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DRONE CLASSIFICATION BASED ON RADIO FREQUENCY: TECHNIQUES, DATASETS, AND CHALLENGES

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Abstract: *This research article presents a comprehensive review of current literature on drone classification (detection and identification) in the radio-frequency domain. The usage of unmanned aerial systems or drones, both for commercial (amateur or civilian) and functional (military or industrial) purposes, has multiplied numerous times over in the last decade. Drones have undergone great improvement, and at the same time, they have become low-priced and easier to manipulate, but on the contrary, they come to be more adaptable to illegal actions. Due to the scope of the subject matter, the review included only the classification of drones via passive, radio-frequency sensors with a description of the classification techniques (set of algorithms, methods, and procedures) and the datasets used for performance testing. Moreover, the challenges of drone classification based on radio-frequency were presented in this work. The general outcome of this study shows that deep learning techniques are currently the best solution for solving the issue of drone classification. However, it should be noted that most modern research is experimental and that there are only limited practical implementations. A particular problem is the lack of a general specification for radio-frequency drone classification that must be based on requirements defined from everyday experience.*

Keywords: *Deep learning algorithm, drone, detection, classification, identification, radio-frequency.*

1. INTRODUCTION

Unmanned aerial systems (UAS), especially commercial off-the-shelf (COTS) ones, become less expensive, equipped with better optoelectronic sensors (daily and night cameras), easier to fly, and have attracted increasing attention due to their boundless applications. However, such imminent technological improvements contribute that UAS being more adaptable for crime, terrorism, or military purposes. Moreover, this caused security forces to be increasingly challenged by the need to quickly detect and identify UAS, especially in security-sensitive areas. With such a huge expansion of UAS applications, which can be harmful, there is a prerequisite to protect sensitive areas and critical points of the vital infrastructure by using specific means, i.e. anti-drone (ADRO) systems. Various ADRO systems can be found on the market presently, and all of them have one important characteristic in common: the usage of several different (optoelectronic, acoustic, radar, and radio-frequency) sensors. Additionally, it can be noted that every ADRO system consists of the following core subsystems: monitoring (sensing), mitigation, and command and control (C2) subsystem [1]. Based on this, the modern ADRO system needs to incorporate different procedures against UAS: detection, spoofing, jamming, and mitigation procedures [2], [3].

Detection or warning procedures are based on various detection devices (sensors) to perform early warning on the presence of any UAS (set of drones with their ground controller and equipment). The additional function of these procedures is the identification and localization (optionally, tracking) of detected drones in order to provide inputs for the next stage of the ADRO system. The spoofing procedure is involved in the next phase but it is not compulsory. With this procedure, the ADRO system deceives drones by sending false radio signals (GPS spoofing is a typical example of an emergency landing). If the spoofing procedure fails, the ADRO system can engage the jamming procedures, where the drone's control and navigation signals are disturbed by posing strong artificial interference. Finally, the ADRO system can use the mitigation procedure, to destroy or capture malicious drones. Although ADRO systems comprise diverse procedures and sensors, practical implementations mainly rely on radar and radio-frequency (RF) sensors, rather than optoelectronic or audio sensors for primary drone detection.

The main advantage of RF sensors is zero irradiated power, a longer detection range, an association with procedures against UAS (especially jamming), and usage of various techniques for exploiting the intercepted RF signal. RF sensor is a passive device that only receives RF signals from UAS (both drone and ground controller) which are present in almost every situation. Contrary to that, radar is an active device that irradiates electromagnetic energy, thus it can be a constraint because it can not be used in every possible scenario. The detection range of RF sensors depends on the surroundings and transmitter power of UAS but usually is comparable with the radar range. Another interesting fact in favor of the RF sensors is a possible connection between the receiver and jammer. Parameters obtained from the UAS detection stage can be used for spoofing and jamming if this is requested. Additionally, an RF receiver is a very resourceful sensor in contrast to the others. The received RF signals can be used for different purposes such as communication protocol detection, drone MAC address detection, feature extraction, or for direct use with some classification algorithms.

The ADRO systems can extract useful information from intercepted RF signals between the drone and the ground controller to resolve communication protocol or the MAC address. Drones use specific protocols for communication which can be used for detection and identification purposes. Additionally, the IEEE 802.11 (Wi-Fi) standard can be exploited to trace the MAC addresses of the specific drone model. However, a major drawback of such ADRO systems is the a priori knowledge of communication protocols and MAC addresses, which in some situations may not be the case (hand-made drones can also have custom-made protocols). Furthermore, the ADRO system can extract some features from intercepted RF signals for detection purposes. In addition, the ADRO system exploits frequency or joint time-frequency signal representation (TFSR) of I/Q data (raw RF signal), to prepare inputs to some classification algorithm.

