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REVIEW PAPERS

Review of RF-based drone classification: techniques, datasets, and challenges

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Abstract:

Introduction/purpose: This article analyzes the publicly available literature on drone classification in the radio frequency domain, focusing on detection and identification. Drones are increasingly used for illegal purposes, making classification techniques crucial. This review paper covers passive radio frequency sensors, classification techniques, and datasets that highlight the challenges.

Methods: Researchers are developing antidrone solutions because drones have become valuable tools and targets for illegal activities. 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

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the datasets used for performance testing. This study introduces a new categorization and offers deeper insights into publicly available drone classification techniques.

Results: Based on the results of this study, it is apparent that deep learning algorithms are presently the most effective approach to addressing the challenge of drone classification within the radio frequency domain. One of the primary obstacles is the absence of a comprehensive standard for classifying drones in the radio frequency domain, which should be based on end-user requirements. Additionally, the results of two ablative experiments highlight the preprocessing of raw I/Q radio signals as an essential step in drone classification.

Conclusion: In summary, the proposed categorization provides a valuable tool for literature review. Deep learning is the most effective technique for drone classification, but publicly available datasets with drone radio signals are limited. The key strength of this study is that it represents the first review of publicly available datasets with drone radio signals.

Keywords: deep learning, drone, detection, classification, identification, radio frequency.

Introduction

Unmanned aerial systems (UAS), primarily commercial off-the-shelf (COTS) ones, have become increasingly popular due to their numerous applications, ranging from commercial to military purposes. However, as technology continues to improve and UAS become more affordable, they have also become more susceptible to criminal and terrorist activities. This has made it vital to have effective antidrone (ADRO) systems in place to protect sensitive areas and critical infrastructure. ADRO systems use a combination of sensors, including optoelectronic, acoustic, radar, and radio frequency devices, to monitor and detect UAS. These systems have three core subsystems: monitoring, mitigation, and command and control (C2). To ensure maximum protection against UAS threats, ADRO systems must incorporate different procedures such as detection, spoofing, jamming, and mitigation (Hassanalian & Abdelkefi, 2017; Ding et al, 2018). In summary, ADRO systems are essential for safeguarding against the potential harm that UAS can cause. By incorporating various sensors and procedures, these systems can effectively detect and neutralize UAS threats, making them a critical tool for security forces. The ongoing military operations in Ukraine and the Gaza Strip serve as evidence that the engagement of UAS worth less than tens of thousands of dollars can effectively neutralize crucial weapons and military assets of the enemy.

The ADRO system relies on various sensors combined with detection or warning procedures to detect UAS, also known as drones. These procedures serve two purposes - early warning (detection) and identification of the detected drones, with optional tracking, which provides inputs for the next stage of the ADRO system. Spoofing is one of the approaches used in the next phase but is not compulsory. The ADRO system can deceive drones by sending false radio signals, typically an emergency landing signal. If the spoofing fails, the ADRO system can engage in jamming procedures, where the drone control and navigation signals are disturbed by posing substantial interference. Finally, the ADRO system can use the mitigation procedure to destroy or capture malicious drones.

Although ADRO systems use various strategies and sensors, radar and radio frequency (RF) sensors are the most practical applications for primary drone detection. RF sensors have several advantages over radar technology. One of the most significant benefits is that they do not emit electromagnetic radiation, making them a safer and covert option. Additionally, RF sensors have a more extensive detection range and can be used to counteract UAS that use jamming techniques. RF sensors are passive devices that only receive RF signals from UAS, which are present in almost every scenario. In contrast, radar is an active device that emits electromagnetic energy, making it unsuitable for specific situations. The detection range of RF sensors depends on the environment and the transmitter power of the UAS but is usually comparable to radar. Another advantage of RF sensors is that they can combine with jammers, which can be used for spoofing and jamming if required. RF sensors are also more versatile than other sensors, as they can be utilized for various purposes such as communication protocol detection, drone MAC address detection, feature extraction, or direct use with multiple classification algorithms.

The characteristics mentioned above, especially those offered by RF sensors, have been verified through a quantitative comparative analysis based on data from (Drone Industry Insights UG, 2023) and (Butterworth-Hayes, 2023). The results of such analysis are shown in Figure 1 and include 295 different antidrone (ADRO) systems. Notably, most ADRO systems engage optoelectronic sensors (35.8%), RF sensors (31.24%), and radars (28.13%), while acoustic sensors (4.83%) are the least represented. The availability of cameras and the variety of computer vision (CV) algorithms are the main reasons that optoelectronic sensors (OES) take the first place. However, a more comprehensive and quality data analysis determines that RF sensors and radars are the primary choice for modern ADRO systems due to their better characteristics. Indeed, this means that cutting-edge ADRO systems have an RF sensor and radar to detect the drone, while the OES is used mainly for closer identification of the drone type.

