Date of publication JUN-30, 2025, date of current version JUN-06, 2025.
www.computingonline.net / computing@computingonline.net

Print ISSN 1727-6209
Online ISSN 2312-5381
DOI 10.47839/ijc.24.2.4023

Intelligent Analysis of Sound Patterns of Unmanned Aerial Vehicle Engines in the Tasks of C-UAS Systems Development

OLEH V. ZARITSKYI[1], OLEKSANDER V. PONOMARENKO[2]
[1]Taras Shevchenko National University of Kyiv, Kyiv, 01601 Ukraine
[2]General Energy Institute of National Academy of Sciences of Ukraine, Kyiv, 03150, Ukraine

Corresponding author: Oleh V. Zaritskyi (e-mail: olegzaritskyi@gmail.com.ua).

ABSTRACT The article is devoted to the topical issues of developing systems for detection and classifying of unmanned aerial vehicles (UAVs). The proposed approach to the implementation acoustic intelligence methods in the tasks of UAV detection and classifying involves combining different principles of building a control system for an interceptor UAV in a single information management system in order to achieve maximum efficiency and effectiveness in countering enemy UAVs. The article discusses the methods of detecting and classifying UAVs using sound patterns of their engines, forming a steering vector of the sound beam shaper to calculate the azimuth and height of the target UAV. The study focuses on barrage munitions with internal combustion engines of the Shahed type, which are classified as Class 2 according to NATO classification. The relevance of the study is due to the massive use of this type of munitions in hostilities, which overloads air defense systems and makes it quite expensive and inefficient to destroy such targets with existing means.

KEYWORDS intelligent data analysis; UAVs; Counter-Unmanned Aircraft Systems; acoustic detection, acoustic intelligence

I. INTRODUCTION

Current global trends in the field of robotization and automation of both individual objects and various civilian and military systems, along with a significant expansion of their capabilities, lead to new security challenges. This issue is especially relevant in the context of building air defense systems to protect both civilian critical infrastructure and military facilities and units on the battlefield due to the massive use of UAV of various classes and purposes.

Research on building air defense systems [1], particularly those countering UAVs - Countering Unmanned Aircraft Systems (C-UAS), reveals that no single technical system or solution can fully address UAV protection. The development of C-UAS systems poses a complex scientific and technical challenge, requiring the resolution of multiple technical and theoretical tasks, which is not a simple feat due to the diverse range of UAV usage scenarios.

To effectively outline the research objectives in developing C-UAS systems, we must examine the current landscape regarding the theoretical foundations, hardware, and software related to UAV detection methods.

But first of all, let's analyze the characteristics of UAVs that allow us to detect and classify them. We can distinguish several large groups of parameters (Table 1):

1. Geometric dimensions or layouts and visibility that allow UAVs to be detected using visual inspection and radar operating in different frequency bands, actively irradiating the UAV. It is clear that the effectiveness of such methods and means depends on the size of the UAV and the characteristics of the detection environment (weather, conditions, flight altitude, etc.).
2. Thermal radiation (IR - infrared) is produced by engine heating, aerodynamic heating of fuselage surfaces, and exhaust emissions. It’s clear that this parameter diminishes when transitioning from jet to electric-powered UAVs, which emit very low levels of radiation in the IR spectrum.
3. The sound generated by UAV engines and propellers. The sound of propellers can be a source for UAV type identification by ground-based arrays of highly sensitive microphones that use Doppler effects in the acoustic spectrum to calculate the azimuth, altitude, and speed of a target.
4. The emission of telemetry signals and video signals (radio frequency radiation) received from video cameras are also parameters used to detect and identify UAVs.

We will focus on Class 2 Shahed UAVs, which cause the greatest damage to critical infrastructure and civilian objects, as well as on fiber-optic UAVs. They have one characteristic feature in common: they do not emit telemetry and control radio signals, which complicates the task of detecting and destroying them.

Table 1. UAV detection means

Characteristics	Means of detection	Limitations	Detection distance, km.
Material object (geometric dimensions)	Radar (active radiation)	▪ High cost of equipment; ▪ Adjustment of frequency bands; ▪ Terrain obstacles.	1 - 20
Material object (visibility)	Optoelectronic cameras	▪ Dependence on the external environment; ▪ Obstacles of the terrain.	0,5 - 2
Thermal radiation	Infrared camera	▪ Low accuracy, especially in the case of UAVs with electric motors.	1 - 10
Radio frequency signal	Radio frequency receiver	▪ Inability to detect for offline flight without radiation.	3 - 40
Acoustic signal	High-sensitivity microphone (array)	▪ Low detection accuracy; ▪ Small detection radius; ▪ High complexity of signal processing.	0,1 - 0,6

Since the use of Shahed-136 UAVs, it has been established that since the beginning of the armed aggression, these UAVs have been used most frequently and are most effective at night, between 23:00 and 06:00. This is when it is difficult to visually detect and determine their number and reduce the effectiveness of means of covering objects.