The disadvantage of RF-based drone detection is ambient RF noise, multipath, and the fact that customized UAS can operate autonomously, without an active communication link between drone and ground controller. Additionally, real-time RF monitoring is a cumbersome process, due to the very specific conditions of the RF domain. It is important to note that all drone RF communication can be organized into three main categories of communications: command and control (uplink), telemetry and video (downlink), and guidance communications. The first two groups are using a wide range of frequencies (between 400 MHz and 6 GHz), while guidance communications use global navigation signals (GPS L1/L2/L2c/L5, Glonass, Beidou, or Galileo). In such a complex environment, RF sensors must be very agile with high-speed scanning performance, highly sensitive, and with a high dynamic range across the whole frequency range.

The rest of the paper is organized as follows: section 2 is a categorization and overview of relevant studies, section 3 describes the comparison of classification techniques, the results of comparative analysis of the most relevant papers are presented in section 4, and finally, the conclusion is given in section 5.

2. CATEGORIZATION AND REVIEW OF LITERATURE

To the best of our knowledge, available studies introduced different classification techniques (approaches) based on the RF sensors. We created a new categorization of these classification techniques according to:

– the method of processing input data:
  – classic engineering techniques that require prior feature extraction in combination with a simple decision threshold mechanism,
  – advanced engineering techniques that do not require prior feature extraction with complex learning procedures for classification purposes (feature extraction is implemented in deep learning algorithms together with the learning process), and
  – hybrid engineering techniques that present a combination of previous ones.

– the type of input data:
  – techniques with classification algorithms that use the MAC address information as input data,
  – techniques with classification algorithms that use the protocol information as input data,
  – techniques with classification algorithms that use features of RF signals as input data, and
  – techniques with classification algorithms that use the entire received I/Q RF signal as input data.

It is important to note that one technique can be categorized by both rules, i.e. some approach is a classic engineering technique that uses protocol information as input data. The categorization presented in this research paper is based on the most relevant research papers that are available in the literature in the last five years. A total of 96 research papers, that are dealing with RF classification (detection and identification) of drones, were incorporated into this research.

2.1. RF techniques according to the method of processing input data

When it comes to input data preparation and processing method, classical engineering techniques require a mandatory step to extract features from intercepted RF signals. This is an important step because only extracted features with a decision threshold mechanism can be used for classification. The main disadvantage of the classic engineering techniques is the complex process of feature extraction which must be adopted according to the nature of input data. This implies that feature extraction is a very demanding and time-consuming process that requires profound engineering skills. Authors in [4] used the standard deviation analysis, maximum slope analysis, and accumulation in azimuth direction as statistical features for drone detection and direction finding. Moreover, the principal component analysis and the empirical mode decomposition (EMD) based wavelet transform (WT) methods were engaged to cope with additive Gaussian white noise. Furthermore, the cyclostationarity signature of the drone RF signal and pseudo-Doppler principle was presented in [5] for the classification issue with a single-channel universal software radio peripheral (USRP) receiver. In [6], the authors described an innovative passive drone detection system (Matthan), based on two key physical signatures of the drones (body shifting and vibration). However, the Matthan approach is challenged with the range constraint, so did not find any practical implementation up till nowadays.

Alternatively, artificial intelligence (AI) algorithms, especially deep learning (DL), approach the problem of classification without prior extraction of features. Advanced engineering techniques use the entire received I/Q RF signal, perform some preprocessing steps and send all data to the learning process. The advantage, compared to the classical engineering techniques is the more robust and scalable approach. However, a huge amount of input data is required for the training process which can be a disadvantage in some cases. Fully connected deep neural networks (FC-DNN) were engaged in [7]–[9] to classify drones. Similarly, convolutional neural networks (CNN) as one of the prominent DL algorithms were used in [10]–[14] for the same purpose.

The quantitative comparison of the techniques that exploit RF sensors according to the method of processing input data is presented in Figure 1.

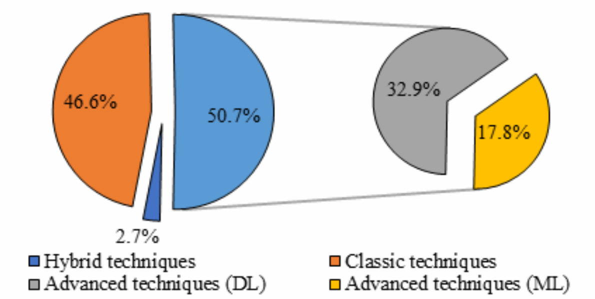

Figure 1. Quantitative comparison of RF techniques according to the method of processing input data.

It should be noted that 50.7% of all research papers rely on advanced techniques compared to 46.6% of classic engineering techniques. This result is not surprising because the analysis included only works in the last five years when advanced techniques began to be widely applied. This also means that classical engineering techniques are being given up in favor of advanced ones. Furthermore, DL and ML algorithms participate with 32.9% and 17.8%, respectively, in advanced engineering techniques.

