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Drone Detection and Identification Using SDR: Analysis of DJI Mini 2 Drone ID Signals

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Abstract

The increasing adoption of Unmanned Aerial Vehicles (UAVs) for both commercial and recreational purposes has raised significant security and privacy concerns. DJI OcuSync 2.0, a proprietary communication protocol used in DJI drones, enables high-definition video transmission and telemetry over dual-frequency bands (2.4 GHz and 5.8 GHz). Detecting and identifying OcuSync signals in a crowded RF environment is crucial for effective drone monitoring and threat mitigation. This study presents an SDR-based detection system utilizing the USRP B210 with a 50 MHz sampling rate to capture OcuSync signals. Signal analysis is performed using Short-Time Fourier Transform (STFT) and Welch's method for estimating Power Spectral Density (PSD). A Non-Parametric Amplitude Quantization Method (NPAQM) is implemented for dynamic threshold estimation to improve detection sensitivity. The system is tested under varying Signal-to-Noise Ratio (SNR) conditions, demonstrating high detection accuracy and robustness against interference. The proposed system provides a reliable framework for real-time OcuSync signal identification and can be adapted for broader UAV detection applications.

A. Introduction

Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, have gained significant popularity and widespread adoption in various fields, including military operations, industrial applications, and consumer markets. Drones are extensively used in surveillance, reconnaissance, agriculture, delivery services, mapping, and entertainment. The increased deployment of drones has introduced both opportunities and challenges, particularly in terms of communication, control, and security. One of the most advanced and widely used communication technologies for drones is DJI OcuSync 2.0**,** which serves as the primary transmission protocol for DJI drones. OcuSync 2.0 provides robust, long-range, low-latency, and high-resolution video and data transmission. Detecting and analyzing OcuSync 2.0 signals is essential for understanding drone behavior, enhancing security, and improving communication performance in complex environments.

1.1 Background

DJI, a global leader in drone technology, introduced OcuSync 2.0 as an upgraded communication system for their high-end consumer and professional drones. OcuSync 2.0 offers improved performance over its predecessor, supporting dual-band transmission at 2.4 GHz and 5.8 GHz, higher data rates, and stronger resistance to interference. The key features of OcuSync 2.0 include:

- **Frequency Hopping:** OcuSync 2.0 uses dynamic frequency selection (DFS) to switch between available channels in the 2.4 GHz and 5.8 GHz bands, reducing the risk of interference and signal loss.
- **OFDM Modulation:** Orthogonal Frequency-Division Multiplexing (OFDM) improves spectral efficiency and robustness to multipath fading.
- **Adaptive Bitrate:** The system dynamically adjusts the bitrate to maintain transmission quality under varying signal-to-noise ratio (SNR) conditions.
- **Low Latency:** Transmission latency is minimized to enable real-time video streaming and control.
- **Long Range:** OcuSync 2.0 provides a maximum transmission distance of up to 10 km (under ideal conditions).

The rise of OcuSync 2.0-based communication in drones creates challenges in signal detection and analysis due to its dynamic nature, frequency hopping behavior, and adaptive modulation schemes. Traditional signal detection methods struggle to maintain high accuracy under these conditions, necessitating the development of more advanced detection algorithms.

1.2 Motivation

The increasing number of drones in public and restricted airspace has raised concerns about unauthorized drone activity, potential security threats, and interference with other communication systems. Accurate and reliable detection of drone signals is critical for the following reasons:

- **Security and Surveillance:** Detecting and identifying unauthorized drone activity near sensitive locations (e.g., military bases, airports) is essential to prevent security breaches.
- **Frequency Hopping:** The signal rapidly changes frequency, making it difficult to detect using conventional methods.

- **Air Traffic Management:** Managing drone activity within controlled airspace requires reliable communication and signal monitoring to avoid collisions and interference with other systems.
- **Spectrum Management:** The 2.4 GHz and 5.8 GHz frequency bands are shared with other wireless communication systems (e.g., Wi-Fi, Bluetooth). Efficient detection and classification of OcuSync signals enable better spectrum utilization and reduce interference.
- **Performance Monitoring:** Monitoring signal quality and transmission characteristics helps improve communication efficiency and drone performance.

Detecting OcuSync 2.0 signals poses significant technical challenges due to:

- **Wideband Transmission:** The signal bandwidth of up to 20 MHz requires high sampling rates and significant computational power for real-time processing.
- **Dynamic SNR:** The signal-to-noise ratio (SNR) varies due to environmental factors and interference, affecting detection accuracy.

Existing signal detection approaches, such as matched filtering, energy detection, and cyclostationary analysis, struggle to cope with the complex nature of OcuSync 2.0 signals. Therefore, a more robust and adaptive detection method is required.

1.3 Problem Statement

Despite the advancements in drone communication technology, detecting and classifying OcuSync 2.0 signals in real-time remains a challenging task due to the following factors:

- **Dynamic Frequency Hopping:** OcuSync 2.0 signals change frequency rapidly and unpredictably, making it difficult to isolate the signal from noise and interference.
- **Wideband Transmission:** The 20 MHz bandwidth requires high computational power for real-time signal processing.
- **Noise and Interference:** Overlapping signals from Wi-Fi, Bluetooth, and other wireless systems in the same frequency band reduce detection accuracy.
- **Adaptive Modulation:** OcuSync 2.0 dynamically adjusts its modulation scheme based on signal quality, further complicating signal identification.

Current detection methods, including energy detection and cyclostationary feature detection, are inadequate for handling the dynamic behavior and complex modulation of OcuSync 2.0 signals. Therefore, there is a need for an adaptive, high-accuracy detection system capable of handling dynamic frequency hopping and wideband signals.