On the marching section, the flight path is straight. The average speed of Shahed-136 kamikaze drones observed during combat use is 140-150 km/h (although movement at speeds of 80 to 180 km/h was observed), and the flight altitude on the marching area is from 700 m to 2000 m, and in the target area it drops to 200 m.

Thus, the issue of detecting and identifying UAVs by sound is a very relevant research topic that will help build an effective anti-UAV system.

The relevance of this study is due to the above-mentioned features of the tactics of use and characteristics of the UAV, namely, the nighttime of use and the characteristic sound pattern of its engine.

The object of study is acoustic intelligence of moving targets in the broad sense of their identification and classification by acoustics approaches. The subject of the study is models for calculating the spatial position of a UAV in flight by the angles of arrival of a sound pattern of its engine on an array of microphones.

The aim of the work is to improve the efficiency of detection and identification of moving targets such as Class 2 UAVs by Beamforming methods in addition to existing machine learning methods.

II. RELATED WORKS

A quick review of the research findings published in various journals and conference proceedings reveals a diverse range of ideas and approaches that researchers are exploring to address the development of C-UAS systems. Let's examine the key research areas, which generally align with the primary detection methods outlined in Table 1.

Paper [2] presents the results obtained from experiments conducted to investigate the viability of acoustic sensing to create the basis for a non-cooperative system for aircraft collision avoidance (ACAS). An UAV equipped with two microphones flew near another onboard UAV to determine the maximum distance at which the offending aircraft could be detected. A method of increasing the detection distance by using the harmonic nature of acoustic signals generated by propeller-driven aircraft is presented. It was found that a small gasoline-powered UAV could be detected at a distance of up to 678 m.

The review paper [3] is interesting in terms of providing a thorough analysis of the methods used to detect and track UAVs or drones. Common methods are described that allow measuring the position, speed, and pitch of UAVs, and then using them for detection and tracking. Hybrid detection methods are also presented. Various technologies are considered, such as infrared cameras, radio frequency scanners, radars, optical cameras, and acoustic sensors. Special attention is paid to the use of deep learning (CNN, YOLO, Faster R-CNN) to automate the process of UAV detection and classification). The article is a quick reference for a wide range of methods used in the process of UAV detection.

Article [4] is devoted to the study of acoustic signatures of aircraft engine and propeller noise in the context of target tracking. The authors analyze harmonics in the spectrograms of light aircraft collected by a stationary microphone array on the ground. Using the Doppler frequency shift model, the speed and height of the target are estimated from the spectrogram of the recorded acoustic signal. The authors focus that frequency destructive interference can affect signal accuracy and must been considered in tracking algorithms.

In [5], the authors tested the applicability of an inexpensive long-wave infrared sensor for detecting various UAVs in flight.

The study found that the limit of detection for the Parrot AR.drone 2 was on average 41 m, for the Phantom 4 was 51 m, and for the hexacopter was beyond the 100 m line of the test track. The study also found that the images obtained from the sensor were noisy, with increased graininess and dynamic brightness range. The study concluded that batteries are the primary heat sources on UAVs. The study also suggested that future work should include testing the detectability of UAVs against more diverse backgrounds and reducing the heat signature of the UAV.

A large number of papers have been devoted to the study of infrared detection methods.

Paper [6] describes a visual and thermal monitoring system that combines detection and tracking modules based on deep learning. The authors present an integrated detection and tracking system that outperforms the performance of each individual module containing only detection or tracking. The proposed system achieves an AUC score of 43.8 on the test set, and the experiments show that the system performs well on real-world drone images with complex backgrounds, even when trained on synthetic data.

The study concludes that the proposed integrated drone monitoring system outperforms the detection-only and tracking-only sub-systems, and that the system can monitor drones during both day and night.

The main approaches for UAV detection based on radio frequencies are communication intelligence (COMINT) in addition to signal intelligence (SIGINT). Despite the fact that the classification accuracy deteriorates with an increase in the number of UAV types (number of classes), the detection accuracy remains satisfactory.

The objective of the study [7] is to investigate non-military grade anti-drone systems, and to propose a hypothetical anti-drone system that presents guidelines for adaptable and effective drone defense operations. The study also aims to contribute to future technology developments.

The study also concludes that integrating detection, identification, and neutralization schemes, and automating the overall system would greatly improve anti-drone system accessibility and reduce labor costs.

The conclusions of the study emphasize the importance of developing guidelines for designing anti-drone systems, and the need for optimal placement of drone detection networks to improve security against illegal drone incursion.

The results of the study show that anti-drone systems should include multiple neutralization solutions and utilize them appropriately to improve defense reliability, and that destructive and non-destructive methods should be separately treated in system design.

The process of detecting UAVs using radar is based on the use of reflected radio signals to calculate and determine their direction, speed, range, and shape. A large number of studies have been devoted to this area of research, since the use of radar began in the Second World War. The modern development of this principle of UAV detection using machine learning methods is reflected in [8], where the authors employed the Holographic RadarTM. This radar uses a 2-D antenna array and signal processing to create a multi-beam, 3-D, wide-area surveillance sensor, achieving high detection sensitivity.