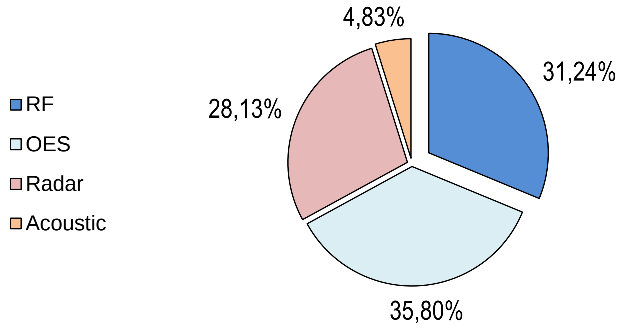

Figure 1 – Quantitative comparison of sensor types in ADRO systems

RF-based ADRO systems can extract valuable information by intercepting signals between drones and ground controllers. This information can be used to detect and identify drones based on their communication protocols and MAC addresses. However, a significant drawback of such systems is that they require prior knowledge of the protocols and addresses which may not be available for custom-made drones. The ADRO system can also extract features from intercepted RF signals for detection and uses frequency or joint time-frequency signal representation (TFSR) of I/Q data to prepare inputs for the classification algorithm.

Unfortunately, ambient RF noise, multipath, and customized drones that operate autonomously without a communication link between the drone and the ground controller can make RF-based detection difficult. Real-time monitoring of RF signals can also be challenging due to the complexity of the RF domain. Moreover, it is worth pointing out that drone RF communication can be categorized into three main groups: command and control (uplink), telemetry and video (downlink), and guidance communications. The first two groups use various frequencies, while global navigation signals are used for guidance and navigation. In such a complex environment, RF sensors must be agile, have high-speed scanning performance, be susceptible, and have a high dynamic range within the whole frequency range.

Section 2 of the paper categorizes and describes the literature to provide a comprehensive overview of relevant studies. Section 3 compares different classification techniques, and section 4 presents the results of the comparative analysis of the most relevant papers. Finally, section 5 provides the conclusion.

Review of literature and RF techniques categorization

Available studies introduced different classification techniques (approaches) based on the RF sensors. We created a new categorization of these RF techniques for classification according to the following:

- The method of input data processing:
  - classic engineering techniques require prior feature extraction in combination with a decision threshold mechanism;
  - advanced engineering techniques engage procedures for classification purposes without prior feature extraction (feature extraction is implemented in AI-based algorithms together with the learning process); and
  - hybrid engineering techniques present a combination of the 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 the 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 both rules can categorize one technique, specifically, a classic engineering approach that uses protocol information as input. The categorization presented in this research paper is based on the most significant research papers available in the literature over the past five years.

A comprehensive literature dataset on counter-unmanned aircraft systems (C-UAS) is available for review in (Sazdic-Jotic, 2024a). This dataset offers information and insights into C-UAS technology, applications, and trends. The framework for this literature review was adopted from (Alzubaidi et al, 2021), starting from the identification, screening, and selection stages, which included almost two hundred (199) research papers in the last five years from publishers such as IEEE, Nature, Springer, ACM, Elsevier, and MDPI. All reviewed papers have tackled the drone classification problem (detection and identification) using RF sensors. Each paper was categorized as a novel approach, survey/review, dataset description, or regulation/standard, with mandatory remarks explaining specific ADRO procedures (e.g., jamming, spoofing, direction finding).

RF techniques according to the method of input data processing

In classical engineering techniques, extracting features from intercepted RF signals is mandatory for data preparation and processing. This step is crucial as only features extracted with a decision threshold mechanism can be used for classification. However, the feature extraction process can be complex and time-consuming, requiring profound engineering skills and adaptation to the nature of the input data. Authors (Lv & Wang, 2019) used standard deviation analysis, maximum slope analysis, and accumulation in azimuth direction as statistical features for drone detection and direction finding. They also employed principal component analysis (PCA) and empirical mode decomposition (EMD) based wavelet transform (WT) methods to cope with additive Gaussian white noise. A similar approach was presented in (Ezuma et al, 2020) involving fifteen (15) different statistical features of RF signals. On the other hand, (Fu et al, 2018) presented the cyclostationarity signature of the drone RF signal and the pseudo-Doppler principle for the classification issue with a single-channel universal software radio peripheral (USRP) receiver. Authors (Nguyen et al, 2018) described a passive drone detection system (Matthan) based on two critical physical signatures of drones: body shifting and vibration. However, the Matthan approach faces a range of constraints, making it impractical for implementation. Another unique way is the received signal strength indicator (RSSI) ratio that engages various factors, such as propagation channels and fading effects, and can help accurately determine the location of a drone.

