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ANALYSIS OF METHODS FOR DETECTING UNMANNED AERIAL VEHICLES

Abstract. In the modern era of increasing use of unmanned aerial vehicles (UAVs) in civilian, commercial, and military sectors, the issue of UAV detection has become critically important. Moreover, the development of artificial intelligence and machine learning algorithms opens new opportunities for improving identification accuracy and reducing false alarms. The use of advanced data processing methods allows detection systems to adapt to changing conditions and enhance their effectiveness in real-world environments. Therefore, research on UAV detection methods is relevant not only from a scientific perspective but also from a practical standpoint, as its findings can be applied to ensure security in urban areas, combat zones, and other critical fields. An unmanned aerial vehicle is an aircraft designed to operate without a pilot on board, with flight control carried out either by a pre-programmed system or via a remote control station located outside the aircraft. UAV detection is the process of locating and, in some cases, identifying an unmanned aerial vehicle. This article examines the primary UAV detection methods, analyzing their advantages and limitations. The study has demonstrated that none of the reviewed detection methods is universal. Each method has its own strengths and weaknesses, which can significantly impact the effectiveness of the system in real-world conditions. Based on the obtained results, promising directions for further research include: development of combined detection systems, application of deep learning methods, exploration of new physical principles for UAV detection. The results of this study lay the foundation for further advancement in UAV detection technologies, contributing to the development of more effective and adaptive security solutions.

Keywords: unmanned aerial vehicle, UAV, detection, RF Spectrum Analysis, Real-Time Drone Monitoring, UAV classification.

Introduction

In today's world, UAVs are increasingly being used across various areas of life, ranging from toys to the military sector. At the same time, the need for effective UAV detection methods is growing. Developing such methods is a challenging technical task, as drones often have small sizes, low visibility, and the ability to operate in complex conditions. This article provides a detailed analysis of the main technologies and solutions for UAV detection. The advantages and disadvantages of these methods are also described. Examining the strengths and weaknesses of each approach allows for a better understanding of their limitations and potential applications under different conditions.

Research Objective. The objective of this research is to analyze and systematize modern methods of UAV detection, taking into account their technical features, effectiveness, and limitations. The research aims to identify the advantages and disadvantages of each method, including radar, acoustic, optical, and radio frequency systems. The results of this research will contribute to building a knowledge base that will support the development of new, more effective technologies for UAV detection.

Research results

Four primary methods of UAV detection can be identified: radar, radio frequency, visual, and acoustic. Each of these methods includes several solutions, which will also be discussed further.

Radar Method. Radar monitoring is a widely used method for airspace surveillance. Radars use radio waves to detect objects in the air. They transmit signals that bounce off the object, and the receiver analyzes these reflected signals to determine the object's position, speed, and flight trajectory. This technology can be utilized to detect fully autonomous UAVs and those that neither send nor receive radio signals.

A Doppler radar can be used for this purpose. Doppler radar is a powerful technology that uses the Doppler effect to measure the velocity of moving objects. The micro-Doppler radar is an advanced version of Doppler radar, capable of detecting differences in speed and motion within objects. It is particularly suited for UAV detection as it can distinguish the propeller rotation of UAVs from, for example, the wing movements of birds [1]. Other radar technologies that can theoretically be applied for UAV detection include:

- over-the-horizon radar;
- ultra-wideband radar;
- millimeter-wave radar [2];
- chaotic monostatic radars;
- bistatic [3] and multistatic radars [4].

However, due to the low radar cross-section [5] and low speed of UAVs, their detection using these radars can be a challenging task [6].

Advantages:

- can detect UAVs over long distances (up to several kilometers);
- operate independently of weather conditions (rain, fog, snow);
- effective for monitoring large areas.

Disadvantages:

- difficulty detecting small UAVs due to their size and low radar reflectivity;
- high equipment costs and complexity of integration;
- possibility of false positives caused by other flying objects (birds, aircraft).