Experimental trials using an L-band 32×8 element receiver array successfully detected a small hexacopter. However, the system's high sensitivity results in the detection of many other small moving objects, particularly birds. To address this issue, an additional processing stage was implemented using a machine learning classifier (decision tree), which effectively filters out non-UAS targets, providing nearly complete elimination of false tracks while maintaining a high probability of drone detection.

Similar to infrared cameras, optoelectronic cameras are being widely researched for use in UAV detection and countermeasures. In recent years, deep convolutional neural networks (DCNN) have become the main tool for the development of visual systems for detecting and classifying UAVs. Paper [9] investigates the issues and various approaches to building convolutional networks in object detection tasks.

The article emphasizes the transition from traditional object detection methods, which relied on handcrafted features, to deep learning approaches that utilize Convolutional Neural Networks (CNNs). This shift has led to substantial improvements in detection accuracy and efficiency.

The article presents experimental evaluations on benchmark datasets such as PASCAL VOC and Microsoft COCO, demonstrating that deep learning models consistently outperform traditional methods. It highlights the importance of multi-scale feature extraction and the integration of contextual information to enhance detection performance.

Despite the advancements, the article identifies ongoing challenges, particularly in detecting small objects and handling occlusions. It suggests that future work should focus on improving localization accuracy and developing models that can adapt to various scales and contexts.

Object tracking is one of the most important tasks in computer vision, which has many practical applications such as motion monitoring, robotics, autonomous vehicle tracking, etc. Various studies have been conducted in recent years, but due to various problems such as occlusion, lighting variations, fast movement, etc., research in this area continues.

The paper [10] investigates various object tracking methods and presents a comprehensive classification that classifies tracking methods into four main categories: feature-based, segmentation-based, estimation-based, and learning-based methods. Each category has its own subcategories and approaches tailored to specific challenges in tracking. The article emphasizes the growing importance of learning-based methods, particularly deep learning techniques, which have shown significant improvements in tracking accuracy. These methods can automatically extract features and adapt to various conditions, making them robust against challenges like occlusion and illumination changes. Various challenges persist in object tracking, including occlusion, illumination variation, fast motion, and background clutter. The article discusses how these challenges necessitate ongoing research and the development of more sophisticated algorithms.

A variety of datasets are highlighted, which are essential for training and evaluating tracking algorithms. These datasets include OTB100, VOT, and TrackingNet, among others, each designed to test different aspects of tracking performance.

In summary, the article concludes that while significant progress has been made in object tracking through learning-based methods, ongoing challenges and the need for robust evaluation metrics and diverse datasets remain critical for future advancements in the field.

The development of machine learning methods for UAV detection and classification requires training datasets that allow training and adjusting model parameters to obtain an acceptable level of detection accuracy, which in turn has created a powerful impetus for the development of research in the field of creating these datasets.

In [11], the authors present a new object detection dataset created entirely for training computer vision-based machine learning object detection algorithms for the task of detecting binary objects. The dataset extends the existing multi-class image classification and object detection datasets (ImageNet, MS-COCO, PASCAL VOC, anti-UAV) with a diverse set of UAV images.

The authors developed a specialized dataset consisting of 51,446 training images and 5,375 test images, specifically designed for detecting drones in real-world scenarios. This dataset includes 52,676 drone instances in the training set and 2,863 in the test set, with bounding box annotations for accurate object detection.

In summary, the article introduces a comprehensive dataset tailored for UAV detection, proposes an efficient labeling methodology, and evaluates different detection approaches to address real-world challenges in drone identification.

The analysis of research in the development of C-UAS systems leads us to the following conclusions:

1. No single technology provides 100% accuracy; combining several methods (hybrid systems) significantly improves results.

2. All of the papers are devoted to theoretical research and, in some cases, description of elements of practical implementation of UAV detection and classification systems. None of the papers consider the implementation of the interception concept as a logical extension of their research.
3. None of the considered approaches fully satisfies the requirements for the implementation of highly efficient C-UAS systems in terms of ensuring the detection of UAVs within the possible scenarios of their use.
4. Due to the rapid development of algorithms and hardware for implementing machine learning methods in object detection and tracking, we are witnessing an intensification of the implementation of convolutional neural networks in UAV detection. Deep neural networks (YOLO, Faster R-CNN, ResNet) are effective for UAV recognition and tracking, especially when using large datasets.
5. Optical and thermal cameras are useful for accurate detection, but depend on weather conditions. Radio frequency scanners are good at detecting drones based on control signals, but have limitations for autonomous UAVs.
6. In terms of the massive use of UAVs at night and on fiber optics, which reduces the possibility of detecting them by visual and radio means, the development of ground-based acoustic systems for detecting UAVs at short distances within the suburbs and combat zones is promising.

The development of machine learning and combined methods is key to improving the effectiveness of drone detection and tracking systems.