1.4 Objectives

The primary objective of this research is to develop a robust signal detection system for DJI OcuSync 2.0 signals using a Software-Defined Radio (SDR)-based platform. The specific objectives are:

- Design and implement a high-resolution signal acquisition system using the USRP B210 with a sample rate of 40 MHz.

- Develop an adaptive signal preprocessing pipeline to correct for IQ imbalance, remove noise, and enhance signal quality.
- Implement a frequency domain analysis using Short-Time Fourier Transform (STFT) and Welch's method to estimate the Power Spectral Density (PSD) of the signal.
- Develop a threshold-based signal detection algorithm using the Non-Parametric Amplitude Quantization Method (NPAQM) to adapt to varying noise levels and interference.
- Validate the performance of the detection system in terms of detection accuracy, false alarm rate, and processing latency under different environmental conditions.

1.5 Contributions

This research makes the following key contributions:

- **High-Resolution Signal Acquisition:** A 40 MHz sampling rate and dual-band operation enable the capture of wideband OcuSync signals in real time.
- Adaptive Signal Preprocessing: The proposed system includes IQ imbalance correction, low-pass filtering, and amplitude normalization to improve signal quality.
- **Advanced Frequency Domain Analysis:** The use of STFT and Welch's method enables high-resolution estimation of the signal's frequency components and power distribution.
- **Adaptive Thresholding with NPAQM:** The proposed thresholding algorithm adapts to changing noise levels, improving detection accuracy under low SNR conditions.
- **Real-Time Performance:** The system is implemented using GNU Radio and Python, providing real-time signal detection and classification with low processing latency.

1.6 Scope of Work

The scope of this research is focused on detecting DJI OcuSync 2.0 signals under realistic environmental conditions. The key aspects of the study include:

- **Frequency Bands:** 2.4 GHz and 5.8 GHz
- **Transmission Bandwidth:** Up to 40 MHz
- **Signal Processing:** Real-time processing using an SDR platform
- **Noise and Interference:** Evaluation under varying SNR levels and interference conditions

The system is not designed to decode or demodulate the OcuSync 2.0 signal content but rather to detect the presence and frequency characteristics of the signal. Furthermore, the research does not address interference mitigation strategies or drone jamming techniques.

B. Background

2.1 Software-Defined Radio (SDR)

Software-Defined Radio (SDR) is a flexible and programmable radio communication system where most signal processing tasks—such as modulation, demodulation, filtering, and tuning—are implemented in software rather than hardware. Traditional radio communication systems rely on fixed hardware components, such as mixers, filters, amplifiers, and demodulators, which limits their ability to adapt to different signal standards and operating conditions. In contrast, SDR systems use general-purpose hardware and configurable software, allowing them to support a wide range of communication protocols and signal types without requiring physical modifications.

An SDR system typically consists of the following key components:

- **RF Front-End:** Handles the reception and transmission of signals at different frequencies. It includes antennas, amplifiers, mixers, and filters to convert signals between RF and baseband.
- **Analog-to-Digital Converter (ADC):** Converts the received analog signal into a digital format for processing.
- **Digital-to-Analog Converter (DAC):** Converts processed digital signals back to analog for transmission.
- **Field-Programmable Gate Array (FPGA) or Digital Signal Processor (DSP):** Handles high-speed, real-time processing of digital signals, including filtering, demodulation, and error correction.
- **Software Interface:** A software layer (e.g., GNU Radio) that defines the signal processing flow and controls the hardware operation.

The key advantages of SDR systems are:

- **Flexibility:** SDR systems can be reprogrammed to support new communication standards without changing hardware.
- **Wideband Operation:** SDR platforms can operate over a wide range of frequencies and bandwidths.
- **Real-Time Adaptation:** SDR systems can dynamically adjust modulation, coding, and frequency hopping patterns to maintain signal integrity.
- **Cognitive Radio Capability:** SDR systems can detect and avoid interference through dynamic spectrum access.

SDR technology is widely used in military communication, spectrum monitoring, wireless research, and signal intelligence. Its flexibility makes it well-suited for detecting and analyzing complex communication protocols such as DJI OcuSync 2.0.

2.2 USRP B210 Platform

The Universal Software Radio Peripheral (USRP) B210, developed by Ettus Research, is a widely used SDR platform known for its high performance, flexibility, and affordability. It supports full-duplex operation (simultaneous transmission and reception) and covers a wide frequency range from 70 MHz to 6 GHz. The USRP B210 features:

- **RFIC (AD9361):** The B210 uses the Analog Devices AD9361 transceiver chip, which supports dual-channel operation, wideband tuning, and complex modulation schemes.
- **Wide Bandwidth:** It supports an instantaneous bandwidth of up to 56 MHz per channel, allowing it to capture wideband signals.
- **High Sampling Rate:** The B210 supports complex baseband sampling rates up to 61.44 MS/s.

- **FPGA (Xilinx Spartan-6):** Handles real-time signal processing, including down-conversion, filtering, and channelization.
- **USB 3.0 Interface:** Ensures high-speed data transfer between the SDR and the host computer.

The USRP B210's wide tuning range and high bandwidth make it well-suited for detecting and analyzing DJI OcuSync 2.0 signals, which use dynamic frequency hopping between 2.4 GHz and 5.8 GHz. Its FPGA-based architecture allows for real-time processing of fast-changing signals, while its high sampling rate ensures accurate representation of wideband transmissions.