Radio Frequency Method. UAVs emitting radio frequency (RF) signals can be intercepted and analyzed to track and determine their location [7]. RF systems scan the spectrum to detect signals transmitted between the UAV and its operator. These systems can identify control and data transmission frequencies, determine the type of drone, and even locate the operator.

In many cases, manually controlled UAVs connect to a ground station and GNSS (Global Navigation Satellite System) for operation, enabling interception of signals and access to information such as coordinates and video feeds. RF monitoring has demonstrated the capability to detect UAVs within a range of up to 5000 meters.

Advantages:

- ability to detect UAVs regardless of weather conditions;
- can identify the location of both the UAV and the operator;
- effective over long distances (up to several kilometers).

Disadvantages:

- ineffective against autonomous UAVs that do not rely on radio communication;
- difficulty in distinguishing signals in dense RF environments;
- high equipment costs.

The process of UAV detection based on radio frequency (RF) typically involves analyzing RF signals to extract characteristic features, which are then compared with a database of UAV RF profiles for identification. In recent years, machine learning-based approaches have gained significant traction, profoundly influencing the development of RF-based UAV detection methods. To enhance the efficiency of these methods, researchers employ various approaches that can be categorized into two main groups.

The first category involves the use of signal processing techniques, such as Fourier Transform, to extract features, followed by classification using algorithms like SVM, decision trees, etc. [8,9]. The second category relies on minimal pre-processing of signals, utilizing neural networks to automatically extract features and identify UAV signals [10–14].

The following presents an overview of both traditional RF-based UAV detection methods and modern machine learning approaches.

Traditional Radio Frequency Detection

Radio frequency detection involves identifying control signals and video transmission signals exchanged between the ground station and the UAV. The primary principle of this approach is based on analyzing frequency, symbol rate, modulation type, channel bandwidth, and other parameters that create a unique "fingerprint" of the UAV signal.

Below are the main methodologies for extracting the spectral characteristics of UAVs:

1. Fractal Dimension [8]: This statistical indicator characterizes the complexity, roughness, and irregularity of a signal. Methods from time and phase domains are used to calculate the fractal dimension. Popular approaches include the correlation dimension, Hausdorff dimension [15], and Higuchi's algorithm [16], which demonstrates about 100% accuracy and effectiveness in identification.
2. Bispectrum: A powerful tool for analyzing nonlinear and non-Gaussian signals, it reduces the influence of white Gaussian noise [17]. Integrated bispectral methods, such as Axially Integrated Bispectra (AIB) [18] and Square Integrated Bispectra (SIB) [19], achieve identification accuracies of 98% and 96%, respectively.
3. Signal Spectrum [9]: Frequency analysis of signals using Short-Time Fourier Transform (STFT) distinguishes UAV signals based on the characteristic vibrations caused by propeller rotation. The accuracy of this method is 97–98%.
4. Wavelet Energy Entropy (WEE) [9]: This approach analyzes sudden short-term signal variations associated with UAV movement in three-dimensional space or wind effects. The accuracy of this method is 93–94%.
5. Spectral Power Entropy (SPE) [9]: This metric describes the relationship between the power spectrum and entropy. UAV signals generally show higher SPE values compared to other signals. The accuracy of this method is 83–84%.

A comparison of these methods shows that fractal dimension, AIB, and SIB offer higher accuracy but are limited to identifying only known UAV types. Methods like signal spectrum, WEE, and SPE can detect unknown UAVs, although their accuracy is slightly lower. A combined application of these approaches can significantly improve identification efficiency.

RF-Based Detection Using Deep Learning

With the development of machine learning methods, researchers are actively exploring new ways to enhance the efficiency of signal feature extraction for more accurate detection and classification. Numerous studies have investigated a wide range of approaches for extracting signal features using deep learning algorithms. Notably, recent research [20, 21] demonstrates that neural networks are highly effective for tasks involving the detection and classification of radio frequency signals, highlighting the immense potential of deep learning in this field.