It is also worth mentioning that the authors in [15]–[20] present classical and advanced engineering techniques in combination with direction-finding (DF) methods. However, the specific hardware and software implementation of the RF-based DF of UAS is presented in [20] because the authors used a single-channel RF sensor and a four-element antenna array, in combination with a sparse denoising autoencoder that is based on a deep neural network (SDAE-DNN). Although, it is important to notice that some authors in [21]–[24] use a hybrid engineering technique or a combination of classical and advanced techniques. In [21] authors used extracted features (the slope, kurtosis, and skewness) of the drone RF signal as input for an FC-DNN. Moreover, in [23], the authors performed feature extraction and used ML algorithms (Logistic Regression). On contrary, authors in [25] used deep learning algorithms (ResNet50) for feature extraction together with ML classifier Logistic Regression. An interesting approach was presented in [24] where authors extracted fifteen statistical features from the UAS RF signal and engaged them with five different machine learning (ML) classifiers at different SNR levels.

2.2. RF techniques according to the type of input data

RF sensors receive an RF signal from a UAS, which can be exploited for different purposes. There are four different techniques for detecting and identifying drones according to the type of input data. The first group includes techniques that use classification algorithms for the detection and identification of the MAC address of the transceiver device in a drone. The second group includes techniques that exploit classification algorithms for the detection and identification of the protocol of communication between drones and ground control devices. These two techniques are the least represented in the available literature because they have major limitations and shortcomings. The main characteristic of both approaches is the use of received and demodulated RF signals for finding information about the MAC address of the RF transceiver installed in the drone and about the type of communication protocol that is unique for certain types of drones. Such obtained information is afterward used for the detection and identification of drones. However, to the best of our knowledge, the technique with classification algorithms based on protocol recognition is more efficient than the previous. Furthermore, there are more practical hardware implementations of ADRO systems based on this technique. Authors in [26] performed device and protocol identification throughout the data format analysis. In [27], features such as packet inter-arrival time and size were analyzed, while in [28] authors studied eight protocols to classify UAS.

Moreover, techniques with classification algorithms that use features of RF signals as input data are more present in the literature. We have mentioned some important studies that exploited features because this is a mandatory step for classical engineering techniques. Nevertheless, more and more research papers are appearing in the literature dealing with the entire intercepted I/Q RF signal. The faster hardware and improved computing power are the reason and the possibility to exploit the full power of DL algorithms which are created for a huge amount of data. Because of that, the techniques with algorithms that perform classification with the entire received I/Q RF signal as input data are becoming widely present solutions providing excellent results. The main characteristic of this approach is the use of RF sensors to record the raw RF signal, followed by different pre-processing steps in order to prepare input data for the classifier. Some authors in [7]–[9] performed magnitude or phase spectrum calculations to obtain 1-D (vector) data with corresponding labels. Others in [12]–[14] used more complex TFSRs such as spectrograms or scalograms to obtain 2-D (image) representations of intercepted I/Q RF signals with corresponding labels for classification purposes. The illustration of one 2-D TFSR obtained from RF activities in the 2.4 GHz is presented in Figure 1. This TFSR is a spectrogram of RF signal when two drones operate simultaneously at 2.4 GHz. It is important to note that two emissions are visually distinctive in Figure 2: the command and control (fixed frequency) and telemetry and video (frequency hopping) emission.

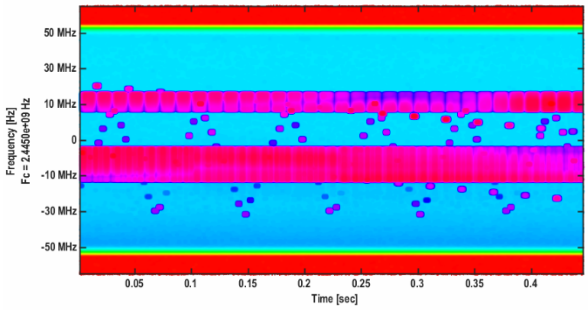

Figure 2. Spectrogram of two RF drone signals.

Depending on the method of preparation of input data, different DL models are used. In [8], [29] authors used an FC-DNN and CNN for single drone classification (detection and type identification) and multiple drone detection. Moreover, in [12] authors examined CNN accuracy with SNR dependency showing that classification is feasible. The quantitative comparison of the techniques that exploit RF sensors according to the type of input data is presented in Figure 3.

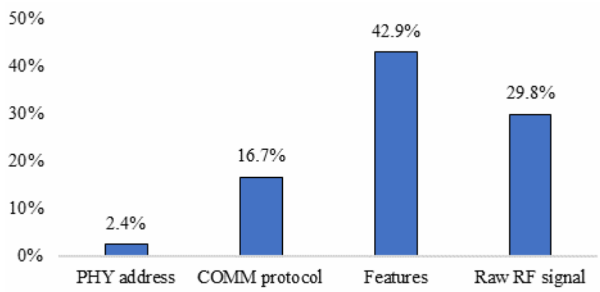

Figure 3. Quantitative comparison of RF techniques according to the type of input data.