The main advantages of using the USRP B210 for OcuSync 2.0 signal detection are:

- **Dual-Band Capability:** Enables simultaneous monitoring of 2.4 GHz and 5.8 GHz bands.
- **Real-Time Processing:** FPGA and high-speed USB interface allow for low-latency signal processing.
- **Wide Tuning Range:** Supports detection of other drone communication signals and interference sources.
- **Open-Source Support:** Compatible with GNU Radio, allowing flexible implementation of custom signal processing algorithms.

2.3 DJI OcuSync 2.0 Protocol

DJI OcuSync 2.0 is a proprietary transmission protocol developed by DJI for long-range, high-quality video and telemetry transmission. It is used in DJI's high-end consumer and professional drone models, including the Mavic series, Phantom series, and Inspire series. OcuSync 2.0 was introduced as an improvement over Lightbridge, DJI's earlier communication protocol, offering better range, higher data rates, and stronger resistance to interference. The key Features of OcuSync 2.0 are as followings:

- **Frequency Hopping:** OcuSync 2.0 operates on both the 2.4 GHz and 5.8 GHz frequency bands, using dynamic frequency hopping to avoid interference. The system continuously scans for available channels and switches frequencies up to 100 times per second to maintain a stable connection. Frequency hopping increases resistance to jamming and improves transmission reliability in crowded RF environments.
- **Dual-Band Transmission:** OcuSync 2.0 can simultaneously transmit signals on both 2.4 GHz and 5.8 GHz, allowing the system to choose the optimal band based on real-time SNR measurements. The system can dynamically switch between bands or aggregate them to increase data throughput.
- **OFDM Modulation:** OcuSync 2.0 uses Orthogonal Frequency-Division Multiplexing (OFDM), which improves spectral efficiency and robustness to multipath fading. OFDM divides the signal into multiple subcarriers and transmits them in parallel, reducing inter-symbol interference and improving noise resistance.
- **Adaptive Bitrate:** OcuSync 2.0 supports adaptive bitrate transmission, adjusting the data rate based on the quality of the communication channel. When the signal quality is high, the system increases the bitrate for better

video quality; when the signal quality drops, the bitrate is reduced to prevent frame loss.

- **Low Latency:** OcuSync 2.0 achieves an end-to-end transmission latency of less than 28 ms for video streaming, enabling real-time remote control and monitoring.
- **Encrypted Transmission:** OcuSync 2.0 employs AES-256 encryption to secure communication between the drone and the remote controller, preventing eavesdropping and unauthorized access.

2.4 Why USRP B210 for OcuSync 2.0 Detection

The USRP B210 provides an ideal platform for detecting and analyzing OcuSync 2.0 signals because:

- The USRP B210's wide tuning range (70 MHz to 6 GHz) covers both the 2.4 GHz and 5.8 GHz bands used by OcuSync 2.0.
- The high sampling rate (up to 61.44 MS/s) ensures high resolution in detecting wideband OFDM signals.
- The FPGA-based architecture allows for real-time frequency hopping and signal analysis.
- SDR platforms support flexible software-based signal processing, enabling rapid adaptation to changing signal characteristics.
- GNU Radio and Python provide a powerful open-source framework and libraries for implementing complex signal processing algorithms.

C. Methodology

The system architecture consists of five main stages: signal acquisition, signal preprocessing, frequency domain analysis, threshold estimation, and signal classification. The methodology leverages Software-Defined Radio (SDR) technology and advanced signal processing techniques to achieve robust detection performance under varying noise and interference conditions.

3.1 Signal Acquisition

The first step involves capturing OcuSync signals using the USRP B210 SDR. The USRP B210 is configured with a high sample rate of 50 MHz to capture the full bandwidth of the OcuSync 2.0 signal. The signal acquisition process is defined mathematically as:

$$y[n] = x[n].\, e^{-j2\pi f_c n T^s} \tag{1}$$

Where,

$y[n]$ is baseband signal,

$x[n]$ is received RF signal,

f_c is center frequency and

T^s is sampling period.

The system is designed to switch dynamically between the 2.4 GHz and 5.8 GHz bands based on signal strength and noise levels. This allows the system to adapt to frequency hopping in the OcuSync protocol. The key parameters for the signal acquisition are:

Table 1. SDR Parameters

No	*Parameter*	*Value*
1	Center Frequency	2.4 GHz and 5.8 GHz
2	Sampling Rate	50 MHz
3	Gain Range	0 dB to 76 dB
4	Bandwidth	50 MHz

3.2 Signal Preprocessing

Once the signal is acquired, preprocessing is applied to improve signal quality and remove noise:

3.2.1 IQ Imbalance Correction

The USRP B210 outputs quadrature signals (I and Q) which can suffer from phase and amplitude imbalance. An adaptive correction algorithm is applied:

$$\hat{x}(n) = x_I(n) + j.x_Q(n).e^{-j\theta} \tag{2}$$

where:

$x_I(n)$ is in-phase component,
$x_Q(n)$ is quadrature component and
θ is phase offset.

3.2.2 Low-Pass Filtering

High-frequency noise is suppressed using a 5th-order Butterworth filter:

$$H(f) = \frac{1}{\sqrt{1+(f/f_c)^{2N}}} \tag{3}$$

where:

f_c is cutoff frequency and
N is filter order.

3.3 Frequency Domain Analysis

Frequency analysis is performed using two key methods:

3.3.1 Short-Time Fourier Transform (STFT)

The Short-Time Fourier Transform (STFT) was used to analyze the recorded drone signals. The STFT provides a time-frequency representation of a signal, allowing for the detection of both time-varying and frequency-varying features of the signal. The STFT of a time-domain signal $x(t)$ is given by:

$$STFT\{x(t)\} = X(t,f) = \int_{-\infty}^{\infty} x(\tau)\omega(\tau - t)e^{-j2\pi f\tau}\, d\tau \tag{4}$$

where,

$x(t)$ is the input signal,
$\omega(\tau - t)$ is the window function centered at time,
t, f is the frequency and
$X(t,f)$ is the resulting complex-valued time-frequency representation.