The primary advantage of deep learning methods lies in the ability of neural networks to automatically extract relevant features directly from raw signals, eliminating the need for complex preprocessing algorithms or signal reconstruction. For instance, the use of convolutional neural networks (CNNs) allows for the efficient extraction of features from compressed probing signals, bypassing the process of restoring the original signal. This significantly simplifies signal processing and reduces computational resource requirements.

Compared to traditional feature extraction methods, the deep learning-based approach demonstrates superior efficiency and accuracy. In certain experiments, the accuracy of UAV signal detection and classification reached 99%. Moreover, deep neural networks have proven adaptable, enabling them to work with various signal types and improve accuracy even in cases of noisy data.

However, despite their high effectiveness, the use of deep learning methods requires large volumes of training data and significant computational power. This remains one of the key challenges that researchers are addressing through neural network architecture optimization and the adoption of approaches for learning from small datasets.

As result, deep learning significantly expands the capabilities of UAV detection and classification based on radio frequency signals, offering more automated, accurate, and adaptive approaches to data processing.

Optical Method. Optical systems use cameras (conventional, infrared, or thermal imaging) for visual detection and tracking of UAVs. Modern systems are often equipped with computer vision algorithms for automatic object recognition. Using machine learning techniques, models can be trained to automatically extract appearance and motion features from UAV datasets, enabling UAV identification and tracking [22]. Additionally, infrared cameras can be used to detect and identify UAVs under low-light conditions [23]. By combining computer vision methods with infrared cameras, UAVs can be detected at different times of the day, both during daylight and nighttime.

However, visual identification methods face challenges. For instance, it is difficult to differentiate UAVs from birds, especially when UAVs operate at significant altitudes. In fact, detecting UAVs beyond 1000 meters becomes exceedingly difficult or nearly impossible.

Advantages:

- provide precise information about UAV location;
- can operate at night using infrared or thermal imaging cameras;
- suitable for operation within the line of sight.

Disadvantages:

- dependence on weather conditions (fog, rain, and snow reduce effectiveness);
- limited range (typically only a few hundred meters);
- require high resolution to identify small drones.

Object detection is a core task in computer vision, which involves locating and classifying specific types of visual objects (e.g., animals, humans, or vehicles) in images or videos. Thanks to development in computational models and methods, computer vision systems can address key questions: What object is present in the scene, and where is it located? This task serves as a foundation for many related tasks, such as instance segmentation, generating image captions, scene analysis, and object tracking in video streams.

From an application perspective, research in object detection is generally divided into two main directions:

1. General object detection – focuses on universal systems capable of detecting various object types within a unified framework, mimicking the human vision system’s ability to recognize multiple objects.
2. Specialized object detection – targets the development of approaches for specific scenarios, such as pedestrian, face, or vehicle detection, or detecting objects in challenging conditions like nighttime or fast-moving environments.

Recent years have been revolutionary for this field due to rapid progress in deep learning methods. The use of neural networks has significantly improved the accuracy, speed, and adaptability of object detection systems. This has led to breakthroughs that outperform traditional methods in both performance and the ability to process large volumes of data.

The following sections will present common object detection methods, including traditional approaches and deep learning-based techniques.

Traditional Object Detection.

Viola Jones Detector. The Viola Jones detector [24] is based on a simple but effective object detection approach known as "sliding windows." In this method, each image is scanned through different positions and scales of a window to determine whether a face is present. Although this approach seems simple, at the time of its development, the computational resources of computers were insufficient for the efficient execution of such operations. To address this issue, the Viola Jones detector integrates three key techniques:

- Integral Image – for fast computation of pixel sums in rectangular regions;
- Feature Selection – for the effective selection of relevant features;
- Detection Cascade – for step-by-step rejection of negative windows and focusing on potentially relevant areas.

These improvements significantly increased the speed and performance of detection, making the method popular.

Histogram of Oriented Gradients (HOG) Detector. The Histogram of Oriented Gradients (HOG) method [25] represented a significant step forward compared to previous approaches, such as Scale-Invariant Feature Transform (SIFT) and contextual shape analysis. The main goal of HOG is to compute image features on a dense grid of uniformly spaced cells. This approach provides a balance between feature invariance (translation, scale, lighting) and the ability to distinguish between object classes.

