3rd URSI AT-AP-RASC, Gran Canaria, 29 May – 3 June 2022

Contribution to the design of Smart Jamming waveforms for UAVs counter-measurement

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Abstract

In recent years, the fight against unmanned aerial vehicles (UAVs) has become a primary concern due to the ease of obtaining a capable drone and the advent of numerous incidents perpetrated with UAVs flying over public or critical sites. Thus, drone jammers are developed and proposed to law enforcement agencies to counter this type of threat. However, these jamming devices can also affect other communications in the same industrial, scientific and medical (ISM) band. In this context, based on Radio Frequency (RF) sensing, a neutralization strategy is proposed in this paper. This RF analysis aims to recognize the drone type in order to optimize the jamming signal and then reducing the total power required to intercept the drone. This strategy should minimize possible collateral effects on other communications.

Keywords— RF sensing, jamming, UAV, detection, classification, Convolutional Neural Network, confusion matrix

1 Introduction

In recent years, UAVs (Unmanned Aerial Vehicles) have become increasingly available to the general public. Malicious use of UAVs constitutes a significant risk to sensitive sites or events with large audiences. They can penetrate protected airspace and threaten the security of sensitive sites [1]. To stop an intruder drone, most techniques use the "jamming" of the drone's control signals, but the technique of full band barrage jamming can affect other ISM band telecommunications channels. Thus, the development of intelligent jamming techniques is necessary to avoid collateral effects on other communication equipment [2].

In this work, a smart jamming strategy is proposed based on passive RF detection, illustrated by Figure 1.

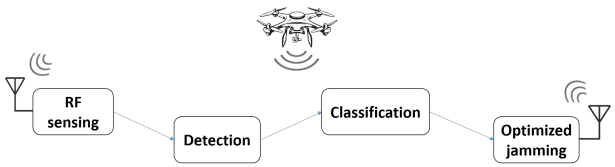

Figure 1. Proposed smart jamming strategy

The approach consists of first detecting and classifying the communication signals specific to the UAV model and its Remote Control(RC), using Machine Learning approaches. Once the communication signals are identified, an optimal jamming method is implemented to reduce the total jamming power required to breakdown the UAV-RC communication and then limiting the impact on other neighboring wireless communications.
UAV identification model is the first step of the proposed solution. Indeed, due to the differences between the existing UAV communication protocols (FHSS, DSSS, LoRa, OFDM, SC-FDM [3]), the optimal jamming waveform to stop the UAV can be significantly different according to the communication protocol. Identifying the drone model can allow the generation of an optimized jamming waveform for the interception of the specific UAV.

This paper is focused on the identification of the drone model. A characterisation test bench of the drone communication signals is presented in section 2. In sections 3 and 4, the algorithms developed in order to separate the uplink and downlink signals between the drone and the remote control and to collect a spectrogram data base representing different drone models are presented. Finally, in section 5, a deep learning approach is employed to classify the spectrograms of the communication signals behind the different models of drone characterized. The classification results are presented in a confusion matrix and analyzed.

2 The UAV Bench Characterisation

To detect and distinguish different UAV models, a characterization bench has been developed (Figure 2) to build a database. This bench allows measuring the RF communication signals of the UAV using a Software Defined Radio (SDR) board. Processing is applied to the measurement results to analyze the RF communication signals of the different UAV models and obtain their spectrograms.