The STFT output provides a spectrogram representation of the OcuSync signal, which reveals the frequency hopping pattern and subcarrier structure of the OFDM signal.

3.3.2 Welch's Method for PSD Estimation:

Welch's method is used to estimate the Power Spectral Density (PSD) of the signal. The signal is divided into overlapping segments, and the periodograms are averaged to reduce variance:

$$p_{xx}(f) = \frac{1}{L}\sum_{i=0}^{L-1}\frac{1}{N}\left|\sum_{n=0}^{N-1} x_i(n)w(n)e^{-j2\pi fn}\right|^2 \tag{5}$$

where:

L is number of segments,

N is number of samples per segment and

$w(n)$ is window function.

The PSD output allows precise identification of the signal's frequency components, bandwidth, and power distribution.

3.4 Threshold Estimation Using NPAQM

Signal detection relies heavily on setting an appropriate threshold to distinguish between noise and meaningful signals. Traditional methods that use a static threshold are often ineffective due to varying noise levels, interference, and environmental changes in real-world scenarios. Therefore, an adaptive thresholding approach is necessary to improve detection accuracy and robustness. In this work, the Non-Parametric Amplitude Quantization Method (NPAQM) is applied for adaptive thresholding, which provides a dynamic and statistically independent way to determine the detection threshold.

NPAQM is a technique used primarily in signal processing, especially in cognitive radio systems and wireless communication technologies. Unlike parametric methods that assume a specific statistical distribution (e.g., Gaussian or Rayleigh), NPAQM does not rely on any prior knowledge of the signal or noise distribution. Instead, it directly quantizes the amplitude of the incoming signal based on its observed characteristics.

The key advantage of NPAQM lies in its non-parametric nature, which allows it to adapt to complex and dynamically changing signal environments. This makes it well-suited for real-time signal detection where noise and interference are unpredictable and time-varying.

Let the received signal in the time domain be represented as:

$$x(t) = s(t) + n(t) \tag{6}$$

where:

$x(t)$ is observed signal,

$s(t)$ is target signal (if present) and

$n(t)$ is additive noise.

To apply NPAQM, the Short-Time Fourier Transform (STFT) is computed to convert the signal to the time-frequency domain (eq-). The amplitude of the STFT result is computed as:

$$|X(f,t)| = \sqrt{\mathrm{Re}(X(f,t))^2 + \mathrm{Im}(X(f,t))^2} \tag{7}$$

The goal of NPAQM is to estimate a dynamic threshold T based on the statistical distribution of the signal amplitude over time. The NPAQM approach proceeds in the following steps:

3.4.1 Sort the Amplitudes

The amplitude values of the STFT result over time are sorted in ascending order:

$$|X_1| \leq |X_2| \leq \cdots \leq |X_n| \tag{8}$$

3.4.2 Partition into Two Groups

The sorted amplitudes are partitioned into two equal parts:

- **Lower Group (P_1):** First 50% of the sorted values
- **Upper Group (P_2):** Fast 50% of the sorted values

3.4.3 Estimate Threshold

The threshold is computed based on the maximum value of each partition:

$$T = \max(\max(P_1), \max(P_1)) \tag{9}$$

3.4.4 Detection Condition

A signal is detected if the maximum amplitude in the STFT exceeds the threshold T:

$$max(|X(f,t)|) > T \tag{10}$$

3.5 Signal Classification

Signal classification is a key step in cognitive radio and wireless communication systems, where the objective is to identify and categorize signals based on their distinct characteristics. In this work, a three-stage classification approach is employed to classify signals based on their period, bandwidth, and occurrence pattern. This structured approach allows for more accurate and efficient classification of dynamic signals, including frequency-hopping signals like those used in the DJI OcuSync 2.0 protocol.

The classification process is divided into three main stages:

- Signal Period Measurement
- Signal Bandwidth Estimation
- Signal Occurrence Pattern Analysis

Each stage extracts specific features from the signal, contributing to an adaptive and reliable classification framework.

3.5.1 Signal Period Measurement

The first step involves measuring the period of the signal directly from the time axis of the Short-Time Fourier Transform (STFT). The STFT represents the signal in the time-frequency domain, making it possible to capture both the periodic nature and frequency content of the signal over time. Unlike traditional period estimation methods, which rely on statistical models or auto-correlation functions, this method measures the period directly from the time axis by analyzing only the peaks of the signal that exceed a defined threshold. This approach ensures that the period estimation is more robust against noise and interference.

To estimate the signal period, the following steps are applied:

- Compute the STFT of the signal using a Hamming window.
- Identify the maximum amplitude along the time axis for each frequency bin.
- Apply a threshold to filter out noise and low-amplitude components.
- Measure the time interval between consecutive peaks that exceed the threshold — this corresponds to the period of the signal.

The period T is estimated as:

$$T = t_{k+1} - t_k \tag{11}$$

where t_{k+1} and t_k are the time indices of consecutive peaks in the time axis of the STFT that exceed the threshold.

3.5.2 Signal Bandwidth Estimation

The second step estimates the signal's bandwidth based on the power spectral density (PSD). The PSD provides a detailed view of the signal's frequency components, helping distinguish between narrowband and wideband signals. Welch's method computes the PSD with reduced noise sensitivity. The bandwidth is calculated based on the range where the PSD exceeds a fixed threshold. The approach is robust to noise and dynamic changes in signal characteristics.

