RF-Based Drone Detection Using RFSoC and SDR:

Analysis and Automation Foundations

BY

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Abstract

This Honors Thesis presents early work on research to develop an automated system for drone detection using the computational power of Radio Frequency System-on-Chip (RFSoC) and the flexibility of software-defined radio (SDR). The ultimate goal is to create a system capable of autonomously detecting and classifying drone communication signals in real-time. By offering high detection accuracy, adaptability, and scalability, this system can provide a viable solution for mitigating the security risks posed by drones in both civilian and military contexts.

While this objective has not yet been fully achieved, significant progress has been made in understanding drone signal characteristics and behaviors. Python-based signal processing techniques and computer vision methods have been used to identify key features, such as channel-hopping behavior, and to model signal propagation of drones in open space. These insights serve as the foundation for future automated packet identification.

Acknowledgment

The success of this research would not have been possible without the support and guidance of several individuals and groups. I would like to express my deepest gratitude to Dr. John Shea and Dr. Tan Wong, whose mentorship, insights, and encouragement were invaluable throughout this project. Their expertise and dedication inspired me to pursue PhD and overcome challenges during this research journey.

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I. Introduction

A. Background and Motivation

Unmanned aerial vehicles (UAVs), or drones, have emerged as transformative tools in both civilian and military sectors because they offer unique capabilities and applications. In the civilian realm, drones are widely utilized for aerial cinematography, precision agriculture, and logistics.

While these advancements showcase the immense benefits of drones, they also bring about significant security challenges. Drones pose risks such as unauthorized surveillance, smuggling, and potential attacks on critical infrastructure and national security [1]. Moreover, their use in recent conflicts, such as the war in Ukraine and the Syrian civil war, highlights their tactical significance for reconnaissance, logistics, and precision strikes.

These threats indicate the necessity for developing robust detection systems capable of processing complex, high-volume data in real-time. Traditional detection approaches, such as radar and optical systems, face limitations in cost, scalability, and resilience to environmental interference, thus making this direction of exploration promising and intriguing.

B. Research Goals and Objectives

This research aims to develop a scalable drone detection framework that integrates the computational capabilities of Radio Frequency System-on-Chip (RFSoC) with the adaptability of software-defined radio (SDR). RFSoC's architecture, featuring high-speed ADC/DACs and FPGA logic, enables real-time acquisition and processing of drone communication signals. Python-based signal processing techniques and computer vision algorithms are employed to analyze drone signal characteristics and identify important drone features.

Although the ultimate goal of an autonomous system for real-time detection and classification has not yet been fully achieved, this study has made significant progress in understanding the nuances of drone communication signals. By addressing current limitations and laying the foundation for future advancements, this research contributes to the development of scalable and adaptable counter-drone solutions for both civilian and military applications.

C. Literature review

1) Traditional Detection Methods

a) **Radar-Based Detection**: Radar systems are widely used for long-range detection of drones as they can measure speed, altitude, and direction.

However, their effectiveness diminishes when detecting drones at low altitudes or slow speeds. Additionally, the high cost of deployment and maintenance remains a significant limitation [1] [2] [3].

b) **Vision-Based Detection**: Vision-based systems, such as cameras and thermal imaging, are cost-effective and provide intuitive detection for human operators. Advanced computer vision algorithms make tracking and recognition of drones more effective. Despite their advantages, these systems are heavily dependent on environmental conditions. Factors such as poor lighting, rain, fog, or dust can drastically affect detection accuracy and reliability [1] [3].

c) **Acoustic Detection**: Acoustic sensors use the unique sound signatures of drone propellers to detect. It can be used in cases where visual or radar methods fail. While effective in isolated or quiet environments, their performance significantly degrades regarding distance and in urban areas or noisy settings due to background noise and overlapping sound sources [1] [3].

d) **Radio Frequency (RF) Detection**: RF-based detection captures and analyzes the RF signals between drones and their controllers. This approach is highly adaptable to various weather conditions and does not require line-of-sight. However, distinguishing drone signals from other RF sources is challenging. This is especially hard in crowded frequency bands, such as urban environments or areas with high electromagnetic interference [1] [3].

2) Advancements in Vision-Based Drone Detection

Recent advancements in machine learning and computer vision have significantly enhanced drone detection capabilities. Deep learning models such as YOLO (You Only Look Once) and ResNet (Residual Neural Network) have been utilized to detect and classify drones with high accuracy [4] [5]. These convolutional neural networks (CNNs) excel at feature extraction and pattern recognition and enable real-time detection on hardware.

Despite these successes, vision-based methods face limitations. Their reliance on line-of-sight detection makes them susceptible to obstructions and environmental factors such as fog, smoke, or dust, which can hinder effectiveness in real-world applications.

3) Limitations of Current RF-Based Detection Research

RF-based drone detection faces challenges that prevent it from reaching the maturity observed in vision-based systems. Many published studies have relied on controlled, indoor experiments that oversimplify the real-world complexities of radio signal propagation [3] [4] [6] [7]. In these investigations, researchers often employ overly simple environmental models that fail to consider the difficulties encountered in actual operating scenarios. As a result, the obtained results cannot be easily translated into real-world progress. Key factors and limitations that need to be addressed include:

a) Non-Standardized Communication Protocols: Commercial drones operate using a variety of non-standardized communication protocols [3]. This variability means that detection approaches for one protocol may fail to detect emissions from other systems effectively. This limits the generalizability of current solutions.
b) Environmental Noise and Frequency Interference: Drone communications often occur on bands such as 2.4 and 5 GHz, which are the same frequency bands heavily used by Wi-Fi and other consumer electronics [6]. This crowded spectrum and ambient noise from nearby devices make it challenging to isolate and accurately detect drone communication signals.
c) Frequency Hopping: Commercial drones often utilize frequency hopping spread spectrum techniques [7] to mitigate jamming and interference. This strategy enables drones to continuously change channels, which complicates both detection and tracking efforts across the RF spectrum.
d) Multipath Effects: Multipath propagation is a significant challenge in urban and rural environments where obstacles cause RF signals to reflect, scatter, and follow multiple paths. As described in Chapter 2 of *"Fundamentals of Wireless Communication"* [8], these multipath components can interfere either constructively or destructively, thus leading to considerable signal distortion.

These limitations reveal that current RF-based detection research has not adequately addressed all the necessary factors for effective real-world performance. This underscores the need for additional research that addresses these challenges in real-world environments.