Artificial intelligence (AI) algorithms, particularly deep learning (DL), provide an alternative approach to the problem of drone classification. Unlike classical engineering techniques, advanced engineering techniques such as DL algorithms use the entire received I/Q RF signal, perform preprocessing steps, and send all data to the learning process without prior feature extraction. This approach is more robust and scalable, but a significant amount of input data is required for the training process, which can sometimes be a disadvantage. Fully connected deep neural networks (FC-DNN) and convolutional neural networks (CNN) are two prominent DL algorithms for drone classification in the publicly available literature. In addition, transformer models - a distinctive DL algorithm with an attention mechanism - are increasingly utilized to attain outstanding outcomes. Authors (Al-Sa'd et al, 2019; Sazdić-Jotić et al, 2022) employed FC-DNN for this purpose, while (Al-Emadi & Al-Senaid, 2020; Allahham et al, 2020; Ozturk et al, 2020; Basak et al, 2021; Mokhtari et al, 2021, 2022; Nguyen et al, 2021) used CNN. Authors (Basak et al, 2023) proposed a unique deep residual network-based autoencoder framework for known drone signal classification, novelty detection, and clustering (DE-FEND).

The quantitative comparison of the techniques that exploit RF sensors according to the method of processing input data is presented in Figure 2.

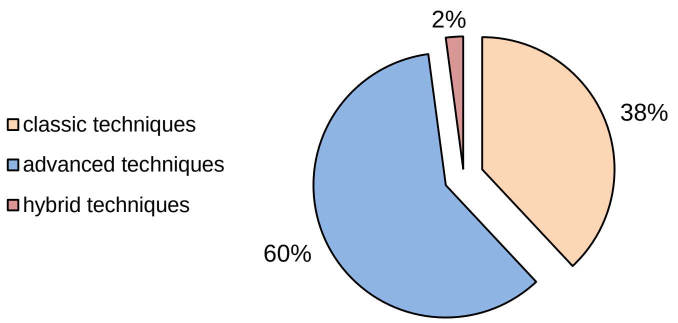

Figure 2 – Quantitative comparison of RF techniques according to the method of input data processing

Notably, more than half (60%) of all research studies rely on advanced techniques, while 38% use classic engineering techniques. The reason behind the absence of classical engineering techniques in the analysis is that only studies from the last five years were considered. This time frame shows a significant increase in advanced techniques, now preferred over classical methods. Hence, it is not unsurprising that there is a lack of classical engineering techniques in the analysis. In the overall research, advanced engineering techniques such as DL and machine learning (ML) algorithms account for 47% and 13% of all research. Compared to the results presented in (Sazdić-Jotić et al, 2023), this is a growth of 9.3% for advanced techniques in favor of classic techniques.

It is also worth mentioning that the authors (Abeywickrama et al, 2018; Shi et al, 2018; Shorten et al, 2018; Basak & Scheers, 2019; Bisio et al, 2021; Bhattacherjee et al, 2022; Lofu et al, 2023) present classical and advanced engineering techniques in combination with direction-finding (DF) methods. The specific hardware and software implementation of the RF-based DF of UAS is presented in (Abeywickrama et al, 2018) because the authors used a single-channel RF sensor and a four-element antenna array in combination with a sparse denoising autoencoder deep neural network (SDAE-DNN). However, it is essential to note that some authors (Zhang et al, 2018; Ezuma et al, 2020; Swinney & Woods, 2021; Medaiyese et al, 2022) use a hybrid engineering technique or a combination of classical and advanced techniques. In (Zhang et al, 2018), the authors used extracted features (the slope, kurtosis, and skewness) of the drone RF signal as an input for an FC-DNN. Moreover, in (Medaiyese et al, 2022), the authors performed feature extraction and used ML algorithms (Logistic Regression). An interesting approach was presented by (Ezuma et al, 2020), where the authors extracted fifteen statistical features from the UAS RF signal and engaged them with five different ML classifiers at various SNR levels.

While advanced techniques may offer a broader range of benefits than classical techniques, they also have certain drawbacks that must be considered. It is essential to thoroughly assess the advantages and disadvantages of each approach before deciding which one to use in a particular situation. Advanced engineering techniques often need help with several challenges that can hinder their successful implementation. One of the most significant obstacles is the requirement for unique training scenarios, which means that engineers must develop customized training models for each specific use case. Additionally, the availability of datasets can be limited, making it challenging to train models effectively. Finally, the transfer learning process can be complex, especially when applying previously learned knowledge to new scenarios. These factors can make it tricky to implement advanced engineering techniques successfully. Moreover, a fusion of different sensor data is also a particular solution to the drone classification problem. This approach involves fusing information from multiple sensors, such as radar, cameras, RF, and acoustic sensors, to create a more comprehensive view of the drone characteristics. This method can provide a more reliable drone classification by analyzing the drone shape, size, movement, and RF signals. It is a promising solution gaining traction in the drone detection and defense industry.