In developing effective and affordable systems for detecting, classifying, and tracking UAVs, initial research highlights the potential of acoustic signatures for accurately detecting and tracking moving targets with distinct sound patterns. This approach could been combined with other methods, such as using infrared cameras to detect and track UAVs, especially since most massive attacks on critical infrastructure occur at night. Integrated systems will enable the full range of tasks for detecting, recognizing, tracking, and intercepting UAVs.

Given the scale of damage caused by Shahed-type UAVs during the full-scale war waged against Ukraine and the state of affairs with the development of C-UAS systems both in terms of methods and mathematical models and in terms of UAV carriers (interceptors) [12], the development of the concept of a promising anti-drone system is an urgent scientific and applied task.

Thus, we can draw a general conclusion about a promising anti-drone system that should been built for specific types and classes of UAVs, taking into account their tactics of use and their characteristics. For example, for Shahed-type UAVs, a combined system that combines detection, identification using machine learning methods, calculation of altitude and azimuth to guide the interceptor to the target, interception using tracking methods, and additional targeting at the affected area using an infrared camera will be effective.

However, in this article, the authors will cover only the issues of acoustic detection and identification, as well as methods for calculating the azimuth to the target.

III. SOUND-BASED DETECTION OF MOBILE OBJECTS

Acoustic Intelligence (ACINT) collects and utilizes acoustic signals or radiation [13]. ACINT has a long history in the study of sound waves in the marine environment (sonar), but it has also been successfully used to detect missile launch locations and artillery installations in counter-battery warfare. Specialized acoustic systems for detecting the spatial position of UAVs in flight have already been developed and are available on the market, but their current effective range is limited to several kilometers. At longer distances, ambient noise will drown out the target sound of the engine or engines and significantly reduce the effectiveness of this class of systems, and sometimes make their use impractical in terms of the probability of UAV detection.

However, at the tactical level, within the combat zone, directly in the suburban area, databases of sound signatures of various types of UAVs could been effectively used as an element of the algorithmic part of the air defense system to intercept them, especially at night, when visual detection is practically impossible [14].

Most UAVs have gasoline or electric propulsion systems that generate a significant amount of noise. Depending on the altitude, the noise can be so loud that it could been used by itself to detect UAVs by ground personnel, even without the use of acoustic detectors. However, unmanned aerial vehicles operating at high altitudes are usually inaudible to humans and require special acoustic sensors to detect them [15].

The noise of the propellers or the engine itself can be measured using ground-based stationary microphones that use the Doppler effect in the acoustic spectrum to calculate the aircraft's altitude, speed, and engine speed. The real-time calculation of such signals can help determine the flight direction or location of the UAV [16].

A. SPECTRAL ANALYSIS OF UAV TYPE SHAHED SOUND PATTERNS

Class I micro and mini UAVs emit significantly less noise than turboprop UAVs. However, the noise level of first-class small and second-class tactical UAVs is still high enough to be heard at certain distances. The typical sound level of micro and mini drones is between 70 and 80 dB measured at a distance of one meter. If the distance to the sound source doubles, the sound pressure level drops by 6 dB. According to Work [1], this formula could been applied to show that the noise level will drop below 20 dB at a distance of around 350 m for a 70 dB drone and 1000 m for an 80 dB drone. This means that in a quiet rural area, the average ambient noise will be loud enough to mask the residual noise of first-class drones from the first and second subgroups.

Very interesting studies on the noise level of first-class UAVs could been found at [17]. As a result, of the study of the noise generated by DJI's Mavic and Inspire 2 drones, the following data were obtained (Table 2).

Table 2. Noise generated by drones

Height, m.	Noise, dB	
	DJI's Mavic	Inspire 2
Environment - 0	43	41
7,5	57	68
15	52	65,5
30	45,5	55,5

As for tactical UAVs of the second-class weighing 150 kg or more, which are usually already equipped with an internal combustion engine or a turboprop or jet engine, the situation with detecting such UAVs is somewhat better in terms of the noise level they generate during flight.

Thus, the Shahed-136 UAV is equipped with a four-cylinder horizontally opposed two-stroke gasoline engine with air cooling (L550E, MD 550), which develops a power of 37 kW (50 h.p) with a rather high power-to-weight ratio: 2.3 kW/kg. It uses pulse ignition, four carburetors, and lubrication with a lubricant mixture with a fuel-to-oil ratio of 25:1 (for mineral oils) or 50:1 (for synthetic oils) [18]. The air cooling system makes the UAV a bright target in the infrared range as well.

The power plant of the Shahed-136 UAV emits powerful sounds in a wide range of frequencies. In calm weather, the noise from a running engine could been heard at a distance of more than 10 km, making them targets suitable for acoustic detection.

The noise spectrum of a propeller power plant includes the tonal components of the propeller noise at frequencies that are multiples of the blade frequency and the piston engine at frequencies that are multiples of the cylinder flash frequency. The frequencies of the cylinder tones ($f_ц$) and engine tones ($f_д$) in the engine noise spectrum have been determined by the relations (1):

$$f_ц = \frac{kn_д}{30s_д}, \qquad f_д = kf_ц N_ц, \tag{1}$$

where k is the number (order) of the tone, $n_д$ - engine speed (revolutions per minute, rpm), $s_д$ - number of engine strokes, $N_ц$ - number of cylinders.