4) Addressing the Gap in RF-Based Methods

Given the growing reliance on drones and their associated security risks [1], there is a need to develop a drone detection solution. Unlike vision-based techniques, RF systems offer unique advantages, including detecting drones operating in poor visibility conditions like heavy rain, fog, or without a clear visual signature. This research seeks to fill the gap in RF-based detection by:

a) Expanding studies to include outdoor environments with realistic interference and noise.

b) Investigating advanced signal processing and machine learning techniques to handle the complexities of real-world RF data.

By addressing these gaps, RF-based detection can evolve into a more robust and reliable counter-drone solution. Ultimately, it can complement existing radar, optical, and acoustic methods.

II. Methodology

The methodology for this research encompasses two primary phases: data collection and data analysis. The objective is to utilize RFSoC and SDR to collect and analyze radio frequency signals emitted by drones and extract meaningful features using Python-based signal processing.

A. Data collection

The data collection process for this research was conducted at the Autonomy Park facility because of the regulatory restrictions on drone flights on campus grounds. The following subsections detail the methodology used to ensure a comprehensive and high-quality dataset.

1) Equipment Setup:

The system utilized two primary platforms for capturing RF signals emitted by drones:

a) **RFSoC 4x2 Platform:** Equipped with high-speed analog-to-digital converters (ADCs), digital-to-analog converters (DACs), and FPGA logic. As shown in Figure 1, RFSoC 4x2 enables real-time RF signal acquisition and preliminary signal preprocessing, such as low noise amplifiers and digitalization.

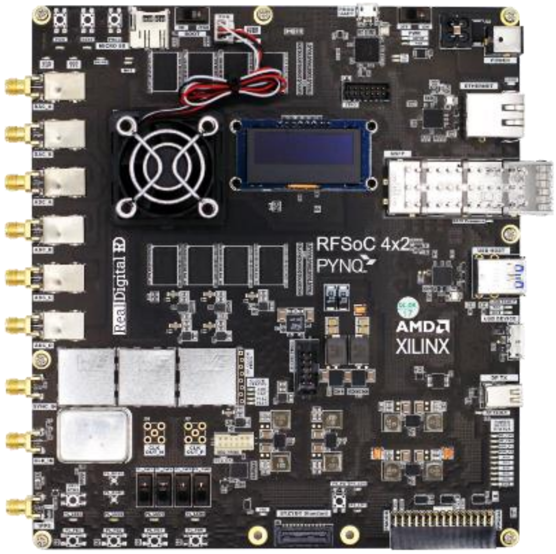

Figure 1: RFSoC platform used for data capture [9]

b) **Ettus USRP B210 Software-Defined Radio (SDR):** Paired with directional antennas, the USRP B210 can also capture RF signals across commonly used drone communication frequency bands. As shown in Figure 2, the device has multiple RF ports and a compact design. Its flexibility and user-friendly setup made it ideal for capturing RF data.

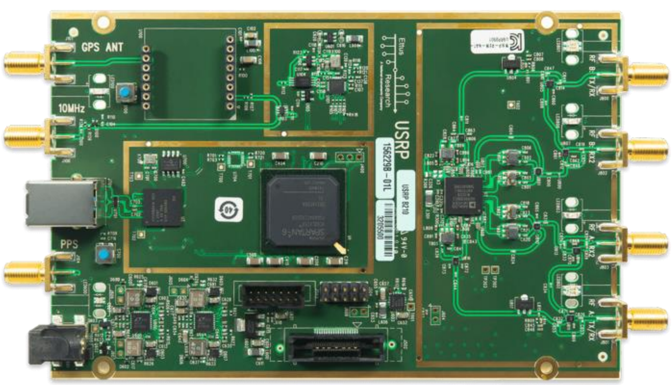

Figure 2: Ettus USRP B210 Software-defined radio [10]

2) **Field Testing Locations:**

The test was conducted at the UF Autonomy Park, which is an open area specifically selected for its balanced RF environment and that complies with local drone flight regulations. As shown in Figure 3Figure 3: Autonomy Park facility , the facility provides clear line-of-sight conditions with netted enclosure flight zones while maintaining sufficient distance from dense urban areas. This environment combines controlled testing conditions with realistic RF challenges, such as incorporating natural multipath effects and moderate background RF interference from nearby facilities. Unlike laboratory settings, this semi-rural location ensures generalizability.

Figure 3: Autonomy Park facility [11]

3) **Drone Signal Capturing:**

   We have designed multiple scenarios to simulate diverse real-world operational conditions:

   a) **Operational States:**

      Hovering: Drones remained stationary to observe signal stability.

      Flying: Drones moved dynamically to capture variations in signal patterns.

      Rotating: Rotational movements for angular spectral characteristics.

   b) **Varying Heights and Distances:**
      Drones were flown at multiple altitudes and distances to study signal attenuation, propagation characteristics, and angular variations in reception.

   c) **Multiple Field Locations:**
      Signals were captured in various locations across the park to account for environmental factors like multipath propagation, signal reflection, and interference from natural and artificial RF sources.

   Additionally, environmental noise and artificial interference, such as other devices (Raspberry Pi) communications in the Wi-Fi channel, were intentionally recorded to ensure the dataset reflects the complexities of real-world scenarios. As shown in Figure 4, we utilized Astro quadrotor drones from Freefly Systems for our data capture experiments. These professional-grade drones provided the stable flight characteristics and consistent RF emissions necessary for creating a reliable detection dataset. This ensures the resulting system's adaptability to practical applications.

Figure 4: Astro quadrotor drones from Freefly Systems used for data capture [12]

4) **Signal Preprocessing:**
   a) **Digitization and Storage:** RF signals were digitized at sampling rates of 128MHz and 24MHz using the RFSoC and B210, respectively, and stored securely for further processing and stored on an external hard drive before being uploaded to Dropbox for secure storage and further processing and analysis.
   b) **Low-Noise Amplifier (LNA):** The LNA was used to amplify weak RF signals from the drones while minimizing noise. This ensured that the system could detect faint signals over long distances and in noisy environments without significant distortion. This amplification was only applied with the B210 setup.
   c) **High-Gain Directional Antennas:** Directional antennas were used to focus reception on signals from particular directions, thus reducing interference from surrounding RF sources.

B. Data Analysis

In the analysis phase, our primary objective is to understand drone RF signal behavior in complex, real-world environments. To achieve this, we capture drone RF packets, measure their power spectral densities, and extract additional critical attributes of drone communications through various signal processing techniques. By analyzing the collected data, we aim to address existing gaps in RF-based detection methods and pave the way toward more automated and robust drone detection systems.