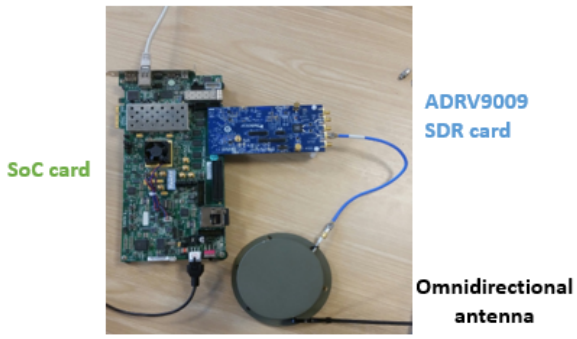

Figure 2. Characterisation bench for the different UAV models

3 Separation of RC and UAV signals in the measured files

To analyze the RC and video signals of the drone, a measurement bench is set up using an SDR board. In the example described below, the center frequency is set to $F_c = 2.44GHz$ and the sampling frequency of $F_s = 122.88MHz$.
All the signals are recorded in files and post-processed. These files contain both signals that correspond to the data transmitted from the UAV to the RC, which includes for example the video data, and signals that correspond to the control commands sent by the remote control to the UAV. To organize the database, these different signals have to be separated.

The first blue curve on Figure 3 shows an example of communications between a drone and its remote control, by a capture of $N_p = 2^{20}$ points in time which corresponds to $T_{capture} = Np/F_s = 8.53\ ms$. The uplink signal (from the RC to the drone) is shorter in time than the downlink signal (from the drone to the RC). To separate these two signals, a source separation algorithm is employed.

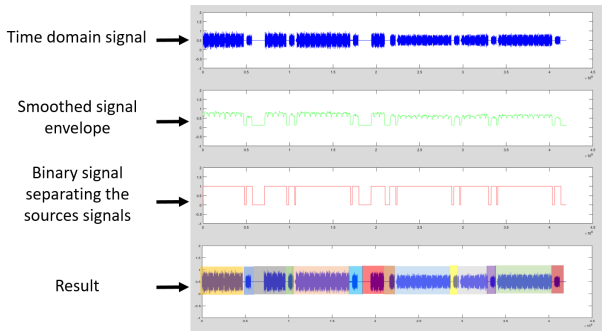

Figure 3. Source separation algorithm applied over a 2^{20} points measurement file

First, the upper amplitude of the signal is determined using the Hilbert Transform (see eq. (1, 2 and 3) and a moving mean filter is applied to smooth the envelope (green curve in Figure 3). Then, a fixed threshold is applied to detect the rising and falling edges of the curve (curve in red on Figure 3). Finally, to obtain the precise coordinate of the edges, a mathematical derivation is applied on the binary signal (in the derivation results, 1 corresponds to the rising edge and -1 to the falling edge).

$$s(t) = \mathscr{H}\{s\}(t) = \text{p.v.}\{(h * s)(t)\} \tag{1}$$

$$s(t) = \frac{1}{\pi}\text{p.v.}\left\{\int_{-\infty}^{\infty} \frac{s(\tau)}{t-\tau}\, \mathrm{d}\tau\right\} \tag{2}$$

p.v. being the abbreviation of the principal Cauchy value:

$$\begin{aligned} &\text{p.v.}\left\{\int_{-\infty}^{\infty} s(\tau)h(t-\tau)\, \mathrm{d}\tau\right\} \\ &= \lim_{\substack{\varepsilon\to 0\\ \varepsilon>0}} \left\{\int_{-\infty}^{t-\varepsilon} s(\tau)h(t-\tau)\, \mathrm{d}\tau + \int_{t+\varepsilon}^{+\infty} s(\tau)h(t-\tau)\, \mathrm{d}\tau\right\} \end{aligned} \tag{3}$$

4 Short Time Frequency Transform (STFT) Algorithm

To benefit simultaneously of the power, the frequency distribution, and the time domains characteristics of the communication signals, we extracted the spectrograms of the separated signals. The spectrograms are obtained with the Short Time Fourier Transform (STFT). The STFT is used to analyze the frequency content of a non-stationary signal over time. The STFT is calculated by shifting an analysis window of length M over the signal and calculating the fast Fourier transform (FFT) of the windowed data.

The columns number in the STFT matrix is given by:

$$k = \left\lfloor \frac{N_x - L}{M - L} \right\rfloor \tag{4}$$

where N_x is the number of samples of the original signal and $x \mapsto \lfloor x \rfloor$ denotes the integer part function of x.