The bandwidth B is calculated as the range of frequencies where the power exceeds a threshold (in this work, 10% of the maximum value):

$$B = f_{max} - f_{min} \tag{12}$$

where:

- f_{max} is highest frequency exceeding threshold and
- f_{min} is lowest frequency exceeding threshold

3.5.3 Signal Occurrence Pattern Analysis

The final step in the classification process involves detecting the occurrence pattern of the signal using its envelope. Pattern analysis is critical for identifying time-division and frequency-hopping signals, such as those used in the DJI OcuSync 2.0 protocol. This step helps distinguish between different signal types based on their repetitive behavior and transmission patterns.

Frequency-hopping spread spectrum (FHSS) signals, like those used in OcuSync 2.0, change their carrier frequency at regular intervals. Time-division signals, on the other hand, transmit in specific time slots. Identifying these patterns allows for accurate classification and better spectrum utilization.

To detect signal patterns, the envelope of the signal is computed using the Hilbert transform. The Hilbert transform provides the analytic representation of a real-valued signal, allowing extraction of the amplitude envelope. The envelope highlights the signal's variations in amplitude over time, making it easier to identify periodic transmission patterns.

The Hilbert transform of a signal $x(t)$ is defined as:

$$H(x(t)) = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} d\tau \quad (13)$$

where $H(x(t))$ is Hilbert transform of $x(t)$ and P is Cauchy principal value. The analytic signal is then computed as:

$$z(t) = x(t) + jH(x(t)) \quad (14)$$

where $z(t)$ is the complex signal representation. The envelope of the signal is obtained as the magnitude of the analytic signal:

$$e(t) = |z(t)| = \sqrt{x(t)^2 + H(x(t))^2} \quad (15)$$

where $e(t)$ is envelope of the signal, $x(t)$ real signal and $H(x(t))$ is Hilbert transform.

Once the envelope is extracted, the next step is to identify recurring patterns in the signal's envelope. This involves:

- Detecting peaks in the envelope using a peak detection algorithm.
- Measuring the time intervals between consecutive peaks.
- Analyzing the regularity of these intervals to classify the signal type.

Let t_k be the time of the k-th detected peak in the envelope. The occurrence interval is computed as:

$$T = t_{k+1} - t_k \quad (16)$$

where t_k represents the time between two adjacent peaks. If the intervals t_k are consistent and periodic, the signal is likely part of a structured transmission protocol (e.g., frequency hopping or time-division multiplexing).

The DJI OcuSync 2.0 protocol relies on FHSS, where the signal rapidly switches between frequencies at fixed time intervals. This produces a regular pattern in the envelope, which can be detected using the Hilbert transform and peak analysis. The regular occurrence of peaks indicates the frequency hopping intervals, aiding in classification.

D. Result and Discussion

The following results are based on 150 ms samples of the recorded signal. These samples were analyzed through a series of signal processing techniques, including thresholding, power spectral density (PSD) estimation, and pattern analysis, to detect and classify DJI Drone signals. The methods used for signal detection and classification provided insights into the characteristics of the signal, its modulation scheme, and its periodic nature, offering a comprehensive view of the signal's behavior and structure.

4.1 STFT Result

A spectrogram as shown in Figure 1 was generated using Equation (4), revealing periodic bursts every 640 ms, each lasting 645 us with energy between 2.405–2.413 GHz. This periodicity aligns with OcuSync 2.0's Drone ID interval (Birnbach et al., 2023).

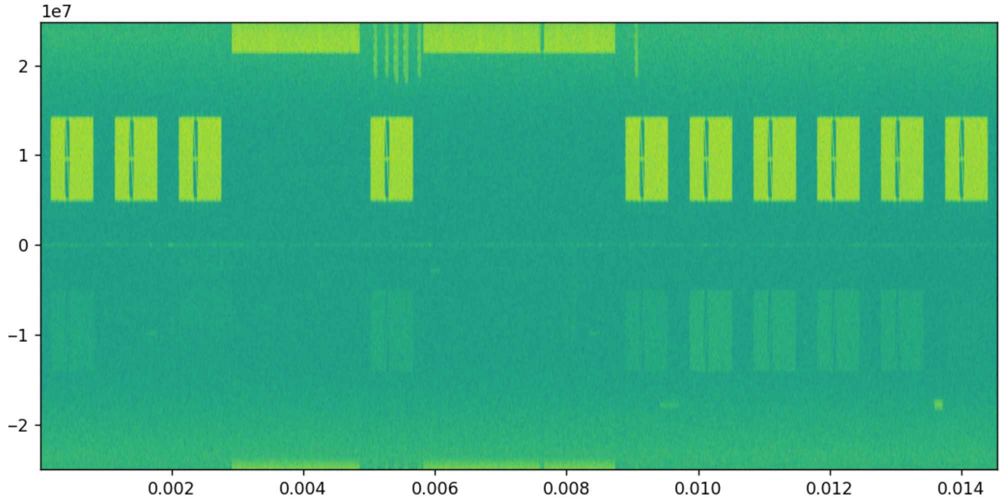

Figure 1. Spectrogram of DJI Mini 2 Drone ID Signal (Time vs. Frequency, Amplitude in Color)

4.2 Thresholding Result

Figure 2 shows the thresholding result based on the time axis of the Short-Time Fourier Transform (STFT). The thresholding process is essential for identifying the presence of a signal by isolating the significant components from background noise and interference.

The thresholding is performed using the Non-Parametric Amplitude Quantization Method (NPAQM), which dynamically adjusts the threshold based on the amplitude distribution of the signal. Unlike static thresholding methods, which can fail under varying noise conditions, the NPAQM adapts the threshold to match the current signal environment. This adaptive behavior ensures consistent signal detection even under fluctuating noise and interference levels.