1) **Signal Processing**

a) **Analysis in the Time and Frequency Domains**

The collected RF signals were analyzed in both the time and frequency domains using Python libraries such as **NumPy** and **SciPy**. This dual-domain analysis provided valuable insights into signal power, carrier frequency, bandwidth, frequency drift, and other critical properties. The key signal processing techniques employed are detailed below:

b) **Fast Fourier Transform (FFT):** FFT was used to efficiently convert discrete time-domain signals into their frequency-domain representations with a time complexity of $O(NlogN)$. The transformations are given as follows:

i. Forward DFT: $X_k = \sum_{n=0}^{M-1} x[n]e^{-j\frac{2\pi kn}{M}}, k = 0,1,2, \dots, M-1$

ii. Inverse DFT: $x[n] = \frac{1}{M}\sum_{k=0}^{M-1} X_k e^{j\frac{2\pi kn}{M}}, n = 0,1,2, \dots, M-1$

c) **Short-Time Fourier Transform (STFT) and Spectrogram Analysis:** The Short-Time Fourier Transform (STFT) is a very effective tool for converting a time-domain signal into a two-dimensional time-frequency representation. By applying a sliding window across the signal, the STFT captures how the signal's frequency content changes over time. This characteristic is especially beneficial in detecting drone packets, which can be visually identified on a spectrogram.
In a spectrogram generated from the STFT, these drone packets show up as distinct localized patterns. This makes it easier to study. The mathematical expression for the STFT is:

i. $X(e^{j\omega}; m) = \sum_{n=-\infty}^{\infty} x[n]\widetilde{w}[n-m]e^{-j\omega n}$

In this equation, $x(t)$ is the input signal, and $w[n]$ represents the window function applied to segment the signal into overlapping time intervals.

Table 1: Mathematical definitions of commonly used windows.

Window name	Formula
Rectangular	1

Bartlett (triangular)	$1-\frac{2\left\lvert n-\frac{L-1}{2}\right\rvert}{L-1}$
Blackman	$0.42-0.5\cos\left(\frac{2\pi n}{L-1}\right)+0.08\cos\left(\frac{4\pi n}{L-1}\right)$
Hamming	$0.54-0.46\cos\left(\frac{2\pi n}{L-1}\right)$
Hanning	$\frac{1}{2}\left[1-\cos\left(\frac{2\pi n}{L-1}\right)\right]$
Kaiser	$\frac{I_0\left(\beta\sqrt{1-\left(\frac{2n}{L-1}-1\right)^2}\right)}{I_0(\beta)}$

The Hanning window was chosen for this study due to its simplicity and balanced trade-off between time and frequency resolution. Figures were generated using Matplotlib and interactive widgets to better understand signal behavior during different drone activities, such as hovering, flying, and rotating.

Using this approach, the STFT allows for easy visualization of transient events like drone packets and supports detailed frequency analysis over time.

d) **Signal Visualization and Analysis Results:**
Representative examples of our captured signals are presented in Figure 5 - 10. Figure 6 shows a time-domain signal captured during drone ascent. Figure 7 displays background noise and interference recorded in the absence of drone activity, serving as our baseline. Figure 8 presents the corresponding frequency spectrum analysis during drone ascent.

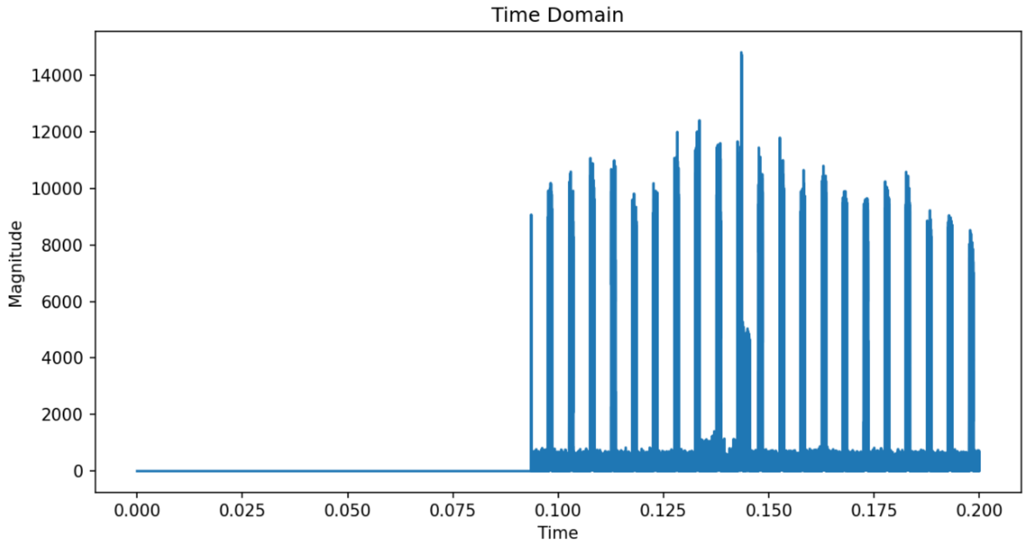

Figure 5: Time-domain signal during drone ascent.

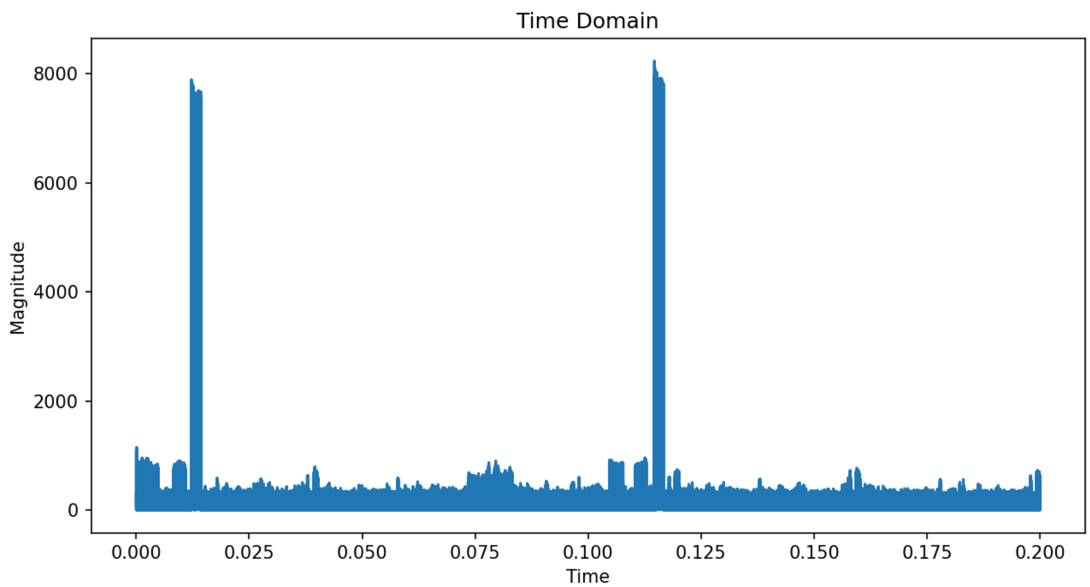

Figure 6: Background noise and interference in the absence of drone activity.

