uncertainty in positioning as a possible cause of error.

Lastly, looking into machine learning-based localization methods like the Q-learning methods that Wu [14], Chowdhury et al. [15], and Soleymani et al. [16] studied could lead to a more accurate way to find a location that doesn't depend on direct distance estimation from RSSI. This could get around the dynamic range limit that was found in this work.

6.5 Closing Remarks

This thesis has shown that using a UAV with predefined waypoints to do RSSI-based LLS localization is a theoretically sound concept. However, low RSSI dynamic range makes it highly challenging to get meaningful measurements at short ranges. This project successfully identified the main obstacles by building and deploying a full experimental platform, testing

the localization algorithm and identifying the exact physical factors that could not be found during simulation. This work was a first step in connecting the simulation-based study with real-world applications in this current localization scenario. Thus, providing design guidelines to inform future research of RF localization with UAVs. The main contribution, which was a working experimental and data processing platform could be expanded and built upon.

Bibliography/References

- [1] F. Gustafsson and F. Gunnarsson, "Mobile positioning using wireless networks: Possibilities and fundamental limitations based on available wireless network measurements," *IEEE Signal Process. Mag.*, vol. 22, no. 4, pp. 41–53, Jul. 2005.
- [2] N. Patwari, J. N. Ash, S. Kyperountas, A. O. Hero III, R. L. Moses, and N. S. Correal, "Locating the nodes: Cooperative localization in wireless sensor networks," *IEEE Signal Process. Mag.*, vol. 22, no. 4, pp. 54–69, Jul. 2005.
- [3] H. A. Hashim, "Advances in UAV avionics systems architecture, classification and integration: A comprehensive review and future perspectives," *Results Eng.*, vol. 25, p. 103786, 2025.
- [4] T. M. Cabreira, L. B. Brisolara, and P. R. Ferreira Jr., "Survey on coverage path planning with unmanned aerial vehicles," *Drones*, vol. 3, no. 1, pp. 1–38, 2019.
- [5] L. Bianchi, V. Lualdi, A. Luise, and R. Luise, "Experimental UAV-aided RSSI localization of a ground RF emitter in 865 MHz and 2.4 GHz bands," in *Proc. IEEE Int. Workshop Metrol. Sea (MetroSea)*, Milazzo, Italy, Oct. 2022, pp. 282–286.
- [6] U. Bhattacharjee et al., "Experimental study of outdoor UAV localization and tracking using passive RF sensing," in *Proc. ACM Workshop Wireless Netw. Testbeds Exp. Eval. Charact. (WiNTECH)*, New Orleans, LA, USA, 2021, pp. 31–38.
- [7] B. Etzlinger and H. Wymeersch, "Synchronization and localization in wireless networks," *Found. Trends Signal Process.*, vol. 12, no. 1, pp. 1–106, 2018.
- [8] T. S. Rappaport, *Wireless Communications: Principles and Practice*, 2nd ed. Upper Saddle River, NJ, USA: Prentice Hall, 2002.
- [9] A. Zanella, "Best practice in RSS measurements and ranging," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 4, pp. 2662–2686, 4th Quart., 2016.