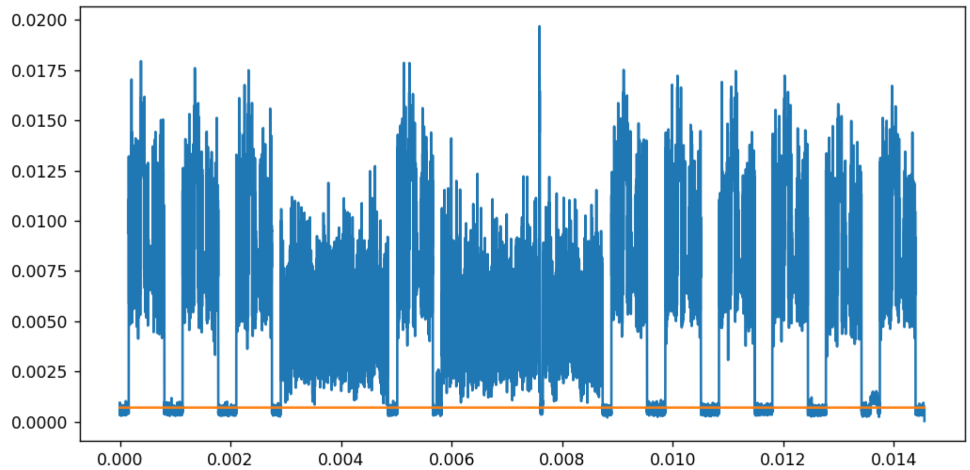

Figure 2. Detection of DJI Drone ID signals using NPAQM Threshold Technique

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4.3 Signal Period Measurement Result

The cross marks in Figure 3 indicate the detected signal periods of the DJI drone identification (ID) signal. The estimated period values are approximately 640 µs, which aligns closely with the expected lengths (periods) of DJI Drone ID signals.

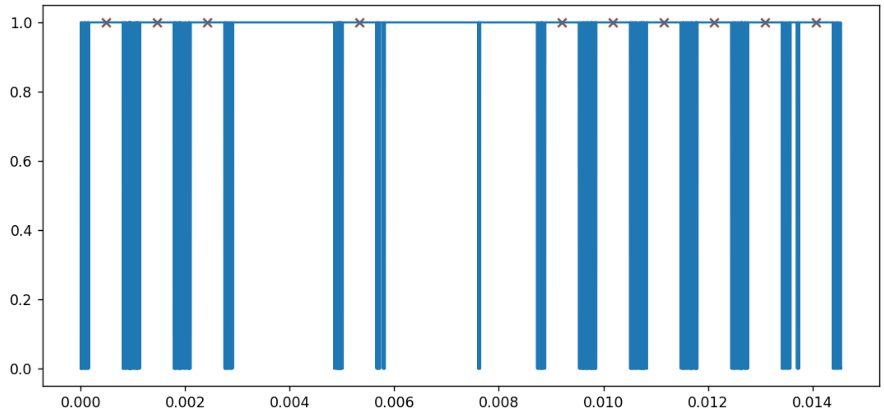

Figure 3. Measurement of length (Period) of DJI Drone ID Signal

4.4 Bandwidth Estimation Result

Figure 4 shows the cropped Short-Time Fourier Transform (STFT) presentation of a signal, which is extracted using the start time and end time of the detected drone signal. Cropping the signal to its active duration allows for focused analysis, reducing the influence of noise and irrelevant data.

After the signal is cropped, the Power Spectral Density (PSD) can be generated using this extracted signal. A PSD plot (Figure 5) was produced via Equation (5), revealing a bandwidth of approximately 9 MHz (ranging from 2.405 GHz to 2.413 GHz).

The plot shows a noise floor at approximately −80 dB/Hz and a signal power at around −50 dB/Hz. These characteristics are consistent with Orthogonal Frequency-Division Multiplexing (OFDM) modulation, which is known for its high spectral efficiency and robustness against multipath interference. The measured bandwidth and power levels align with the expected transmission parameters of the DJI OcuSync 2.0 protocol, confirming the presence of an OFDM-based signal structure.