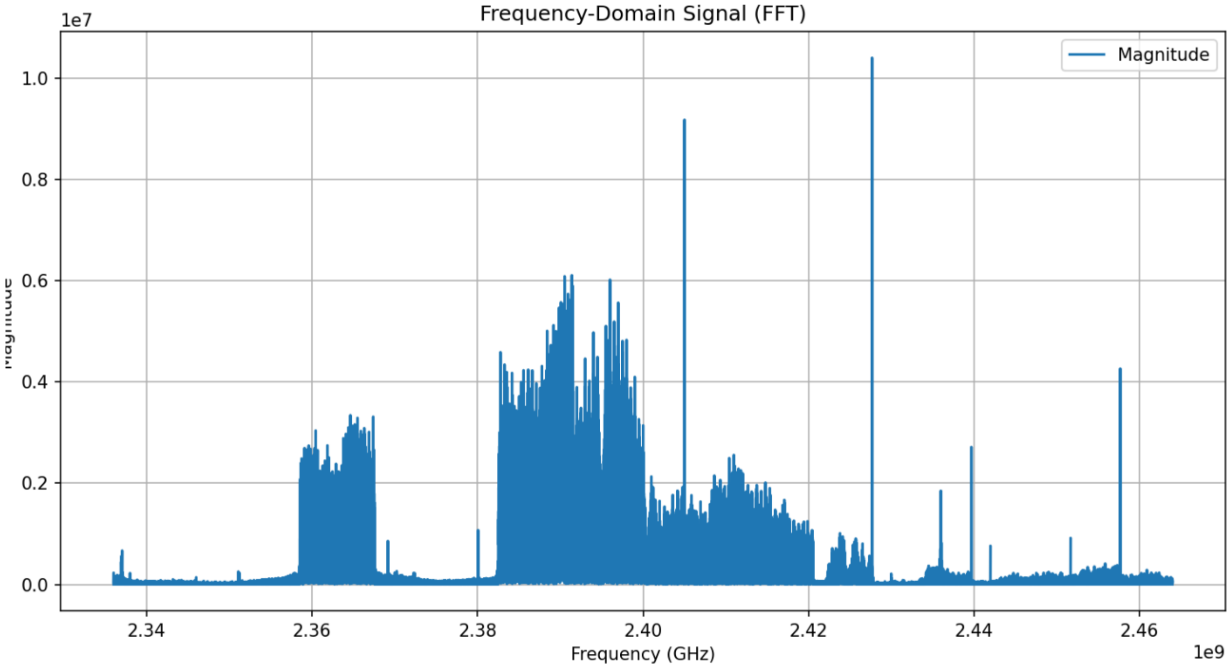

Figure 7: Frequency spectrum during drone ascent.

Figure 8 displays a spectrogram captured during drone ascent, showing RF signals across six Wi-Fi channels (20 MHz each). The color intensity corresponds to relative signal power (dB). The bright horizontal bands at -1 MHz and -3 MHz represent the drone's control signals, while the periodic vertical patterns at 0.003s and 0.007s intervals indicate the drone data transmission. Unlike typical Wi-Fi traffic, these drone signals exhibit characteristic burst patterns with consistent intervals, providing distinct features for our detection algorithms.

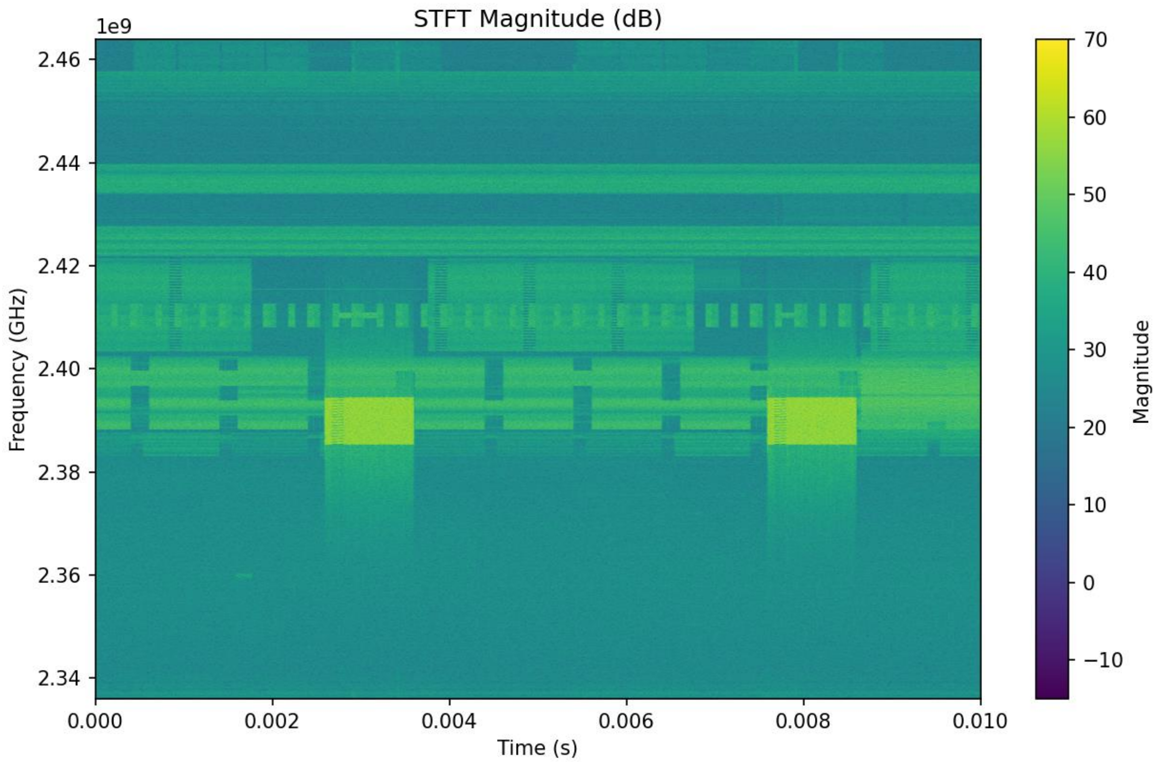

Figure 8: Overall spectrogram during drone ascending, covering six Wi-Fi channels, each with 20 MHz bandwidth.