Thus, for a four-cylinder two-stroke engine MD 550 with a speed in the range of 4000 - 7500 rpm, given a cruising speed of 140-150 km/h (5500-6000 rpm), we can obtain the following calculated data of the sound frequency in Hz (Table 3).

Table 3. Shahed sound frequency

Engine speed, rpm.	Number (order) of the tone, k			
	1	2	3	4
4000	267	1067	2400	4267
5500	367	1467	3300	5867
6000	400	1600	3600	6400
6500	433	1733	3900	6933
7500	500	2000	4500	8000

The spectral analysis of the sound fragment (duration 14 seconds, Fig. 1a), made by the author of the article using a real flight recording of the UAV Shahed-136, confirms the calculated results regarding the range of engine operation frequencies (Fig.1b).

The main sound samples were in the range up to 3 kHz (Fig. 2). Fig. 2 shows fragments of the spectra of two sound samples, one of which (Fig. 2a) corresponds to the sample (Fig. 1) made over the city and obviously more noisy, and the sound recorded outside the city on the flight path (Fig. 2b), which has more clearly defined peaks of the fundamental frequency and harmonic components.

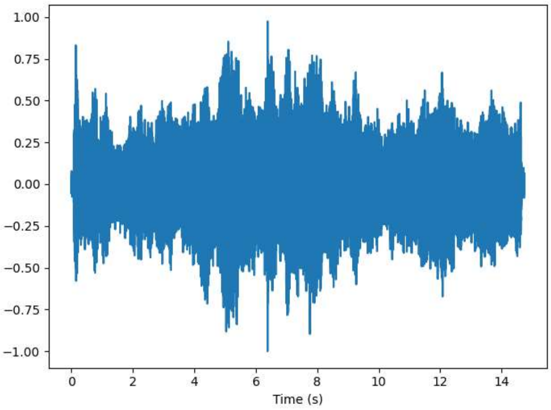


Figure 1a. Sample of the Shahed-136 sound

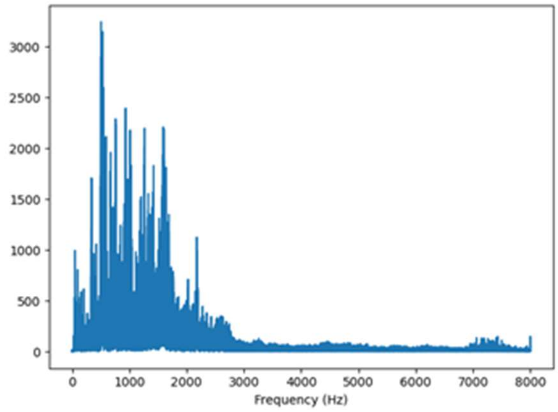
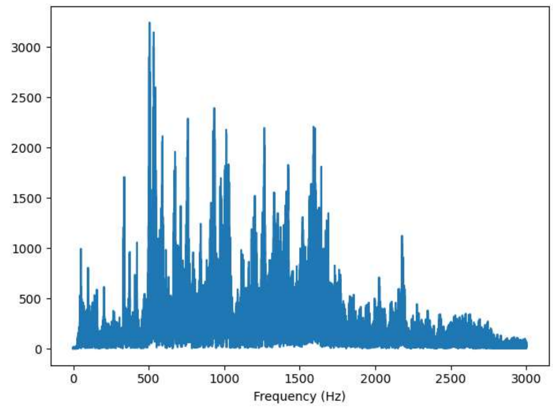
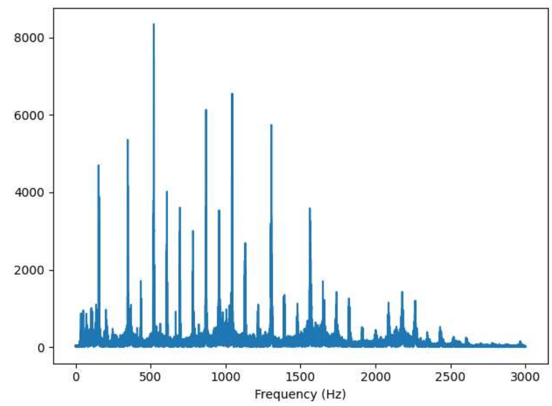


Figure 1b. Spectral analysis of the Shahed-136 sound.



a) Sound made over the city



b) Sound recorded outside the city on the flight path
Figure 2. Spectral analysis of the Shahed-136 sound.

Obviously, the flight carried out at speeds close to the maximum at the time of the target approach. The spectral analysis of the sound of the Shahed-136 UAV engine could been used in further studies of acoustic detection methods.

B. MODELING THE DETECTION OF SOUND DIRECTION OF THE SHAHED TYPE UAVS

The approaches to acoustic analysis and detection of UAVs considered in [2-4] involved the use of ground-based acoustic arrays of highly sensitive microphones to detect objects and transmit data to the relevant information systems or mobile response teams. In addition, some works [19, 20] considered the principles of building systems for preventing collisions with other UAVs, which could been used as starting points for building interception systems.