To improve accuracy, the method uses local contrast normalization in overlapping "blocks," making the analysis more robust to lighting changes. Although HOG can be used for detecting objects of various classes, its primary goal is pedestrian detection.

The detection process in HOG involves resizing the input image while keeping the detection window size fixed. This allows for successful various sizes objects recognition.

Thanks to its efficiency and versatility, HOG has become a key component in many computer vision tasks. Over the years, this method has been widely applied in fields such as security (video surveillance) and the automotive industry (pedestrian detection).

Object Detection Based on Deep Learning. RCNN uses a selective search approach to extract a set of candidate regions from an image [26]. Then for each region uses a convolutional neural network (CNN), pre-trained on ImageNet, which scales the region to a fixed size (e.g., as in the AlexNet model) for feature extraction. The final stage involves classifying these regions using a linear SVM classifier to determine the presence of objects and their class. The RCNN method significantly improved the average precision (mAP) of detection, increasing it by 8.5%.

SPPNet, introduced by K. He in 2014 [27], addresses the issue of fixed-size input data, which is typical of CNNs. The key innovation in this architecture is the Spatial Pyramid Pooling (SPP) layer, which allows generation of fixed-length features for images of any size. This eliminates the need to resize images or regions of interest, as feature computation is performed only once for the entire image.

The SPPNet approach greatly accelerates the object detection process, reducing processing time by 20 times compared to RCNN, without significant loss in accuracy.

In 2015, R. Girshick proposed the Fast RCNN method [28], which improved the RCNN and SPPNet architectures. Using the Fast RCNN detector, both the bounding box regressor and object detector are trained with the same network configuration, which is an improvement over the previous two-stage approach used in RCNN and SPPNet. The streamlined Fast RCNN architecture significantly accelerated processing, making it more than 200 times faster than RCNN, while saving high detection accuracy. This method became a key step towards efficient object detection, providing a balance between performance and accuracy.

In 2015, S. Ren introduced Faster RCNN [29], which was a further improvement over Fast RCNN. It was the first detector to demonstrate end-to-end deep learning capable of almost real-time performance. Faster RCNN integrated detection proposals, feature extraction, and bounding box regression into a single architecture. Due to its high speed and accuracy, this method became widely used in object detection tasks.

YOLO, proposed by R. Joseph in 2015 [30], became a revolutionary single-stage approach to object detection. Its main advantage is extremely high speed. For example, the fast version of YOLO achieves a performance of 155 frames per second. Unlike traditional methods, which used the "object detection + classification" approach, YOLO applies a single neural network to the entire image. The image is divided into a grid of cells, each predicting its own bounding boxes and probabilities. Despite the high speed, YOLO's accuracy decreases when localizing small objects compared to two-stage detectors. Nevertheless, YOLO is one of the most popular algorithms for UAV detection due to its speed and acceptable accuracy. In recent years, the algorithm has become the basis for many studies focused on UAV detection [31, 32].

SSD, developed by W. Liu in 2015 [33], became the second single-stage detector in deep learning. This model introduced a multi-scale approach and detection with varying resolutions, significantly improving accuracy, especially for small objects. SSD performs object detection at five different scales at different network levels, which distinguishes it from previous methods that worked only with higher levels. SSD outperforms many previous detectors in both speed and accuracy.

RetinaNet, proposed by Lin in 2018 [34], is a single-stage detector that addresses the problem of class imbalance between positive and negative examples, which is typical for single-stage models. Unlike two-stage methods that achieve high accuracy through dense region proposal definition, single-stage approaches face difficulties in training due to the large number of negative examples. To overcome this issue, RetinaNet introduced a new loss function — the focal loss. This function modifies the standard cross-entropy loss to enable the detector to focus more on hard-to-classify examples during training, reducing the impact of well-classified or easy examples. The use of focal loss significantly improves RetinaNet's accuracy while maintaining the speed typical of single-stage detectors.