III. Results and Discussions

In this section, we present the outcomes of our investigation into the RF signals emitted by drones across various operational scenarios using RFSoC and SDR. Our analysis revealed useful insights into drone communication patterns and signal propagation behaviors and highlighted a promising future for automating drone detection.

A. Observation

1) Drone Packets

The captured RF signals represent the communication packets from the drone models used in this study. These packets revealed specific patterns tied to different operational states, such as hovering, flying, and rotating.

As shown in Figure 9, drone packet signals can be observed against background noise. Figure 10 provides another representation of these captured drone and controller packets. It clearly illustrates the communication exchanges between drones and their controllers. The distinct temporal and frequency characteristics visible in these figures form the foundation for our detection approach.

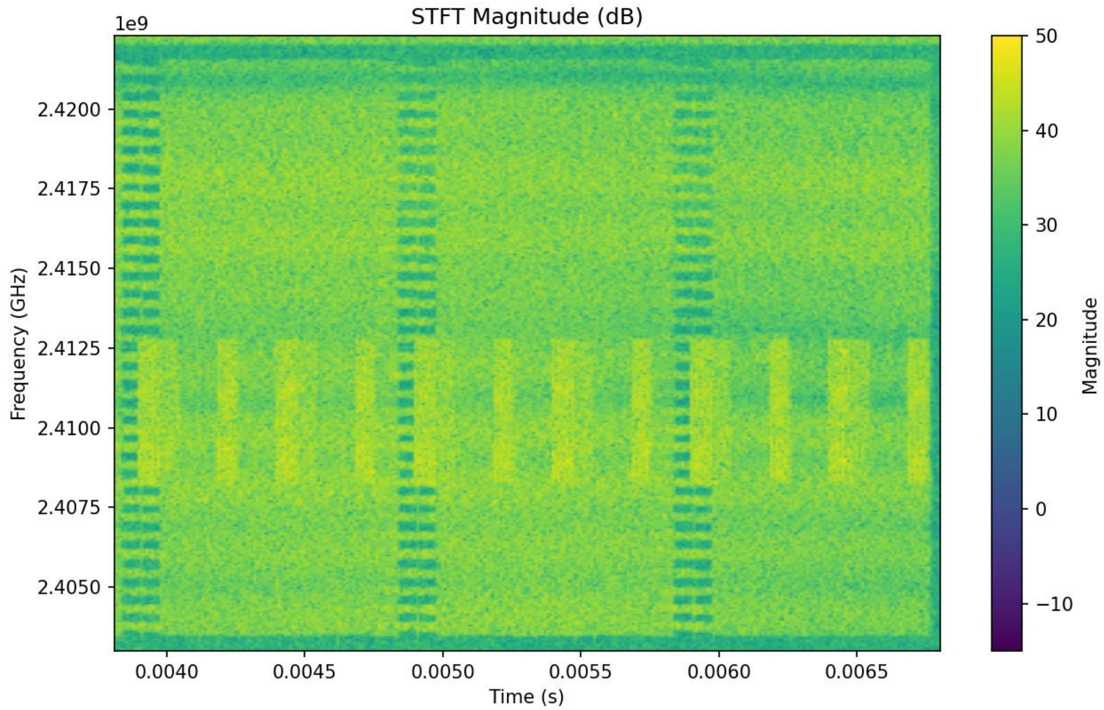

Figure 9: Drone packet signals with observable background noise.

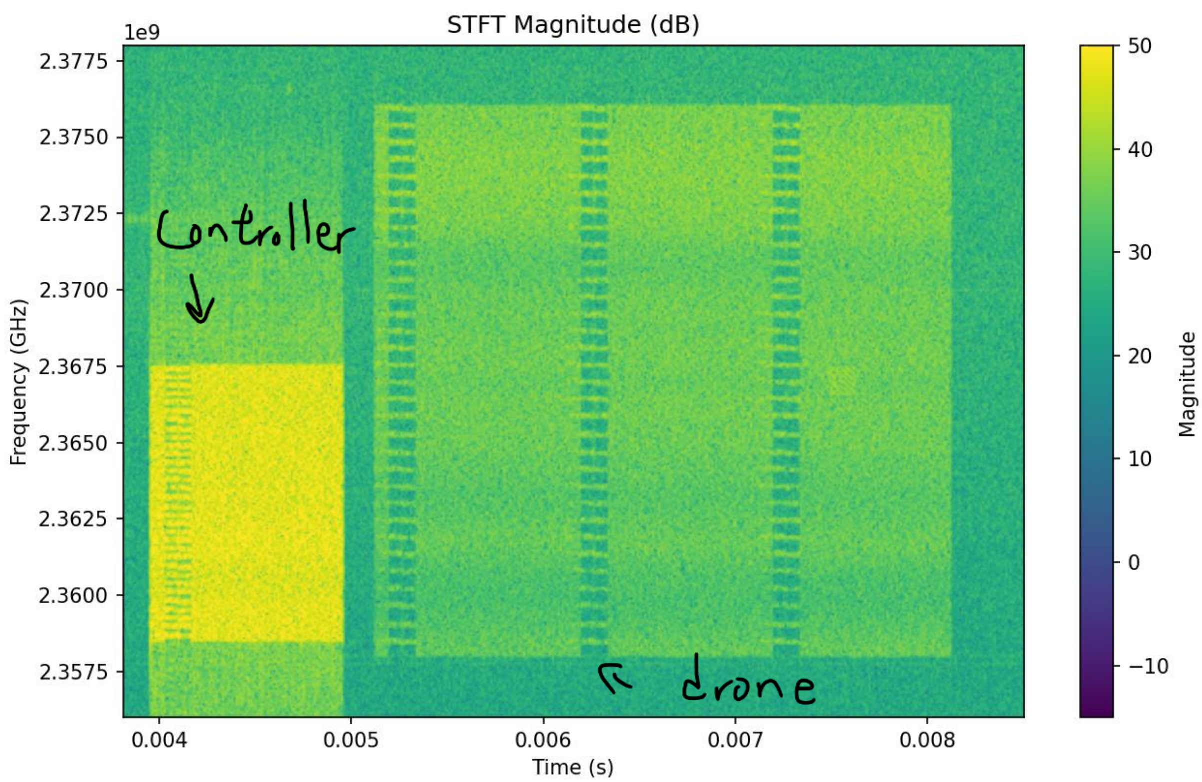

Figure 10: Drone and controller packets with observable background noise.