The detection of the direction of sound radiation is based on an approach described in the literature as beamforming. Beamforming is a signal processing operation used by antenna arrays to create a spatial filter; it filters out signals from all directions except the desired one [21]. Beamforming could been used to increase the signal-to-noise ratio (SNR) of desired signals, to create a beamforming pattern, or even to transmit/receive multiple data streams simultaneously and at the same frequency. Beamforming is a signal processing technique that aims to estimate the direction of signals entering a sensor array. In beamforming, we use weights that are applied to each element of the array in digital or analog form. We experiment with the weights to form the beam(s) of the array, which is what gave rise to the name beamforming. We can steer these beams extremely fast; much faster than mechanically rotated antennas, which can be seen as an alternative to phased arrays.

Let us consider the simplified mathematics of beam formation (Fig. 3).

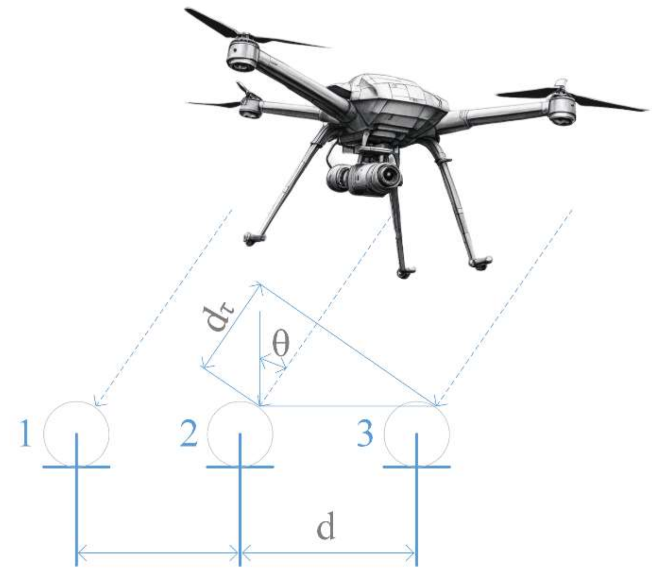


Figure 3. Beamforming.

If the sound wave arrives at an angle θ other than zero at the third microphone, then it arrives at the 1st and 2nd microphones with a delay τ_2, τ_3 due to the need to travel an additional distance d_τ (2).

$$d_\tau = d\cos(90-\theta), \tag{2}$$

$$\tau = \frac{d\sin\theta}{c},$$

where c is the speed of sound under certain environmental conditions.

The sound generated by the UAV is transmitted in a certain band $x(t)$ with a carrier frequency f_c and can be written as: $x(t)e^{2j\pi f_c t}$.

If the first microphone receives the signal at time t, then the second microphone will receive the signal at time $t-\tau$, i.e. $x(t-\tau)e^{2j\pi f_c(t-\tau)}$. If we replace t with Tn, where T is the sampling period and $n = \{1,2,3,\dots\}$ and considering that τ is much smaller than Tn, we can write (3)

$$x(n)e^{-2j\pi f_c d\sin\frac{\theta}{c}}. \tag{3}$$

Given that $f_c = c/\lambda$ and moving from distances to the ratio between the sound wavelength and the distance between microphones $d_\lambda = d/\lambda$, we can write (4) for the kth element:

$$x(n)e^{-2j\pi k\, d_\lambda \sin\theta}. \tag{4}$$

For an array of K microphones, the expression could been written as a vector (5):

$$x\begin{bmatrix} e^{-2j\pi(0)\,d_\lambda\sin\theta} \\ e^{-2j\pi(1)\,d_\lambda\sin\theta} \\ e^{-2j\pi(2)\,d_\lambda\sin\theta} \\ \dots \\ e^{-2j\pi(K-1)\,d_\lambda\sin\theta} \end{bmatrix}, \tag{5}$$

The vector x is called the *steering vector*, which is often referred to in the beamforming literature as the s vector [22].

To simulate the operation of a linear array of three microphones, let's apply the control vector s to the sound signal (Fig. 1), assuming that the sound came at an angle of 20 degrees ($\theta = 20^\circ$), and the ratio of the distance between the microphones to the wavelength is 0.5. The result (Fig. 4) shows three sound signals shifted in time by t.

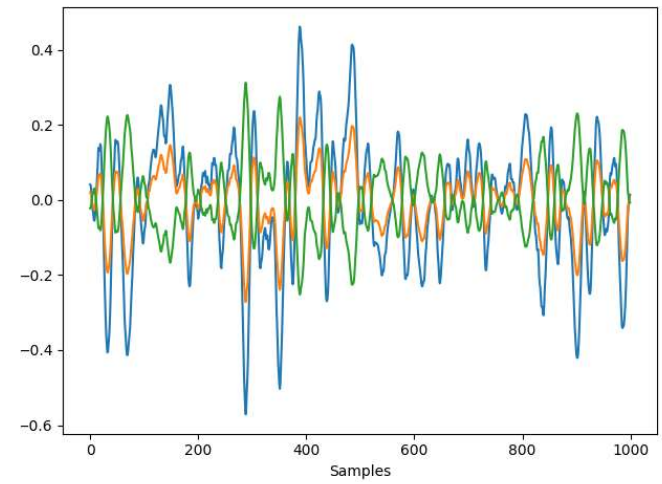


Figure 4. Three sound signals shifted in time by steering vector.