RF techniques according to the type of input data

RF sensors receive an RF signal from a UAS for various purposes. Four techniques exist for detecting and identifying drones based on the input data type. The first technique uses classification algorithms to detect and identify the MAC address of the transceiver device in a drone. In contrast, the second technique employs classification algorithms to detect and identify the communication protocol between drones and ground control devices. These techniques are the least represented in the literature because they have significant limitations and shortcomings. Both approaches use received and demodulated RF signals to obtain information about the MAC address of the RF transceiver installed in the drone and the type of communication protocol unique to certain types of drones. The information obtained is used for the detection and identification of drones. (Schiller et al, 2023) analyzed the security and privacy of the DJI's tracking protocol (DroneID), presenting sixteen vulnerabilities that can be adopted. In addition, there are more hardware implementations of ADRO systems based on this technique. Authors (Haluza & Čechák, 2016) performed device and protocol identification through data format analysis. In (Sciancalepore et al, 2020), features such as packet inter-arrival time and size were analyzed, while (Stoica et al, 2020) studied eight protocols to classify UAS. The technique with classification algorithms based on protocol recognition is more efficient than the previous one, proven by practical implementations of such ADRO systems. (Oh et al, 2020) also proposed long-range (LoRa) modulation exploiting wireless communication protocol for drone identification.

Furthermore, techniques with classification algorithms that use features of RF signals as input data are more present in the literature. Essential studies that exploited features have been mentioned because this is a mandatory step for classical engineering techniques. Nevertheless, an increasing number of research papers in the literature deal with the entire intercepted I/Q RF signal. Faster hardware and improved computing power have allowed it to exploit the full power of DL algorithms created for a considerable amount of data. As a result, the techniques with algorithms that classify the entire received I/Q RF signal as input data are becoming widely present solutions providing excellent results. RF sensors are used to record the raw I/Q RF signal, and different preprocessing steps are taken to prepare input data for the classifier. Some authors (Al-Sa'd et al, 2019; Sazdić-Jotić et al, 2022) calculated the magnitude or phase spectrum to obtain 1-D (vector) data with corresponding labels, while others (Ozturk et al, 2020; Basak et al, 2021; Nguyen et al, 2021; Mandal & Satija, 2023) 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. Figure 3 illustrates one 2-D TFSR obtained from RF activities in the 2.4 GHz range.

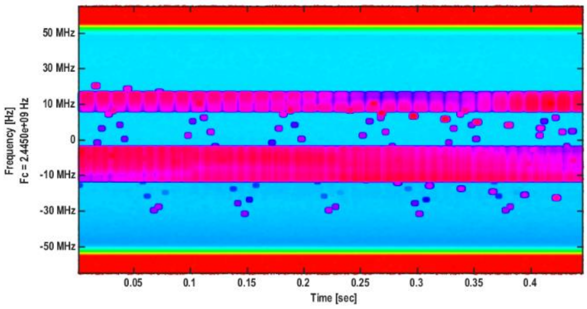

Figure 3 – Spectrogram of two RF drone signals

This TFSR is a spectrogram of the RF signal when two drones operate simultaneously at 2.4 GHz. Two emissions are visually distinctive in Figure 3: the command and control (fixed frequency, FF) and telemetry and video (frequency hopping, FH) emissions. Subsequent image processing techniques based on morphological operations of the obtained spectrograms can extract all emissions. Moreover, it is possible to determine the technical parameters of the detected radio signals (the number of the detected radio signals, the total width of the frequency range, and the width of the frequency range of one channel). The technical parameters estimation of the detected radio signals must be divided into two branches, i.e., analysis of FH or FF emissions. This way, the channel raster, the FH hop durations, and the time between two successive FH hops can be estimated. In the case of the DJI Phantom IV Pro drone, one FF and FH emission was detected with a total band of 75 MHz in the spectral domain. This drone has the highest hop duration (6 ms) with a simple FH emission comparable to a sweep frequency signal. In contrast, the DJI Mavic 2 Zoom and Enterprise drones have three types of FH emissions, which depend on operation modes (a drone is connecting to the flight controller, a drone is hovering, a drone is flying, and a drone is flying with recording) (Sazdić-Jotić, 2024b).

Different DL models are used depending on the preparation method of input data. In (Mokhtari et al, 2021; Sazdić-Jotić et al, 2022), the authors used an FC-DNN and CNN for single drone classification (detection and type identification) and multiple drone detection. Moreover, (Ozturk et al, 2020) 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 4.