Acoustic Detection. Acoustic systems use microphones and sound processing algorithms to detect specific noises created by the engines and propellers of UAVs. Sound waves generate a unique "audio fingerprint" for each UAV, enabling individual identification. However, detecting these sound waves can be challenging in practice due to factors such as environmental noise and sound wave attenuation. Machine learning models have been applied to improve the effectiveness of this approach. By training these models on datasets of acoustic signatures, they can learn to distinguish UAV engine or propeller sounds from noise and other interference, improving accuracy and reliability [35]. Nonetheless, acoustic monitoring is highly sensitive to background noise and has a limited detection range. Advantages:

- easily detects drones at low altitudes;
- relatively inexpensive and simple to use;
- operates in real-time.
- Disadvantages:
- efficiency decreases in noisy environments (wind, urban noise);
- limited detection range (up to 500 meters).

Acoustic detection of UAVs is another popular technical solution for their identification. Despite differences between sound and electromagnetic waves, audio detection methods share similarities with radio frequency methods, as both are based on wave characteristic analysis.

Sound-based detection methods can be divided into two main categories: traditional acoustic detection and acoustic detection using deep learning.

Traditional Acoustic Detection

This approach involves processing audio signals using methods such as spectral analysis, short-time Fourier transform (STFT), wavelet transform, and other sound processing algorithms. The main goal is to extract characteristic features such as frequencies, amplitudes, or harmonics that may be specific to UAV engines or propellers. Traditional methods are less resource-intensive; however, their accuracy and robustness to external noise are often limited. They work well in conditions where the acoustic signal is clearly separated from background noise. Cepstral analysis is one of the most common methods for processing audio signals, based on the inverse Fourier transform of the logarithmic power spectrum. This technique allows the extraction of unique features inherent to audio signals, which is particularly useful for UAV detection tasks. Common cepstral coefficients include linear predictive cepstral coefficients (LPCC) and Mel-frequency cepstral coefficients (MFCC) [36].

The Mel scale is a nonlinear frequency scale that models the human ear's perception of sound. It does not have a linear correspondence to frequencies in Hertz, making it better suited for analyzing acoustic characteristics. MFCC are spectral features calculated using the Mel scale. This method has found widespread use in speech recognition tasks and is also employed in UAV detection due to its ability to extract unique acoustic features characteristic of propeller or engine sounds [37,3 8–41]. The process of calculating MFCC includes the following steps:

- audio signal segmentation into frames: The signal is broken into short time intervals;
- application of window functions: A window function is applied to each frame to reduce spectral leakage;
- fast Fourier transform (FFT): The linear spectrum of each frame is computed;
- Mel filterbank processing: A set of filters distributed according to the Mel scale is applied;
- logarithmic spectrum calculation: The filtered spectrum is logarithmically transformed to obtain a spectrogram;
- discrete cosine transform (DCT): The spectrogram is transformed, retaining the required number of coefficients to form MFCC.

Despite MFCC's limitations in the high-frequency range (due to reduced accuracy at higher frequencies), this method demonstrates high efficiency in UAV detection tasks, achieving an accuracy of over 97%.

Linear Predictive Cepstral Coefficients (LPCC)

LPCC is a variant of MFCC and is used for audio signal analysis based on linear prediction methods [42]. In the calculation of LPCC, linear predictive filters are used instead of Mel filters, enabling more accurate identification of resonance peaks (formants) of the signals. This method has certain advantages over MFCC, especially in the presence of Gaussian white noise, as LPCC better highlights important signal characteristics. However, the high computational complexity of LP filters is a disadvantage, requiring a balanced approach in practical applications. LPCC is usually used in combination with MFCC, and the fusion of these two features is often employed to improve UAV detection performance [39]. The combination of MFCC and LPCC helps compensate for the weaknesses of each method, enhancing overall UAV identification accuracy. This combined approach ensures robustness to external noise and high performance even in challenging acoustic conditions.