The steering vector, which depends solely on the angle of incidence and the geometry of the microphone array, is calculated for these conditions as follows:

[1.+0.j, 0.47618256-0.87934645j,-0.54650034-0.83745888j].

The Delay-and-Sum Beamformer applies a time delay to the input signal from each element and sums the output. If we set the time delays correctly, we will have one high output signal. We can then use the time delays that created this signal to determine the angle of its arrival.

The search for the sound wave's direction-of-arrival (DOA) involves scanning (sampling) all directions of arrival from -π to +π (from -180 to +180 degrees), for example, in 1-degree increments. In each direction, we calculate weights (steering vector coefficients) using a beamformer. Applying the weights to our input signal (previously passed through the 20 degree beamforming procedure) will give us a one-dimensional array of samples as if we received it with 1 directional antenna. We can then calculate the signal strength by calculating the correlation of the shifted signals for each scan angle. The signal of maximum power (correlation) will correspond to an arrival angle of 20 degrees (Fig. 5a).

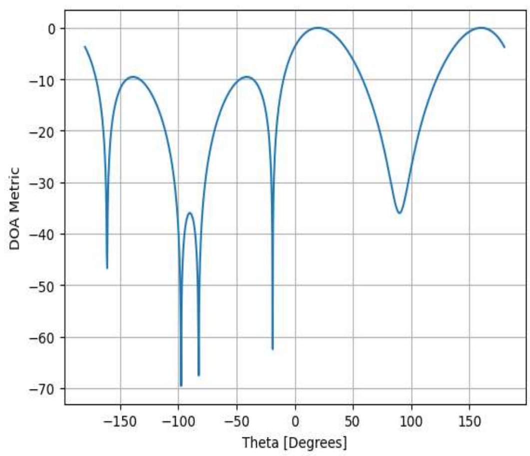


Figure 5a. The signal of maximum power (20 degrees)

We can steer the array at different angles and choose the angle that gives the best response. We process the input signal with the control vector to get the response of the array. The angle that produces the largest response is the most likely sound arrival angle. The response of the array is determined by the dispersion of the output vector, a small dispersion means that the received signals have a high degree of constructive interference (maximum correlation) and the output signal will be the largest. If the variance is very large, the steering vector (time delays) is much deviated from the angle of the input signal.

The modeling results are also presented using the polar coordinate system (Fig. 5b), which allows us to detect a second peak at 160 degrees. This ambiguity is associated with the linearity of the microphone array, which can receive a signal from both the front and the back $(180 - \theta)$. This problem can be solved with the help of both software tools and by implementing volumetric (non-linear) arrays, such as 2 and 3D arrays.

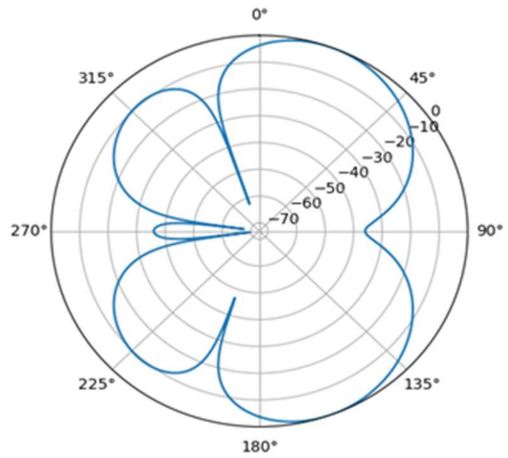


Figure 5b. DOA in polar coordinate system (20 degrees)

C. MODELING THE DETECTION OF SOUND DIRECTION FROM TWO SHAHED UAV

There are several approaches to forming a steering vector [21] and finding the angle of incidence of the signal, among which we can distinguish Bartlett Beamformer and Capon Beamformer. In both cases, the input signal is considered as a sequence of discrete power (amplitude) values at certain moments of time, the so-called snapshot model. In theoretical studies, a uniform linear matrix (ULM), or Uniform Linear Array (ULA), as described above, with K microphones and D signals is considered for all signals and models, for which the snapshot model notation can be written as (6):

$$x(t) = v(t)f(t) + n(t), \tag{6}$$

where $\vec{x}$ is a vector of input signal of dimension $(K \times 1)$ received at time t, v is a matrix of control vectors of dimension $(K \times D)$, $f(t)$ is a random vector with zero mean values, which includes desired and possibly undesired input signals, with dimension (D × 1), $n(t)$ is a complex additive white Gaussian noise.