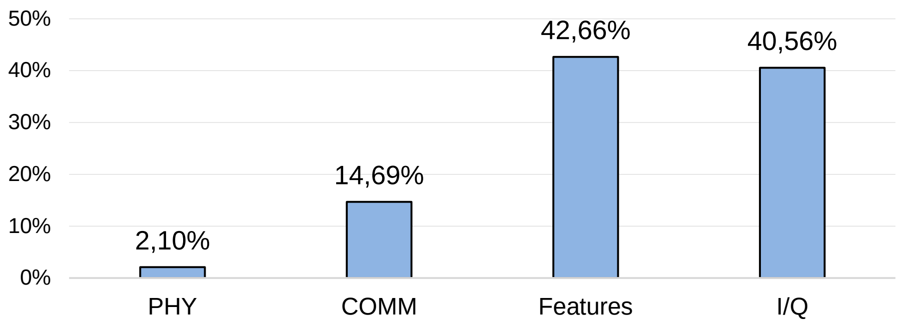

Figure 4 – Quantitative comparison of the RF techniques according to the type of input data

It is important to note that the techniques that use features and raw I/Q RF signals as input data are the most exploited, with 42.66% and 40.56%, respectively. The techniques that use MAC addresses (PHY) and communication protocols (COMM) for drone classification are the least concurrent in the reviewed literature. Compared to the results presented in (Sazdić-Jotić et al, 2023), this is an increase of 10.8% for the I/Q RF signal as input data. This fact is unsurprising due to the expansion of the DL and ML research papers. More interesting is that more than 95% of all papers that use the whole received I/Q RF signal as input data use advanced engineering techniques.

Datasets and comparison of RF techniques

The main goal of this research was to review and categorize all available RF-based drone classification research papers and datasets. Extensive research was conducted to support and highlight the best RF-based drone detection technique by performing a comprehensive comparative analysis. The most relevant research papers were utilized, and the comparison was made based on the dataset used and engineering techniques. The publicly available studies verified on the DroneRF dataset, and the VTI_DroneSET were presented and classified according to our categorization and results from three experiments. This method was intentionally employed to compare different approaches to detecting or identifying the same number of classes.

It is worth noting that only a few publicly available datasets contain drone RF signals. Only two datasets have the records of RF signals from industrial, scientific, and medical (ISM) radio bands, but only one has multiple drones that operate simultaneously. Additionally, some authors

(Ezuma et al, 2021) and (Vuorenmaa et al, 2020) used ground controllers for classification, which can be valuable in various research. Furthermore, RF receivers generate vast amounts of data during the recording process, leading to massive datasets. It is essential to consider that such an amount of information can be a disadvantage in certain situations due to the requirement for excellent computers, storage, and GPUs - Table 1 lists publicly available datasets containing RF signals from UAS.

Table 1 – The RF drone publicly available datasets

Reference	Number of UAS	Multiple drones	2.4 GHz	5.8 GHz	Size [GB]
(Allahham et al, 2019)	3	-	+	-	3.75
(Soltani et al, 2020)	unknown	-	+	-	4.5
(Vuorenmaa et al, 2020)	10	-	+	+	3,800
(Sazdic-Jotic et al, 2021)	3	+	+	+	3.35
(Ezuma et al, 2021)	17	-	+	-	124.13
(Medaiyese et al, 2023)	unknown	-	+	-	66.26
(Swinney & Woods, 2022)	7	-	+	-	65.76

It is worth mentioning that there are additionally publicly available RF fingerprinting datasets (Al-Shawabka et al, 2020) and (Soltani et al, 2020) that can be used for automatic modulation classification in ADRO systems. Such datasets can be used to train the ADRO system to filter out non-interesting RF signals (Wi-Fi, Bluetooth) and concentrate on drone RF signal classification procedures.

Authors (Allahham et al, 2019) presented a DroneRF dataset incorporating three drones, recorded in four operating modes in only one ISM band (2.4 GHz). This dataset was used in over 60% of the reviewed literature. The studies whose results were verified on the DroneRF dataset are presented in Table 2.

The inscription "H" stands for hybrid and "A" for advanced engineering techniques. The inscription "F" stands for features and "R" for raw I/Q RF signal. It is important to note that no classic engineering techniques are employed on the DroneRF dataset. Moreover, for drone detection, there are several approaches with excellent results that are lower for drone identification and flight mode identification.