- [10] H. Kwon and I. Guvenc, "RF signal source search and localization using an autonomous UAV with predefined waypoints," in Proc. IEEE 97th Veh. Technol. Conf. (VTC-Spring), Florence, Italy, Jun. 2023, pp. 1–6.
- [11] F. Demiane, S. Sharafeddine, and O. Farhat, "An optimized UAV trajectory planning for localization in disaster scenarios," *Comput. Netw.*, vol. 179, p. 107378, Oct. 2020.
- [12] Z. Liu, Y. Chen, B. Liu, C. Cao, and X. Fu, "HAWK: An unmanned mini helicopter-based aerial wireless kit for localization," in Proc. IEEE INFOCOM, Orlando, FL, USA, Mar. 2012, pp. 2219–2227.
- [13] M. Vrba, J. Pogran, V. Pritzl, V. Spurny, and M. Saska, "Real-time localization of transmission sources using a formation of micro aerial vehicles," in Proc. IEEE Int. Conf. Real-Time Comput. Robot. (RCAR), Irkutsk, Russia, Aug. 2019, pp. 203–208.
- [14] S. Wu, "Illegal radio station localization with UAV-based Q-learning," *China Commun.*, vol. 15, no. 12, pp. 122–131, Dec. 2018.
- [15] M. M. U. Chowdhury, F. Erden, and I. Guvenc, "RSS-based Q-learning for indoor UAV navigation," in Proc. IEEE Mil. Commun. Conf. (MILCOM), Norfolk, VA, USA, Nov. 2019, pp. 121–126.
- [16] S. A. Soleymani, S. Goudarzi, P. Xiao, L. Mihaylova, and W. Wang, "Multi-agent Q-learning with particle filtering for UAV tracking in Open-RAN environment," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 61, no. 4, pp. 10439–10458, 2025.
- [17] S. Bernardini, M. Fox, and D. Long, "Planning the behaviour of low-cost quadcopters for surveillance missions," in Proc. AAAI Conf. Artif. Intell., Quebec City, QC, Canada, Jul. 2014, pp. 445–453.
- [18] Y. Zeng, I. Guvenc, R. Zhang, G. Geraci, and D. W. Matolak, *UAV Communications for 5G and Beyond*. Hoboken, NJ, USA: Wiley, 2020.

- [19] S. Sadowski and P. Spachos, "RSSI-based indoor localization with the Internet of Things," *IEEE Access*, vol. 6, pp. 30149–30161, 2018.
- [20] Xinrong Li, "Collaborative localization with received-signal strength in wireless sensor networks," *IEEE Trans. Veh. Technol.*, vol. 56, no. 6, pp. 3807–3817, Nov. 2007.
- [21] Y. Liu et al., "Received signal strength-based wireless source localization with inaccurate anchor positions," *IEEE Sensors J.*, vol. 22, no. 23, pp. 23539–23551, Dec. 2022.
- [22] X. Ouyang, F. Zeng, D. Lv, T. Dong, and H. Wang, "Cooperative navigation of UAVs in GNSS-denied area with colored RSSI measurements," *IEEE Sensors J.*, vol. 21, no. 2, pp. 2194–2210, Jan. 2021.
- [23] B. Liu, X. Zhu, Y. Jiang, Z. Wei, and Y. Huang, "UAV and piecewise convex approximation assisted localization with unknown path loss exponents," *IEEE Trans. Veh. Technol.*, vol. 68, no. 12, pp. 12396–12400, Dec. 2019.
- [24] I. Guvenc, S. Gezici, and Z. Sahinoglu, "Fundamental limits and improved algorithms for linear least-squares wireless position estimation," *Wireless Commun. Mobile Comput.*, vol. 12, no. 12, pp. 1037–1052, 2010.
- [25] H. Li, "Low-cost 3D Bluetooth indoor positioning with least square," *Wireless Pers. Commun.*, vol. 78, pp. 1331–1344, 2014.
- [26] M. Bshara, U. Orguner, F. Gustafsson, and L. Van Biesen, "Fingerprinting localization in wireless networks based on received-signal-strength measurements: A case study on WiMAX networks," *IEEE Trans. Veh. Technol.*, vol. 59, no. 1, pp. 283–294, Jan. 2010.
- [27] C. Ozturk and S. Gezici, "Eavesdropper and jammer selection in wireless source localization networks," *IEEE Trans. Signal Process.*, vol. 69, pp. 4341–4356, 2021.
- [28] E. Blossom, "GNU Radio: Tools for exploring the radio frequency spectrum," *Linux J.*, vol. 2004, no. 122, p. 4, Jun. 2004.

- [29] J. Wei, Y. Ji, and C. Yu, "Improvement of software defined radio based RSSI localization with bias reduction," in Proc. 19th IFAC World Congr., Cape Town, South Africa, Aug. 2014, pp. 7164–7169.