The STFT matrix is given by $X(f) = [X_1(f)\ X_2(f)\ \ldots\ X_k(f)]$ such that the mth element of this matrix is:

$$X_m(f) = \sum_{n=-\infty}^{+\infty} x(n)g(n-mR)e^{-j2\pi fn} \tag{5}$$

where $g(n)$ is the window function of length M, $X_m(f)$ is the FFT of windowed data centered on time mR and R is the step between successive time windows.

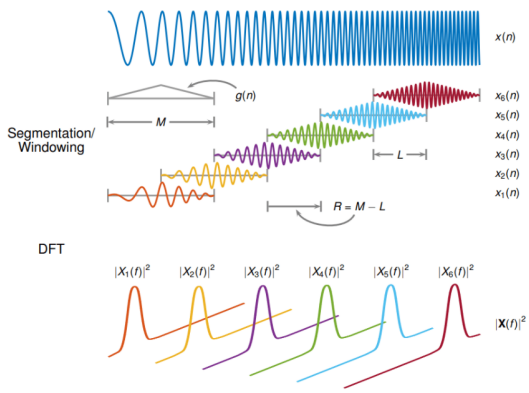

Figure 4. Illustration of the STFT algorithm

The STFT algorithm allows us to recover the protocol signature of the modulated communication signal. In Figure 5, we illustrate a spectrogram of communication signals between a drone and its remote control.

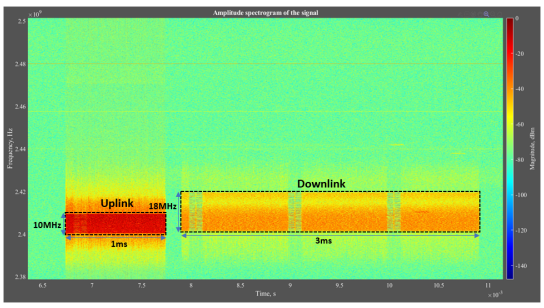

Figure 5. Spectrogram of the Herelink drone model, including Uplink and Downlink communication signals.

5 Database and Classification Process

The RF communication streams of three drones had been collected beforehand using the characterisation bench described in the section 2. Then, the region Separation algorithm was applied on the measured files, as illustrated in the left part of the figure 6. Finally, the STFT algorithm is applied on each separated regions, giving the spectrograms illustrated in the right part of the figure 6.

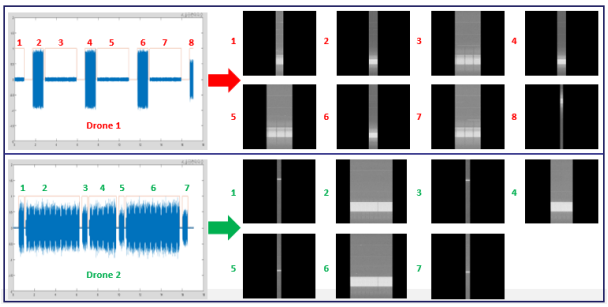

Figure 6. Example of two UAVs communication with application of region separation and STFT algorithms

The obtained spectrograms are treated as images. Due to the differences between the analyzed signals durations, a $[F_s \text{ x } T_{capture}]$ constant time frequency space is defined in which the images are placed in the center. To optimize the training step, the resolution of images is reduced to (180x180) in a gray-scaling format as shown in Figure 6 (right).

A 1000 spectrogram images database is created and each image is labeled with the name of the associated drone, and with the signal type,i.e. signal sent by the UAV or signal sent by the RC. Subsequently, 80% of the images are used as input to a Convolutional Neural Networks (CNN) for training, and 20% are used to test and validate the constructed model [5]. Finally, the classification test is presented by the confusion matrix in Figure 7.

