

# Efficient Identification of UAVs through Automatic Communication Frame Linking

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**Abstract.** Unmanned Aerial Vehicles (UAVs) are increasingly utilized across both professional and private sectors. However, their ability to transmit sensitive information poses potential threats to public safety. Current detection techniques often monitor radio frequencies to identify drones and ascertain their models. Despite this, they are unable to differentiate between two UAVs of the same model. This paper aims to address this limitation by identifying individual UAVs of the same model. We conducted a measurement campaign to capture RF communication signals from two DJI MAVIC 2 Zoom drones. We characterized the communication frames, timing, intervals, power, and shape through a detailed statistical analysis of these signals. This analysis revealed distinguishing characteristics that enable the identification and tracking of individual UAV communications, even when multiple UAVs of the same model are present. Based on these findings, we developed a system that automatically links communication frames to specific UAVs, allowing for accurate counting of UAVs in a given area.

**Keywords:** RF monitoring, UAVs Detection, RF Statistical analysis, UAVs Identification, Signal processing.

## 1 Introduction

Unmanned aerial vehicles (UAVs), commonly known as drones, are becoming ubiquitous. By incorporating state-of-the-art technologies, UAVs can perform various tasks such as healthcare [1], commercial ventures [2], etc. However, easy access to these drones has also led to their exploitation in malicious activities, including drug trafficking, smuggling, and bombing [3, 4]. These activities represent a significant threat to public safety and must be detected. UAVs operate with varying levels of autonomy, typically functioning in one of two primary modes: following pre-programmed flight routes via Global Navigation Satellite System (GNSS) signals or under direct remote control. As a result, a range of technologies can be employed to detect and track these UAVs. UAV detection methods include RF signals based, imaging, radar sensors, and acoustic technologies. In this study, we focus on remotely controlled UAVs and those that transmit signals such as video feedback or positional information. These UAVs can be effectively detected through the analysis of their RF signals.

Most UAV detection studies focus on commercially available UAVs, which typically operate using proprietary protocols instead of known standards [8, 9]. These studies successfully identified various communication protocols (such as standard Wi-Fi, Enhanced Wi-Fi, LightBridge, Ocusync, etc.) and pinpointed specific UAV models. However, to our knowledge, no study has been conducted to identify two drones of the same model. For securing sensitive areas, it is crucial to differentiate between authorized drones and those that could pose a threat. Therefore, tracking the communication frames of authorized drones and accurately identifying frames associated with potentially threatening drones to take appropriate countermeasures is vital.

To address this challenge, we propose a study of the RF signals from two UAVs of the same model (MAVIC 2 Zoom) to characterize their communication and track their communication frames. This paper is organized as follows to detail the identification process. First, we describe the experimental setup used to build our database, along with the data collection and preprocessing methods employed for our identification framework. Next, we present a statistical analysis of the communication characteristics of the two UAVs. Finally, we develop a system to trace the communication frames of these UAVs using the distinctive characteristics identified in the statistical analysis.

## 2 Database Construction

In this section, we discuss the construction of the database, detailing the measurement setup, the parameters used, and the preprocessing of the RF signal.

### 2.1 Experimentation

For this study, we selected various equipment to establish our experimental setup. The setup includes a Software-Defined Radio (SDR) controlled by a laptop, a directional antenna, and two MAVIC 2 Zoom UAVs. The SDR used in this study is designed from the ADRV9026 card. It is configured to monitor a 100 MHz band centered on the frequency 2.45 GHz. The sampling rate is 122.88 MHz for a time window of 40 ms. This configuration allows us to measure 4915198 frequencies within the band. For the acquisition, adding the saving time, we can acquire IQ matrices of size  $4915198 \times 2$  per second. Figure 1 shows the configuration in which measurements are acquired. This experiment aims to characterize UAV communications separately and test the algorithm used to link the communication frames to the drone.