2) **Correlation Analysis for Packet Identification**

Correlation-based techniques were employed to identify and analyze drone communication packets. After trials with various correlation formulas, the **Normalized Correlation Coefficient** was determined to be the most effective in distinguishing drone signals from background noise and interference.

The correlation formula used is as follows:

$$\text{Normalized Correlation Coefficient} = \frac{\sum_{x',y'}\left(T'(x',y') \cdot I'(x+x',y+y')\right)}{\sqrt{\sum_{x',y'} T'(x',y')^2 \cdot \sum_{x',y'} I'(x+x',y+y')^2}}$$

As shown in Figure 11, this correlation technique was applied to identify drone communication packets within the RF spectrum. The yellow rectangular region highlights an area where drone signal patterns were detected. Using this approach, we were able to distinguish characteristic drone communication signals from background noise.

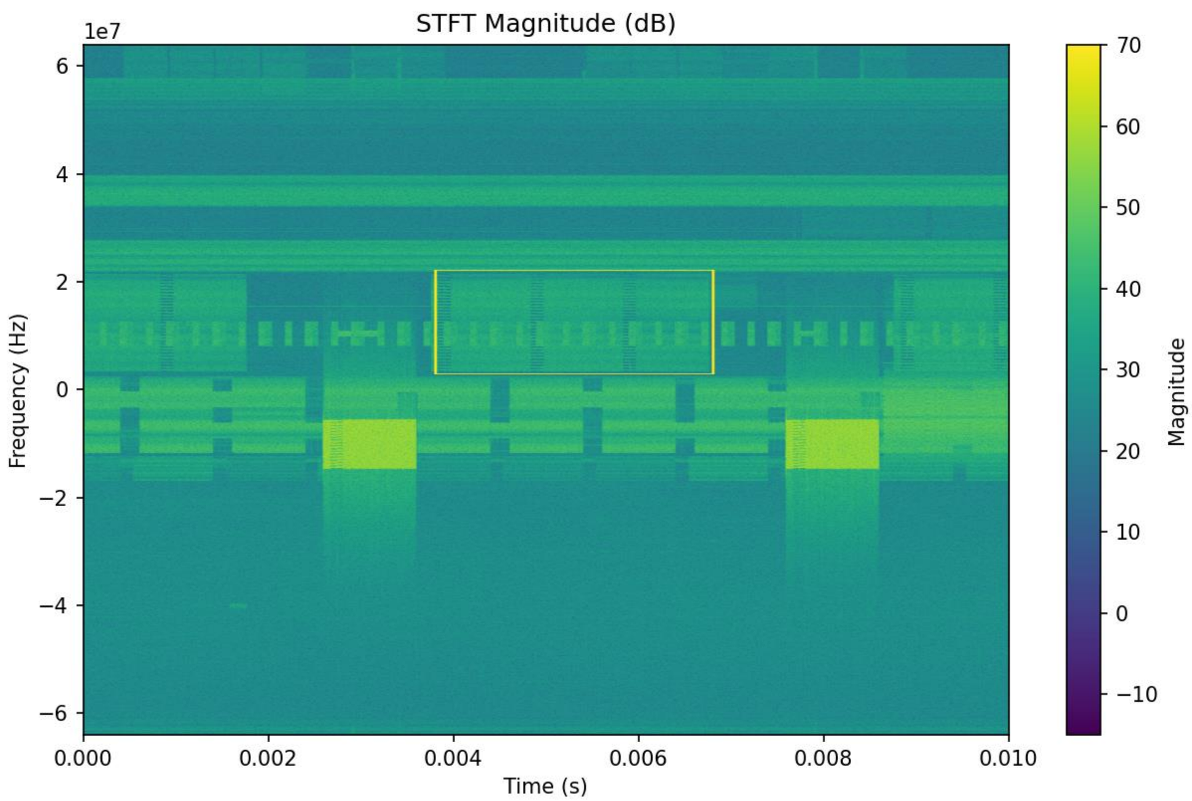

Figure 11: Application of correlation techniques to identify drone communication packets.

3) **Dynamic Channel-Hopping Behavior**

One significant observation was the dynamic channel-hopping behavior exhibited by the drones. When traffic was detected on a specific frequency channel, the

drones switched to less congested channels to maintain reliable communication. As shown in Figure 12, this behavior is visualized using a correlation-based detection algorithm that identifies signal packets (blue rectangular boxes) across different frequency channels (vertical axis) over time (horizontal axis).
Our methodology is discussed in the previous section.

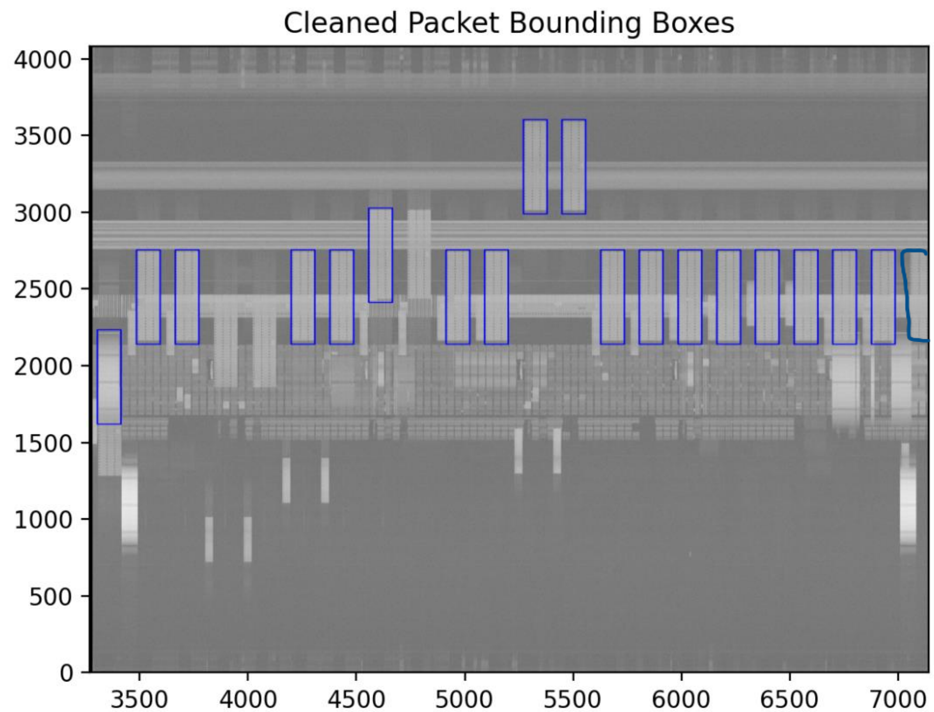

Figure 12: Captured drone packets switching channels during operations (visualization created using computer vision techniques, representing approximate packet boundaries). Notice that the algorithm misses some packets.