Table 2 – Comparative analysis of publicly available studies verified on the DroneRF dataset

Reference	Technique	Features	Drone detection	Type identification	Flight mode identification
(Al-Sa'd et al, 2019)	A	R	99.7	84.5	46.8
(Allahham et al, 2020)	A	R	<u>100.0</u>	94.6	87.4
(Al-Emadi & Al-Senaid, 2020)	A	R	99.8	85.8	59.2
(Akter et al, 2020)	A	R	-	92.5	-
(Swinney & Woods, 2020)	A	F	<u>100.0</u>	90.4	87.5
(Zhang, 2021)	A	R	<u>100.0</u>	<u>98.7</u>	79.2
(Kılıç et al, 2022)	A	F	<u>100.0</u>	98.6	95.1
(Huynh-The et al, 2022)	A	R	99.9	98.6	95.3
(Donatus et al, 2023)	A	R	99.7	94.2	81.5
(Mohammed et al, 2023)	A	R	99.6	96.9	<u>96.0</u>

Similarly, (Sazdic-Jotic et al, 2021) introduced a dataset with three drones recorded in four 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.

Such data makes the VTI_DroneSET unique because there is no such dataset in the available literature.

Three studies whose results were verified on the VTI_DroneSET are presented in Table 3.

Table 3 – Comparative analysis of publicly available studies verified on the VTI_DroneSET

Reference	Technique	Features	Drone detection		Type identification		Multiple drone detection	
			2.4GHz	5.8GHz	2.4GHz	5.8GHz	2.4GHz	5.8GHz
(Sazdić-Jotić et al, 2022)	A	R	<u>98.6</u>	99.8	96.1	<u>95.7</u>	96.2	97.3
(Mokhtari et al, 2021)	A	R	-	-	<u>100.0</u>	-	-	-
(Mokhtari et al, 2022)	A	R	-	-	99.9	-	-	-
(Sazdić-Jotić et al, 2023)	A	R	<u>98.6</u>	<u>100.0</u>	98.8	<u>95.7</u>	<u>99.0</u>	<u>99.2</u>

It is worth mentioning that the VTI_DroneSET provides multiple drone detection on real RF signals rather than simulated RF signals. It is essential to note that authors (Sazdić-Jotić et al, 2022) engaged FC-DNN while (Mokhtari et al, 2021), (Mokhtari et al, 2022) and (Sazdić-Jotić, 2024b) investigated CNN and CNN with recurrent layers (CRNN), respectively.

It is crucial to consider the input data and the corresponding preprocessing steps for adequate results of comparative analysis. Authors (Sazdić-Jotić et al, 2022) used power spectrum data obtained from raw I/Q radio signals for TFSR. Other authors engaged spectrograms as images for input data and achieved better results because they kept more valuable features for CNN/CRNN learning and testing. Moreover, through ablative analysis, it is possible to establish which TFSR is the best for processing raw I/Q radio signals when CNN is engaged as a neural network. The accuracy results of such an experiment are presented in (Sazdić-Jotić, 2024b) and shown in Table 4. The ablative experiment was performed with the AlexNet model introduced by (Krizhevsky et al, 2017) for the 2.4 GHz frequency band.

The results shown in Table 4 show that TFSR choice is essential for CNN accuracy. Moreover, the Short-Time Fourier Transform (STFT) method outperformed the Continuous Wavelet Transform (CWT) and the Wigner-Ville Decomposition (WVD) methods for all scenarios in the presented ablative experiment.

Table 4 – Comparative analysis of accuracy for different TFSRs in 2.4 GHz in ablative experiments

the AlexNet / TFSR	Drone detection	Type identification	Multiple drone detection
STFT	97.3	96.6	99.1
CWT	95.3	96.2	97.9
WVD	86.6	86.0	96.6

An additional ablative experiment compares CNN accuracy with the radio signal segment length on which TFSR is performed. The accuracy results of such an ablative experiment for drone detection are presented in (Sazdić-Jotić, 2024b) and shown in Table 5.

Table 5 – Comparative analysis of the accuracy for different lengths of input data in ablative experiments

Segment length [samples]	Segment duration [ms]	Drone detection (the AlexNet model / 2.4 GHz frequency band)
100,000	0.67	97.3
200,000	1.34	100.0
700,000	4.69	100.0

This ablative experiment was performed within the AlexNet model, the STFT method, with radio signals in the 2.4 GHz frequency band and with three-segment lengths (100,000, 200,000, and 700,000 samples). It can be observed that with the increase in the segment length of the drone radio signal, the accuracy improves. Moreover, the detection accuracy is 100% when a segment length is bigger than 200,000 samples.

Challenges in RF-based drone classification

Drone classification procedures encounter a complex challenge regardless of the sensor type and input data. As discussed in the paper (Aledhari et al, 2021), one solution, such as optoelectronic and radio sensors, uses sensor fusion. However, sensor fusion is not widely utilized in this application due to its complex implementation. Moreover, radio sensors are often paired with diverse DL algorithms to navigate the complex and frequently unpredictable RF environment. Such a robust combination enables the ADRO system to classify and identify drones accurately, even in challenging conditions.