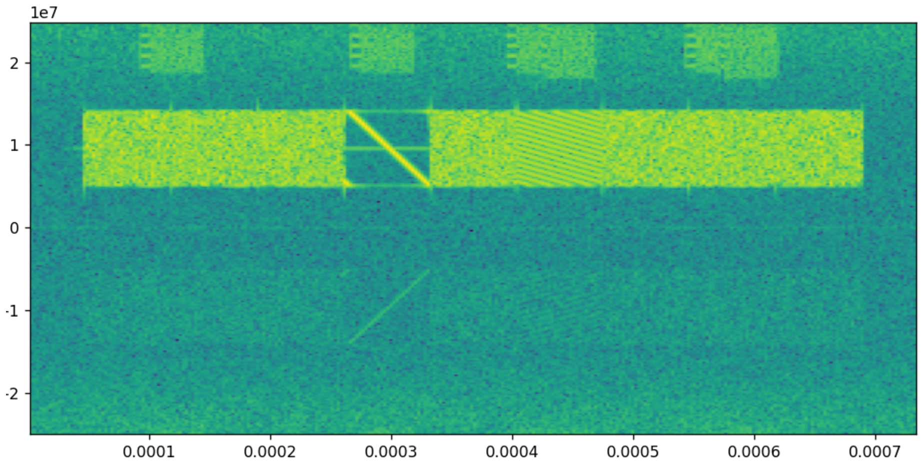

Figure 4. Cropped Short-Time Fourier Transform (STFT) Presentation of a Signal

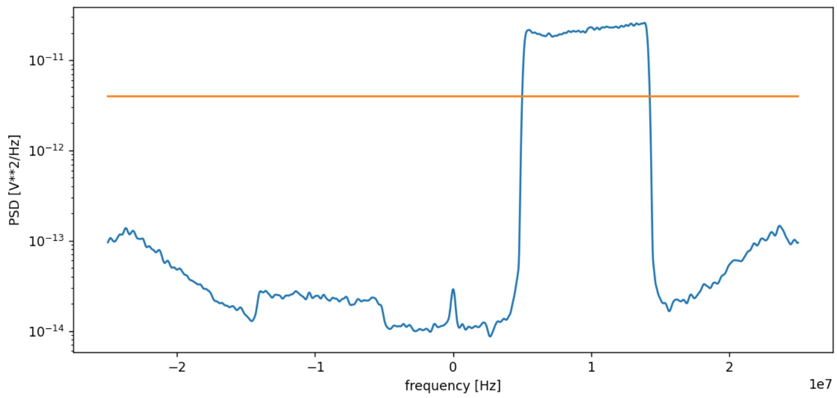

Figure 5. Power Spectral Density of DJI Mini 2 Drone ID Signal (Frequency vs. PSD)

4.5 Signal Occurrence Pattern Analysis Result

The signal period results shown in Figure 2 reveal the repetitive occurrence of DJI Drone ID signals at specific time intervals. In this case, the interval is approximately 640 us. This periodicity indicates that the DJI Drone broadcasts the Drone ID packet every 640 us. The repetitive nature of these signals reflects a structured transmission pattern, which is characteristic of the underlying communication protocol.

The occurrence pattern can be calculated using the time intervals between successive detected signal periods. By analyzing these intervals, it is possible to identify the signal structure and confirm the cyclic nature of the transmission. This information provides insight into the signal's modulation characteristics and aids in distinguishing between different types of signals in a complex RF environment.

4.6 Other Detected Characteristics of DJI Drone ID Signal

The packet used in the DJI OcuSync 2.0 communication protocol contains nine symbols as shown in Figure 6, of which two Zadoff-Chu (ZC) synchronization symbols (located at Symbol 4 and Symbol 6) play a crucial role in enabling synchronization between the transmitter and the receiver. These synchronization symbols are designed to assist in time and frequency synchronization, making it easier for the receiver to lock onto the transmitted signal.

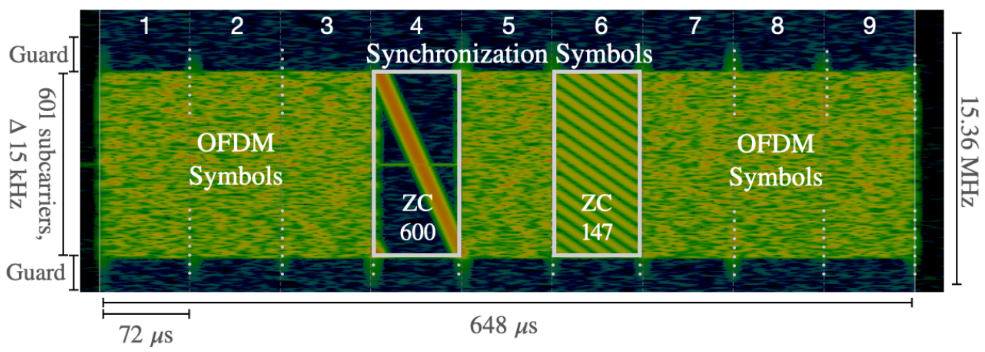

Figure 6. Spectrum view of a DroneID packet with highlighted Zadoff-Chu synchronization symbols.

The remaining symbols in the packet consist of OFDM (Orthogonal Frequency Division Multiplexing) data symbols, which utilize 601 subcarriers: 600 data subcarriers and 1 DC subcarrier. The data subcarriers carry the modulated information, while the DC subcarrier is used for the reference, typically set to zero to avoid interference at the center of the frequency band.

The subcarriers are spaced by 15 kHz, which is a standard subcarrier spacing for many wireless communication systems. In order to apply the Fast Fourier Transform (FFT) in the subsequent processing step, the carriers are padded to the next power of two. This results in a total of 1024 subcarriers, which helps optimize computational efficiency during the FFT operation.

The total bandwidth of the signal, including the guard bands, is 15.36 MHz. This bandwidth accommodates the 1024 subcarriers and ensures that the transmitted signal occupies the designated frequency range while providing sufficient protection against interference and maintaining signal integrity. The guard bands, typically positioned at the edges of the frequency spectrum, help reduce interference between adjacent channels and improve overall system performance.