Acoustic Detection Using Deep Learning. This modern approach utilizes deep learning algorithms, specifically Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), to automatically extract features and classify audio signals. By using raw audio data, neural networks can learn to identify different sound characteristics such as frequency spectrum, propeller or engine noise, even in complex background noise conditions. These methods demonstrate higher robustness and accuracy, achieving 95-98% accuracy depending on the quality of the training data. Acoustic detection of UAVs has two primary research directions. The first focuses on precise and fast separation of sound sources and identification of UAV acoustic signals in noisy environments. The second focuses on detecting UAVs in time-varying scenarios, which is important due to the rapid movement of UAVs and the need to track their acoustic signatures over time [43].

Although acoustic detection is less commonly used in commercial and military counter-UAV systems due to its limited detection range, this approach still holds significant potential for application in urban environments, such as residential areas, schools, and business districts. By using unique UAV acoustic signatures, this approach can help identify and track UAVs in real-time.

In addition to traditional signal processing methods, learning-based methods are also widely used for feature extraction in sound-based UAV detection. Recent studies [37, 44] have shown that deep learning models can also be employed to extract features from UAV acoustic signals for detection purposes.

Conclusions

Research on UAV detection methods demonstrates that each of the approaches examined has its advantages and limitations. Radar systems provide long-range detection and effectiveness in challenging weather conditions, but struggle with detecting small UAVs. Acoustic sensors are affordable and easy to use, but their effectiveness significantly decreases in noisy environments. Optical systems offer high visual tracking accuracy but rely on weather conditions and line of sight. Radio frequency systems not only detect UAVs but also locate their operators; however, they are ineffective against autonomous devices.

The optimal solution is the integration of these approaches into combined systems, which help mitigate the drawbacks of each method. Such systems provide high accuracy, reliability, and versatility in various conditions, which is crucial for effective UAV detection.

The results of this research lay the foundation for further advancements in UAV detection technologies. The development of integrated systems using the latest data processing algorithms and artificial intelligence will significantly improve the efficiency of these systems.

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Аналіз методів виявлення безпілотних літальних апаратів

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Анотація. У сучасних умовах зростаючого використання безпілотних літальних апаратів (БпЛА) у цивільних, комерційних та військових сферах питання їх виявлення набуває критичної важливості. Крім того, із розвитком штучного інтелекту та алгоритмів машинного навчання відкриваються нові можливості для підвищення точності ідентифікації та зменшення кількості хибних спрацювань. Використання сучасних методів обробки даних дозволяє адаптувати системи виявлення до змінних умов та підвищити їхню ефективність у реальному середовищі. Таким чином, дослідження методів виявлення БпЛА є актуальним не лише з наукової точки зору, а й з практичної, оскільки його результати можуть бути застосовані для забезпечення безпеки в містах, у зонах бойових дій та в інших важливих сферах. Безпілотний літальний апарат — повітряне судно, призначене для виконання польоту без пілота на борту, керування польотом якого здійснюються відповідною програмою або за допомогою спеціальної станції керування, що знаходиться поза повітряним судном. Виявлення БпЛА – процес під час якого йде знаходження і, в деяких випадках, ідентифікація безпілотного літального апарата. У статті розглянуто основні методи виявлення безпілотних літальних апаратів. Проаналізовано переваги та недоліки таких методів. Проведене дослідження продемонструвало, що жоден із розглянутих методів виявлення БпЛА не є універсальним. Кожен з них має як переваги, так і обмеження, які можуть суттєво впливати на ефективність системи в реальних умовах. З огляду на отримані результати, перспективними напрямками подальших досліджень є: розвиток комбінованих систем виявлення, застосування методів глибокого навчання, дослідження нових фізичних принципів виявлення. Результати цього дослідження формують основу для подальшого вдосконалення технологій виявлення БпЛА.

Ключові слова: безпілотний літальний апарат, БПЛА, виявлення, аналіз радіочастотного спектра, моніторинг дронів у реальному часі, класифікація БПЛА.