This behavior highlights the complexity of modern drone communication protocols and emphasizes the need for sophisticated hardware capable of capturing real-time data.

4) **Signal Nulls and Propagation Behavior**

As illustrated in Figure 13, the two-Ray Ground Reflection model offers similar behavior to the captured propagation characteristics of drone-emitted RF signals in outdoor environments. This model, accounting for both direct and reflected signal paths, offers a possible explanation for observed attenuation and interference patterns. Figure 14 demonstrates the theoretical gain variation with respect to distance.

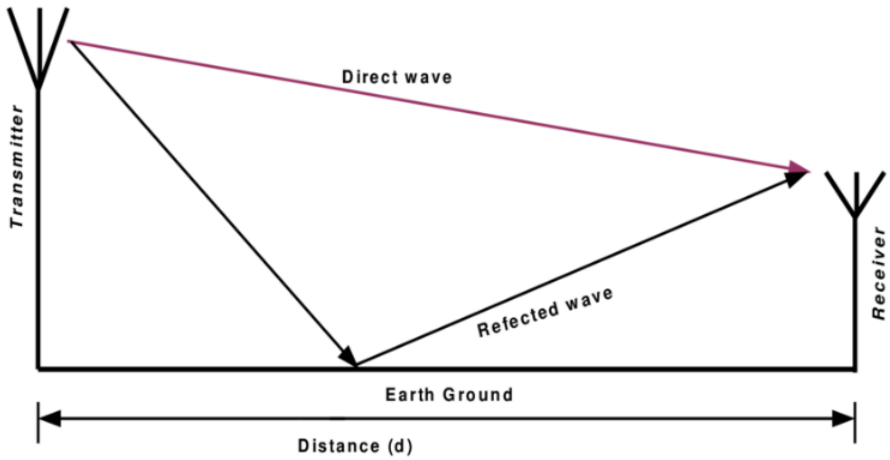

Figure 13: Illustration of the Two-Ray Ground Reflection model [13].

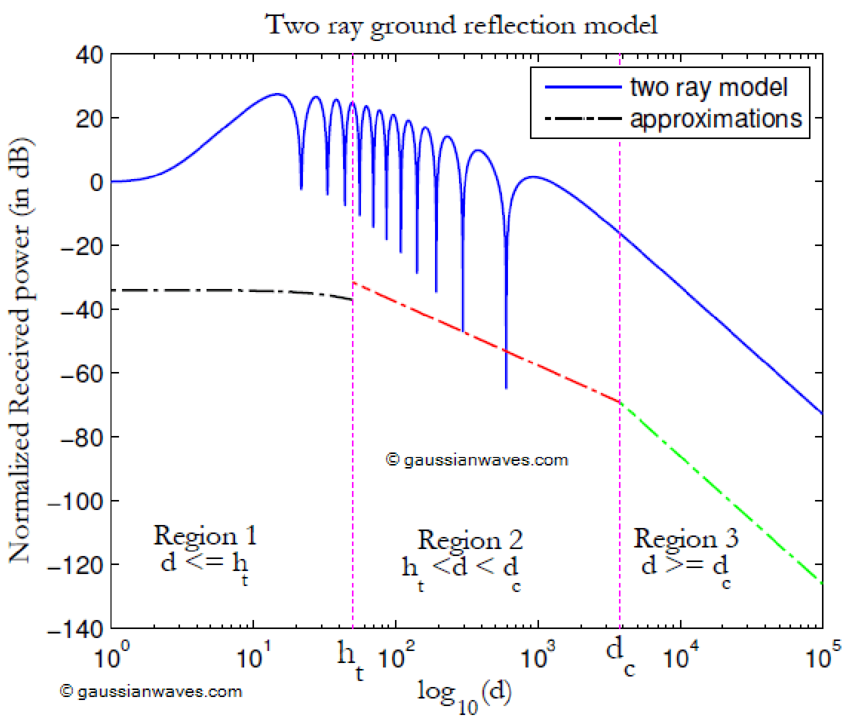

Figure 14: Gain variation with respect to distance under the model [14].

The occurrence of signal nulls, which are the regions of significant signal attenuation caused by destructive interference, was especially notable in our field tests, as shown in Figure 15. In this visualization, the red outline markers specifically highlight the null signal regions, where significant drops in signal power most likely occur due to destructive interference between direct and ground-reflected waves.