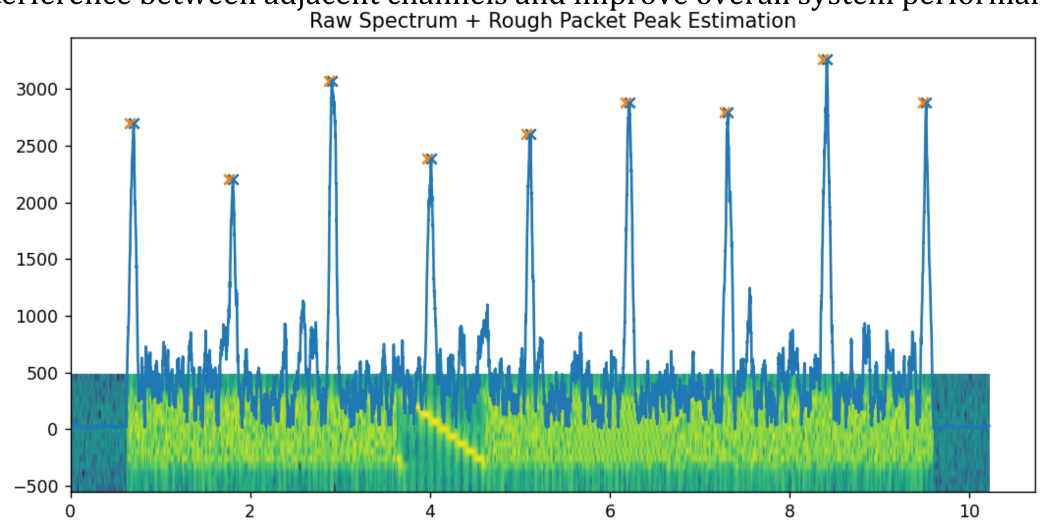

Figure 7. Extracted Zadoff-Chu synchronization symbols of DJI Drone ID Packet

Figure 7 shows the extraction of the synchronization symbols (Symbol 4 and Symbol 6) from the recorded signal. These Zadoff-Chu symbols are key elements of the DJI Drone ID packet, serving as synchronization markers that allow for signal alignment and demodulation. By isolating these symbols from the received signal, it becomes possible to identify the presence of the DJI Drone signal amidst potential interference, confirming the packet's structure and its alignment with DJI's communication protocol.

E. Conclusion

This study presents a robust signal detection methodology for identifying DJI Drone ID signals, utilizing a combination of thresholding, power spectral density (PSD) analysis, and signal occurrence pattern analysis. The proposed system successfully detected and classified DJI Drone ID signals through the analysis of their periodicity, spectral characteristics, and modulation scheme, providing valuable insights into the underlying communication protocol used by DJI drones. The thresholding process, based on the Non-Parametric Amplitude Quantization Method (NPAQM), proved effective in isolating the signal from noise and interference, while the PSD analysis confirmed the expected bandwidth and power characteristics of the signal. The repetitive nature of the signal was clearly observed through the signal occurrence pattern, which confirmed the presence of time-division multiplexing or frequency-hopping techniques commonly used in DJI's communication systems. Additionally, the extraction of Zadoff-Chu synchronization symbols from the recorded signal demonstrated the system's ability to handle complex modulation schemes like Orthogonal Frequency Division Multiplexing (OFDM), further validating the detection approach. These findings underscore the potential of this methodology in drone signal detection applications, offering a reliable solution for identifying DJI drones in various environments. Future work should focus on optimizing the system for real-time applications and expanding it to detect a wider range of drone communication protocols, enabling broader coverage and improving the adaptability of the detection system to different operational environments.

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G. References

[1] Zhao, J., & Rhee, I. (2018). *Drone Identification Using Signal Characteristics in Wireless Communications.* IEEE Transactions on Aerospace and Electronic Systems, 54(4), 1649-1658.

[2] Nallanathan, A., & Ding, Z. (2017). *Signal Detection Techniques for Cognitive Radio Systems: A Survey.* IEEE Transactions on Signal Processing, 65(2), 250-263.

[3] Burr, A., & Murillo, D. (2019). *A Survey on Signal Detection and Classification in Cognitive Radio Networks.* Wireless Communications and Mobile Computing, 2019, Article ID 3189304.

[4] Jiang, H., & Wu, S. (2015). *Signal Detection and Classification Techniques for Cognitive Radio Systems.* Springer, Berlin, Heidelberg.

[5] Boccardi, F., & Hepsaydir, E. (2018). *Principles of OFDM in Cognitive Radio Networks.* Journal of Communications and Networks, 20(3), 283-294.

[6] Li, Y., & Liu, H. (2020). *Drone Signal Identification Based on Non-Parametric Thresholding.* International Journal of Electronics and Communications, 133, 107543.
[7] Fan, Y., & Zhang, L. (2017). *Non-Parametric Amplitude Quantization for Signal Thresholding in Cognitive Radio.* IEEE Access, 5, 18188-18198.
[8] Tosato, F., & Rupp, M. (2016). *Orthogonal Frequency Division Multiplexing in Drone Communications: Challenges and Solutions.* IEEE Communications Magazine, 54(5), 48-56.
[9] Chong, Y., & Lee, H. (2018). *Signal Detection Using STFT and Wavelet Transforms in Drone Communication Systems.* IEEE Transactions on Wireless Communications, 17(2), 671-680.
[10] Zhou, T., & Wang, X. (2019). *Drone Communication and Spectrum Utilization in the 2.4 GHz ISM Band.* IEEE Transactions on Wireless Communications, 18(12), 5980-5993.
[11] Liu, Z., & Xie, L. (2016). *A Comprehensive Survey of Wireless Drone Networks: Communication and Detection Methods.* Journal of Network and Computer Applications, 68, 36-52.
[12] Kim, J., & Lee, W. (2021). *Detection of UAV Signals in Complex Communication Environments.* IEEE Access, 9, 151327-151339.
[13] Chong, Y., & Lee, H. (2020). *Signal Classification Techniques for Drone Communication Systems Using FFT and STFT.* Journal of Electrical Engineering & Technology, 15(3), 1315-1322.
[14] Huang, Z., & Li, X. (2018). *Analysis of Spectrum for Drone Communication in the 2.4 GHz Band.* IEEE Transactions on Vehicular Technology, 67(7), 6157-6167.
[15] Ali, R., & Cheng, R. (2021). *Classification and Detection of Drone Communication Signals Using Time-Frequency Analysis.* IEEE Transactions on Signal Processing, 69, 5739-5749.