At (Ozturk et al, 2020; Medaiyese et al, 2022; Noh et al, 2022; Mohammed et al, 2023), great emphasis is placed on signal preprocessing as a crucial step in enhancing the accuracy and reliability of detecting and identifying drones. By carefully processing and analyzing incoming signals, it is possible to uncover hidden patterns and extract valuable information that would have otherwise been missed. This meticulous approach enables researchers to deliver superior results and stay ahead of the curve in the fast-evolving field of drone technology with improved accuracy of DL algorithms.

Finally, the multistage classification presented in (Medaiyese et al, 2022) is often employed to enhance the accuracy of the classification process and minimize the inclusion of superfluous input data. Typically, the initial stage entails detecting the drones and classifying the specific drone types. The final stage of identifying drone behavior is generally not required in practical applications.

Conclusion

This study provides a comprehensive analysis of the existing research on drone classification in the radio frequency domain and explores the potential of deep learning algorithms in addressing this issue. According to the findings, the proposed algorithms exhibit promising results in effectively resolving the problem of drone classification. However, further research is necessary to evaluate their practical implementation and testing in real-world antidrone systems. According to the findings in our review, the most effective method for categorizing drones in the radio frequency domain is through deep learning techniques. Nonetheless, it is crucial to remember that most of the research in this area is still in the experimental phase and needs to be implemented practically. One of the significant challenges is the need for a general specification of a drone classification system based on real-world requirements and experience from combat engagement.

Future research should focus on merging multiple datasets or evaluating classification techniques on different datasets to address this issue. Additionally, it is crucial to investigate the new multimodal deep learning algorithm that combines various features and raw I/Q radio signals for more accurate drone classification. Overall, this study contributes to drone classification in the radio frequency domain and highlights the need for further research.

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Revisión de la clasificación de drones basada en RF: técnicas, conjuntos de datos y desafíos

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CAMPO: ciencias de computación, telecomunicación
TIPO DE ARTÍCULO: artículo de revisión

Resumen:

Introducción/objetivo: Este artículo analiza la bibliografía disponible públicamente sobre la clasificación de drones en el dominio de la radiofrecuencia, centrándose en la detección e identificación. Los drones se utilizan cada vez más con fines ilegales, lo que hace que las técnicas de clasificación sean cruciales. Este artículo de revisión cubre sensores pasivos de radiofrecuencia, técnicas de clasificación y conjuntos de datos que destacan los desafíos.

Métodos: Los investigadores están desarrollando soluciones anti drones porque los drones se han convertido en herramientas valiosas y objetivos para actividades ilegales. Debido al alcance del tema, la revisión incluyó solo la clasificación de drones mediante sensores pasivos de radiofrecuencia con una descripción de las técnicas de clasificación (conjunto de algoritmos, métodos y procedimientos) y los conjuntos de datos utilizados para las pruebas de rendimiento. Este estudio introduce una nueva categoría y ofrece información más profunda sobre las técnicas de clasificación de drones disponibles públicamente.

Resultados: Con base en los resultados de este estudio, es evidente que los algoritmos de aprendizaje profundo son actualmente el enfoque más eficaz para abordar el desafío de la clasificación de drones dentro del dominio de la radiofrecuencia. Uno de los principales obstáculos es la ausencia de un estándar integral para clasificar los drones en el dominio de la radiofrecuencia, que debería basarse en los requisitos del usuario final. Además, los resultados de dos experimentos ablativos destacan el *preprocesamiento de señales de radio I/Q sin procesar como un paso esencial en la clasificación de drones.*

Conclusión: En resumen, la clasificación propuesta proporciona una herramienta valiosa para la revisión de la bibliografías. El aprendizaje profundo es la técnica más eficaz para la clasificación de drones, pero los conjuntos de datos disponibles públicamente con señales de radio de drones son limitados. La fortaleza clave de este estudio es que representa la primera revisión de conjuntos de datos disponibles públicamente con señales de radio de drones.

Palabras claves: aprendizaje profundo, drone, detección, clasificación, identificación, radiofrecuencia.

Обзор классификации дронов на основании радиочастотного диапазона: методы, наборы данных и вызовы

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РУБРИКА ГРНТИ: 28.23.37 Нейронные сети (Искусственный интеллект)
ВИД СТАТЬИ: обзорная статья

Резюме:

Введение/цель: За последнее десятилетие многократно возросло использование беспилотных летательных аппаратов или дронов как в коммерческих (гражданских или любительских), так и в функциональных (военных или промышленных) целях. В связи с этим в данной статье представлен всесторонний обзор общедоступной и актуальной литературы по классификации (обнаружению и идентификации) дронов и их радиочастотного спектра. Особое внимание уделено алгоритмам глубокого обучения и результатам, полученным из общедоступного набора данных VTI_DroneSET.