6 The Confusion Matrix

Figure 7 shows the confusion matrix obtained with 3 different UAV models. This matrix contains 7 classes. Indeed, for each drone, the spectrograms corresponding to the remote control (RC) signals and the video signals are separated and define two different classes. The "environment" class corresponds to measurements that do not include drone signals. This environment class can include other surrounding communication signals such as Wi-Fi or Bluetooth communications.

For each class, 800 images are used for the training step, and 200 for the testing step. The confusion matrix in Figure 7 shows encouraging results. In this matrix, the diagonal values in red represent the successful classifications, and the off-diagonal elements represent the confusion between the different classes. We can see, for example, that on the 1st column of the matrix, the trained model correctly separated 198/200 images, the error is only 2/200 images. Concerning the distinction between the different UAV models, confusions between the RC signals of UAV 2 and 3 occur, this can be explained by the fact that these two UAVs use a similar communication protocol.
On the other hand, there is a good separation between the "environment" class and the different classes of drones. This illustrates

Output Class \ Target Class	Drone 1 RC	Drone 2 RC	Drone 3 RC	Environment	Drone 1 Video	Drone 2 Video	Drone 3 Video
Drone 1 RC	198	0 0%	0 0%	0 0%	1 0,1%	0 0%	0 0%
Drone 2 RC	0 0%	141	4 0,3%	1 0,1%	0 0%	1 0,1%	1 0,1%
Drone 3 RC	0 0%	58 4,1%	193	2 0,1%	0 0%	0 0%	1 0,1%
Environment	0 0%	1 0,1%	2 0,1%	196	2 0,1%	7 0,5%	7 0,5%
Drone 1 Video	0 0%	0 0%	1 0,1%	0 0%	193	9 0,6%	1 0,1%
Drone 2 Video	2 0,1%	0 0%	0 0%	0 0%	2 0,1%	181	4 0,3%
Drone 3 Video	0 0%	0 0%	0 0%	1 0,1%	0 0%	2 0,1%	186

92,1% ⟸ Accuracy
7,9% ⟸ Error

Figure 7. Confusion matrix resulting from the classification performed with three drone models

the good ability to detect the presence of the drone in a complex environment by this approach.

7 Conclusion

To develop an optimal and smart jamming strategy to intercept UAVs, we worked on the recognition of specific UAV models by an RF analysis of the wireless communication signals. The method is based on the separation of the signals corresponding to different sources and on the spectrogram of each separated signal. A CNN approach is then applied on the spectrograms to classify then and identify the drone model to which they correspond. In this communication, we considered seven classes to detect and distinguish 3 different UAVs, with Downlink and Uplink signals. The environment class takes into account all other radio frequency sources that are not drones, like Wi-Fi or bluetooth communications. After a training over 800 spectrogram images, the classification of the 200 test spectrograms by a CNN approach gave satisfyingly results with 92% of precision for seven classes. The next step will consist in enriching the database with the spectrograms of new UAVs, and making the model evolve to include new classes. We have to check if increasing the diversity of the database does not degrade the classification ability.

References

[1] ITV, "Flights briefly grounded at Frankfurt Airport after drone sighted", Germany, 2020.

[2] F. Mehouachi, J. Galvis, S. Morales, M. Meriac, F. Vega, C. Kasmi, "Detection and Identification of UAVs based on Spectrum Monitoring and Deep Learning in Negative SNR Conditions", *URSI GASS 2021*, Roma, Italia, 2021.

[3] S.Atoeva, O.Kwon, S.Lee and K.Kwon, "An Efficient SC-FDM Modulation Technique for a UAV Communication Link", *Electronics*, 7(12), 352, Corea, 2018.

[4] Wikipedia. 2022, "Frequency-hopping spread spectrum.", `https://en.wikipedia.org/wiki/Frequency-hopping_spread_spectrum`, Last modified: January 15, 2022.

[5] M.Wu, W.Xie, X.Shi, P.Shao and Z.Shi, "Real-time Drone Detection using Deep Learning Approach, Third International Conference MLICOM 2018, China, 2018.