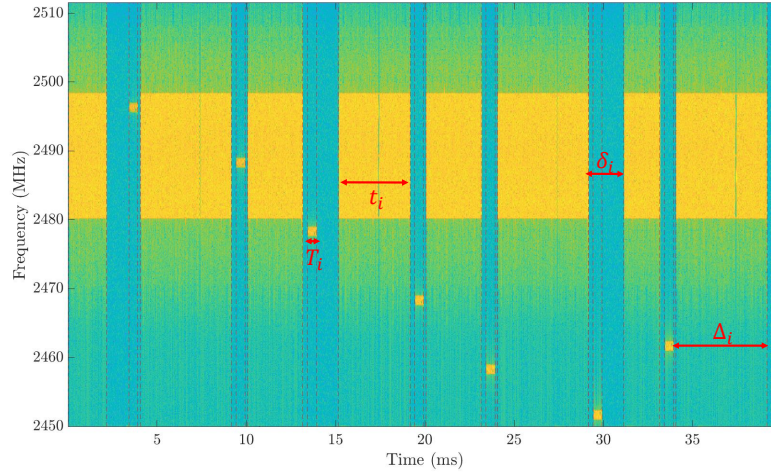
### 2.2 Dataset and Preprocessing

Correlation techniques can be employed to effectively separate RC (Radio Control) signals and video signals within a composite signal due to their ability to identify and isolate distinct patterns within a signal. The RC signals typically



**Fig. 1.** Configuration of the experimentation using two UAVs.

used for controlling devices and video signals, carry unique characteristics in their frequency and modulation patterns. By applying a correlation technique, one can match these patterns against known templates of RC and video signals. This involves cross-correlating the composite signal with predefined reference signals for RC and video. Peaks in the correlation output indicate the presence and timing of these reference signals within the composite signal. The RC signal has a specific modulation scheme, and the correlation with its reference template will reveal its exact occurrence. It can be extracted by isolating these peaks. Similarly, the video signal with a different frequency range and modulation pattern can be identified and separated using its unique correlation signature.



**Fig. 2.** Representation of the times indicators.

To characterize and compare the two UAVs, we collect the average power of control communications ( $A_i$ ) in dB, the average power of communications from the UAV ( $a_i$ ) in dB, the time intervals between the control communications ( $\Delta_i$ ) in ms, the time intervals between the communications from the UAV ( $\delta_i$ ) in ms, the duration of control communications ( $T_i$ ) in ms and the duration of communications from the UAV ( $t_i$ ) in ms. The duration and time interval indicators are shown in Figure 2, which represents the duration and time interval indicators.

### 3 Characterization of UAV Communications

For each of the UAVs, we aim to characterize the communications between the remote control and the UAV. We study the characteristics of video and control communications separately for each of the two UAVs. In addition to comparing these two UAVs independently, we also characterized them when no flight command is transmitted by the controller (“stationary mode”) and when the controller sends motion information (“flying mode”). The table 1 contains the average value of these indicators, respectively noted as  $\bar{A}$ ,  $\bar{a}$ ,  $\bar{\Delta}$ ,  $\bar{\delta}$ ,  $\bar{T}$  and  $\bar{t}$ .

**Table 1.** Average value  $\bar{A}$ ,  $\bar{a}$  in dB and  $\bar{\Delta}$ ,  $\bar{\delta}$ ,  $\bar{T}$ ,  $\bar{t}$  in ms.

ID	mode	$\bar{A}$	$\bar{a}$	$\bar{\Delta}$	$\bar{\delta}$	$\bar{T}$	$\bar{t}$
UAV 1	stationary mode	55.3822	71.4989	4.4625	1.1491	0.5119	3.6182
	flying mode	55.1249	71.3536	4.3294	1.2414	0.5210	3.5506
UAV 2	stationary mode	57.8625	72.1214	4.5874	1.1025	0.4944	3.6711
	flying mode	58.7050	72.2870	4.4130	1.3551	0.5111	3.5367