Методы: Благодаря значительному прогрессу дроны стали полезным инструментом в осуществлении различных целей. Дополнительным преимуществом является то, что они стали дешевле и доступнее, вследствие чего увеличилась опасность от использования дронов в противозаконной деятельности. Такое развитие событий вызвало повышенное вовлечение исследователей в разработку решений по борьбе с дронами. С учетом большого объема общедоступных исследований в данной статье рассматривается исключительно вид дронов, *собирающих данный с помощью пассивных радиочастотных датчиков с описанием используемых методов (набора алгоритмов, методов и процедур) и наборов данных, используемых в испытаниях эффективности. Для понимания проблемы классификации дронов был проведен количественный и качественный анализы методами технического анализа и обработки радиосигналов. Количественные показатели с графическим изображением использовались в систематизации собранных статей, в то время как для определения возможности классификации дронов по радиочастотному диапазону использовались алгоритмы глубокого обучения. Помимо этого, в данной статье представлены вызовы и ограничения классификации дронов на основании радиосигналов.*

Результаты: Результаты данного исследования доказывают, что алгоритмы глубокого обучения в настоящее время являются наиболее эффективным подходом к решению проблемы классификации дронов по радиочастотному диапазону. Однако следует отметить, что большинство современных исследований имеют экспериментальный характер, следовательно, они ограничены в практическом применении. Главной проблемой является отсутствие общей спецификации в классификации дронов по радиочастотному диапазону, основанной на требованиях, исходящих из ежедневной практики.

Выводы: Вклад данного исследования заключается в систематизации всех доступных работ, посвященных классификации дронов по радиочастотному диапазону, и представлении некоторых возможностей алгоритмов глубокого обучения. Можно сделать вывод, что предложенные алгоритмы могут быть использованы в решении этой проблемы, а в ближайшем будущем можно будет испытать на практике в реальных сценариях антидрон систему защиты от беспилотных летательных аппаратов.

Ключевые слова: глубокое обучение, дроны, обнаружение, классификация, идентификация, радиочастоты.

Преглед класификације дронова у радио-фреквенцијском домену: технике, скупови података и изазови

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Сажетак:

Увод/циљ: Коришћење беспилотних ваздухоплова – дронова, током последње деценије многоструко се увећало, како за комерцијалне (цивилне или аматерске), тако и за функционалне (војне или индустријске) потребе. У овом истраживачком раду представљен је свеобухватан преглед јавно доступне и актуелне литературе о класификацији (детекција и идентификација) дронова у радио-фреквенцијском домену. Посебан аспект представљају алгоритми за дубоко учење и резултати који су добијени са јавно доступним скупом (базом) података VTI_DroneSET.

Методе: Захваљујући значајним унапређењима дронови су постали корисна средства за различите намене. Додатна погодност јесте што су јефтинији и приступачнији за коришћење, што представља опасност од њихове злоупотребе. Стога је појачано ангажовање истраживача на развоју антидрон решења. Због обима јавно доступних истраживања, овај рад је обухватио само класификацију дронова путем пасивних радио-фреквенцијских сензора са описом коришћених техника (скуп алгоритама, метода и процедура) и скупова података који се користе за тестирање перформанси. Ради разумевања проблема класификације дронова извршена је квантитативна и квалитативна анализа са методама техничке анализе и обраде радио-сигнала. Квантитативни показатељи са графичким илустрацијама коришћени су за систематизацију прикупљених радова, док су за утврђивање могућности класификације дронова у радио-фреквенцијском домену коришћени алгоритми дубоког учења. Штавише, представљени су изазови и ограничења класификације дронова на основу радио-сигнала.

Резултати: Показано је да су алгоритми дубоког учења тренутно најбоље решење за решавање питања класификације дронова у радио-фреквенцијском домену. Међутим, већина савремених истраживања је експериментална и има ограничену практичну имплементацију. Посебан проблем представља недостатак опште спецификације за класификацију дронова у радио-фреквенцијском домену на основу захтева из свакодневног искуства.

Закључак: Допринос овог истраживања је у систематизацији свих доступних радова који се баве класификацијом дронова у радио-фреквенцијском домену, као и у приказу неких могућности алгоритама дубоког учења. Може се закључити да се предложени алгоритми могу искористити за наведену примену, те да је у

наредном периоду могуће тестирати практичне имплементације, као и вршити тестирање у реалним сценаријима употребе антидрон система.

Кључне речи: дубоко учење, дрон, детекција, класификација, идентификација, радио-фреквенција.

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