It is important to note that techniques with classification algorithms that use features of RF signals as input data are the most exploited with 42.9%, followed by the techniques with classification algorithms that use the entire received I/Q RF signal as input data with 29.8%. More interesting is the fact that 95.9% of all papers that use the entire received I/Q RF signal as input data are used advanced engineering techniques.

3. COMPARISON OF DETECTION TECHNOLOGIES

An extensive comparative analysis of all literature was performed in order to support the proposed categorization and to emphasize the best RF-based drone detection technique. The most relevant research papers were used for this purpose. The comparison was done according to the used dataset and engineering techniques. The publicly available studies whose results were verified on the "DroneRF dataset" and the "VTI_RF_Dataset" was presented. Additionally, these studies were classified according to our categorization, together with results from three different experiments. This was done intentionally as it is the only way to compare different approaches according to the detection or identification of the same number of classes.

It is important to notice that there are very few publicly available datasets that contain RF signals from drones. It should be emphasized that only two datasets have records of RF signals from both industrial, scientific, and medical (ISM) radio bands, but just one has multiple drones. Additionally, some authors in [30] and [31] used ground controllers for classification which can be valuable in various researches. Moreover, RF receivers generate a vast amount of data during the recording process, which leads to huge datasets. This can be a disadvantage in some situations because of the prerequisite for superb computers, storage, and GPUs. The list of publicly open datasets that contains RF signals from UAS is presented in Table 1.

Table 1. The RF drone publicly available datasets.

Reference	Number of UAS	Multiple drones	2.4 GHz	5.8 GHz
[32]	3	-	+	
[33]	3	+	+	+
[30]	17	-	+	
[34]	NaN	-	+	
[35]	7	-	+	
[31]	10	-	+	+

Authors in [32] presented a "DroneRF" dataset that incorporated three different drones, recorded in four different operating modes in only one ISM band (2.4 GHz). This dataset was used in over 60% of reviewed literature which is an impressive result. Analogous, authors in [33] introduced a similar dataset with three drones, recorded in four different operating modes in two ISM bands (2.4 and 5.8 GHz). Moreover, this dataset contains records of multiple (two and three) drones operating at the same time simultaneously. This makes "VTI_RF_Dataset" unique because to the best of our knowledge there is no such dataset in the available literature.

4. RESULTS

The main goal of this research was to review and categorize all available RF-based drone classification research papers and datasets. The studies whose results were verified on the "DroneRF dataset" are presented in Table 2.

Table 2. Comparative analysis of publicly available studies verified on the “DroneRF dataset”.

Reference	1st	2nd	Drone detection	Type identification	Flight mode identification
[7]	A	R	99.7	84.5	46.8
[10]	A	R	100.0	94.6	87.4
[25]	H	F	-	-	91.0
[11]	A	R	99.8	85.8	59.2
[36]	A	R	100.0	99.6	99.3
[37]	A	F	100.0	98.6	95.1
[38]	H	F	-	-	99.2
[39]	A	R	99.8	98.5	95.3

The notation “H” stands for hybrid and “A” for advanced engineering techniques. The notation “F” stands for features and “R” for raw I/Q RF signal. It is important to note that the best results were achieved in [36] with multistage DNN and CNN algorithms. More important, there are no classic engineering techniques employed on the “DroneRF dataset”. Additionally, some of the studies whose results were verified on the “VTI_RF_Dataset” are presented in Table 3.

Table 3. Comparative analysis of publicly available studies verified on the “VTI_RF_Dataset”.

Reference	1st	2nd	Drone detection	Type identification	Multiple drone detection
[8]	A	R	99.8	96.1	97.2
[29]	A	R	-	100.0	-
[40]	A	F		99.9	

It is worthy of mention that “VTI_RF_Dataset” provides multiple drone detection on real RF signals, rather than simulated RF signals.

5. CONCLUSION

This study set out to establish the new categorization and provided a deeper insight into the publicly available drone classification techniques in the radio-frequency domain. Overall, the following conclusions can be pointed out: the proposed categorization provides a useful tool for a literature review, the comparative analysis shows that deep learning techniques are currently the best solution for solving the issue of drone classification, and there is a little number of publicly available datasets with radio signals from drones. The main strength of this study is that it represents the first comprehensive review of publicly available datasets with RF signals from drones.

Further research should focus on determining an approach to merge two or three datasets or to test the classification techniques on different datasets. Additionally, it is important to examine the new multimodal deep learning algorithm which will incorporate different features and raw radio signals for solving the classification issue.

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