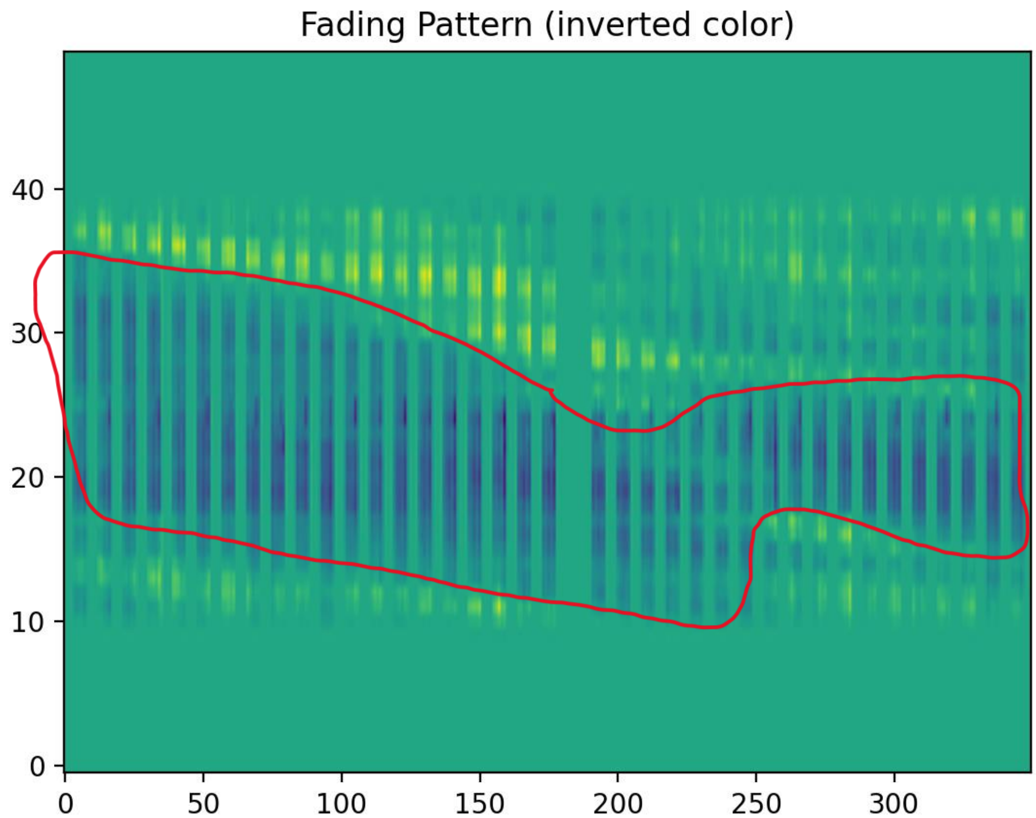

Figure 15: Signal nulls observed during propagation. The red contour lines trace the boundaries of signal null regions, where destructive interference causes significant signal attenuation.

IV. Progress Toward Automation

While full automation is not yet achieved, this study lays a solid foundation for future developments. Key advancements include:

1. **Feature Extraction:** We identified key drone-specific signal features through spectral and temporal analysis. Our approach successfully identified distinctive RF characteristics including modulation types, the dynamic channel-hopping behavior documented in Figure 12, and propagation phenomena such as signal nulls illustrated in Figure 15. However, our feature extraction approach showed limitations in practical applications. Feature reliability varied with distance and environmental conditions. For example, in Figure 9 and Figure 10, the spectrograms clearly reveal background noise patterns that interfere with our drone communication packets. Complex environments with multiple reflection surfaces affect our ability to identify and utilize certain features consistently. This suggests the need for more robust extraction methods that can adapt to varying signal conditions.

2. **Preprocessing Pipelines:** We developed workflows suitable for future integration with machine learning algorithms by using both RFSoC and SDR hardware. Our RFSoC implementation can capture 1-2 seconds of signal data at a high sampling frequency of 128MHz, which provides sufficient information and spectral resolution necessary for advanced analysis.

3. **Pattern Recognition Techniques:** Correlation techniques were employed to establish packet detection protocols, as demonstrated in Figure 11. Our correlation-based approach demonstrated promising capabilities but exhibited limitations in practical application. The technique performed optimally only when drone signals closely matched our template patterns. As evident in Figure 11, our algorithm did not detect several drone packets because their signal characteristics deviated from our established template patterns. This shows reduced effectiveness with unfamiliar drone models or modified communications protocols.

These efforts provide a strong basis for future work to develop a fully automated drone detection system while highlighting the specific challenges that must be addressed. The limitations lead to some of our proposed future research directions described in Section VI-B.

V. Conclusion

This research demonstrated the feasibility of using RFSoC and SDR for drone detection by capturing and analyzing RF signals emitted during various drone operations. The following key findings highlight the study's contributions:

1. **Dynamic Channel-Hopping Behavior:** The analysis revealed adaptive communication patterns, where drones switched channels to maintain reliable connections in congested environments.

2. **Signal Propagation Modeling:** The Two-Ray Ground Reflection model offers a possible explanation for the signal behaviors in outdoor environments.

3. **Correlation-Based Packet Identification:** Correlation techniques successfully identified communication packets, laying the groundwork for automating drone signal detection and classification.

These findings demonstrate the potential of RF-based detection systems to address real-world security challenges. Furthermore, the study lays a robust foundation for future advancements toward fully automated systems capable of drone detection and classification.

VI. Future Works

A. Challenges and Limitations

Despite the promising results, this study faced several limitations that highlight areas for improvement. Full automation remains a future goal. Regulatory constraints, such as prohibitions on on-campus drone flights, added logistical challenges and reduced the scope of experiments. The absence of machine learning-based classification models restricted the system's ability to automate drone packet identification and classification.

Additionally, limited access to diverse commercial drones, including advanced platforms like DJI models, affected the generalizability of findings. These limitations demonstrate the necessity of robust datasets, scalable frameworks, and refined methodologies to improve system performance and applicability.

B. Advancing Toward Full Automation

To overcome the current challenges and extend our work, we propose the following steps:

1. **Machine Learning Integration:** The next phase will involve integrating advanced machine learning models to achieve automation.

a) **Convolutional Neural Networks (CNNs):** Employ models such as YOLO and ResNet for automated packet detection and classification.

b) **Transformer-Based Models:** Utilize recent advances in transformer architecture. Its attention mechanisms may outperform traditional CNNs in RF signal analysis and generalize across various models.

c) **Hybrid Approaches:** Combine deep learning model with wavelet transforms and correlation-based template matching to improve signal analysis accuracy.

2. **Real-Time Implementation of RFSoC and FPGA:** Leverage the hardware acceleration capabilities of RFSoC and FPGA to enable low-latency, real-time processing. This ensures the system's feasibility in dynamic, real-world scenarios.

3. **Dataset Expansion:**

a) **Acquisition of Diverse Drone Models:** Securing funding to include advanced commercial drones (e.g., DJI) in the dataset.

b) **Complex Scenarios:** Develop experimental setups with high noise, interference, signal jamming, and interception scenarios to test system robustness.

c) **Environmental Diversity:** Expand the dataset to encompass both outdoor and indoor operational scenarios to enhance model generalizability.

This systematic approach is intended to bridge the gap between theoretical insights and real-world application. It paves the way for a fully automated system.

C. Laying the Groundwork for Future Systems

This research establishes a strong foundation for integrating machine learning models with traditional signal processing techniques. Future systems can bridge the gap between classical methodologies and modern AI-driven approaches by addressing observed limitations.

The combination of machine learning models, wavelet transforms, and correlation analysis will allow for scalable, real-time systems capable of addressing evolving security challenges in both civilian and military contexts.

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Appendix

Table 2: Correlation functions

Name of correlation function	Formula
Normalized Correlation Coefficient	$\frac{\sum_{x',y'}\left(T'(x',y') \cdot I'(x+x',y+y')\right)}{\sqrt{\sum_{x',y'} T'(x',y')^2 \cdot \sum_{x',y'} I'(x+x',y+y')^2}}$