For each indicator, we test the equality of distribution between UAVs for each mode and the difference in distribution between modes for each UAV. The tests used to compare the distributions are a Wilcoxon-Mann-Whitney test (MW-test). For this test, the null hypothesis is given by  $H_0 : \eta_1 - \eta_2 = 0$  and the alternative hypothesis is given by  $H_1 : \eta_1 - \eta_2 \neq 0$  where  $\eta$  is the median value. In these tests, with  $\alpha$  as the risk, a  $p - value \leq \alpha$  indicates that the difference between the medians is statistically significant, leading to the rejection of the null hypothesis  $H_0$ . The table 2 contains the p-values associated with these tests and a Boolean (B) associated with test rejection. This boolean will take the value 1 if the initial hypothesis  $H_0$ , equality between the compared distributions is rejected, 0 otherwise.

Firstly, an analysis of the distribution of various criteria revealed a difference between the communications of the two MAVIC 2 Zoom UAVs in stationary mode. Only the video communication times were not significantly different. In the case of UAVs receiving movement instructions, the communication intervals and times were not significantly different, allowing us to assume that the method

**Table 2.** Wilcoxon-Mann-Whitney test.

	$A$		$a$		$\Delta$		$\delta$		$T$		$t$	
	p-value	B	p-value	B	p-value	B	p-value	B	p-value	B	p-value	B
Stationary mode												
UAV 1 vs 2	0	1	0	1	0.000287	1	0.00017	1	0	1	0.08145	0
Flying mode												
UAV 1 vs 2	0	1	0	1	0.3616	0	0.5059	0	0.0576	0	0.9891	0
Flying mode vs Stationary mode												
UAV 1	0.095498	0	0	1	0.17913	0	0.63013	0	0.0010262	1	0.3694	0
UAV 2	0.0013939	1	0	1	0.051068	0	0.26641	0	0	1	0.87389	0

of sending instructions is similar for both UAVs. Interestingly, for the same UAV, only the transmission times of the control signals change when motion commands are sent to the UAV, while the time intervals remain not significantly different. In conclusion, using criterion  $A$  appears to be a good indicator for identifying frames from the same UAV. Signal strength is ignored in this analysis despite a significant difference between the two UAVs on this criterion due to the lack of UAV mobility in this experiment.

#### 4 Automatic Linking of Communication Frames Results

Our study of the two MAVIC 2 Zoom UAVs has enabled us to highlight the differences and similarities between these UAVs of the same model. In order to associate the communication signals with the corresponding UAVs, we need to account for the fact that the signals from the UAVs are different from those emitted by the controllers. This necessitates a two-step process in our tracking approach. First, we differentiate between the signals emitted by the controllers and those emitted by the UAVs. Then, we analyze these differentiated signals to link the communications accurately to the associated UAVs. For the signal from the drone, the allocation of the frame is done as follows:

- Identifying the appearance of a drone frame using cross-correlation with a reference drone frame: Compare incoming frames with a reference frame to detect drone frames,
- Identifying the time of the next emission using our database to ensure the signal is emitted within a characteristic interval: Use our database to verify that signals are emitted within expected intervals,
- Associate the frame to the corresponding UAV: link identified frames with the related UAVs based on their unique characteristics and emission patterns.

Frame association is performed similarly to UAV communication for signals from the remote controller. The key differences lie in the reference frame and the communication interval.

Using this process to allocate the frame to the corresponding drone when the two drones operate, the identification process made no error in associating the

frame to the corresponding UAV, and this is due to the stability of the UAV characteristics in an anechoic chamber. Regarding the controller's communication, we obtain an error of 6.9%.

## 5 Conclusion.

This study demonstrated the ability to identify and allocate communication frames to a characterized drone accurately. However, it is essential to note that the experiment was conducted in an anechoic chamber. Therefore, verifying the stability of the indicators in real-world scenarios is necessary. Additionally, further research should include more measurements and incorporate other UAV models or UAVs using different communication protocols to enhance the robustness of our findings.

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