To simplify calculations in hardware of low power and performance, model (6) is represented in a vectorized form (7):

$$X = VF + N, \tag{7}$$

in which all terms correspond to the model (6) in terms of content, and in their dimensions 1 is replaced by T.

Bartlett Beamformer is a beam scanning algorithm that scans beams using a steering vector and collects the response of an array of microphones (sensors) for each angle of incidence [23]. The angle with the highest response level is recognized as the Angle of Arrival (AoA), and if there are several angles of incidence, several peaks will be calculated, which will represent the angles of arrival of the signals.

The Delay-and-Sum Beamformer estimates the variance of the output vector (the response of the control vector to the input signal) to estimate the signal power for each angle of incidence (arrival) θ, as described in the previous section. Bartlett Beamformer is able to directly estimate the signal power in the direction of θ using expression (8) - the time-averaged power of the output vector [24]:

$$\mathcal{P} = \frac{1}{T}\sum_{t=0}^{T-1}[v^*(\theta_s)^T x(t)]^2, \tag{8}$$

Using the time-averaged power of the output vector (), we can obtain a formula for calculating the Bartlett power of the signal using only the control vector and the correlation matrix of the input signal R_X (9):

$$\mathcal{P}_B = v^{*T} R_X v, \tag{9}$$

where

$$R_X = \frac{XX^{*T}}{K}.$$

Capon Beamformer, also known as Minimum Variance Distortionless Response (MVDR) Beamformer, is also a ray-scanning algorithm for determining the angles of incidence, which minimizes the variance of signals during their processing and allows, in addition to detecting the angles of incidence, to make a complete reconstruction of signals that came from different directions and were heavily noisy. The signal power is calculated using expression (10) [25]:

$$\mathcal{P}_C = \frac{1}{v^{*T} {R_X}^{-1} v}, \tag{10}$$

We will search for the angles of arrival of the sound signal from two UAVs using the Bartlett Beamformer and Capon Beamformer (Minimum Variance Distortionless Response Beamformer, MVDR) approaches to calculating the power of the output signals. As input data for the modeling, we will use sound signals recorded during the actual use of the UAV Shahed-136 at different times. The first sound signal (Fig. 1), which was used in the previous study, came at an angle of 10 degrees and the second signal of slightly lower power (recorded for UAVs at a greater distance) came at an angle of 55 degrees are shown in Fig. 6.

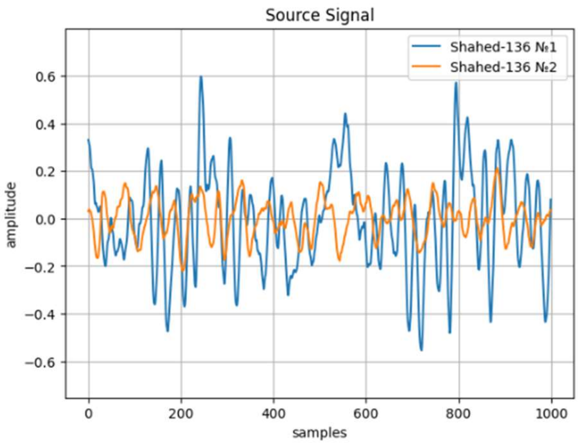


Figure 6. Sound from two Shahed UAV

The result of processing the signals with an input array consisting of 4 microphones and creating a steering vector of dimension (4 × 2):

(array([[1.+0.j, 1. +0.j],
[0.85485145-0.51887281j,-0.74183541-.67058201j],
[0.46154202-0.88711835j,0.10063955+0.99492295j],
[-0.06575172-0.99783601j,0.5925194-.80555614j]]),
(4, 2)),

is shown in Fig.7.

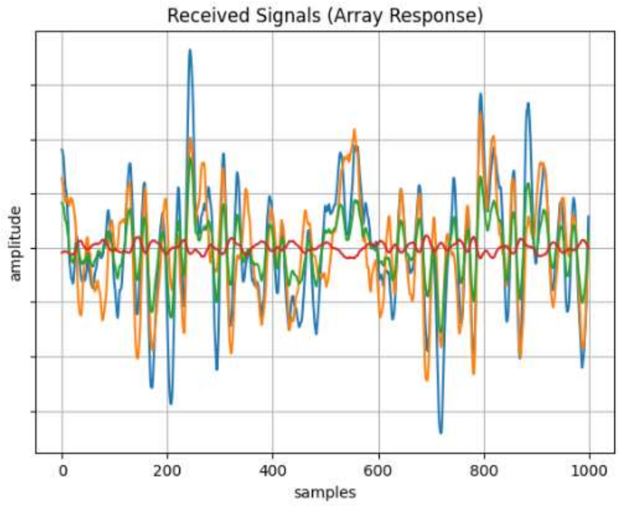


Figure 7. The result of processing two input signals

The correlation matrix R_X of size (4 × 4) for the received signals (Fig. 7) was as follows:

(array([[0.06260932+0.j, 0.0448803 +0.03258401j,
0.02869024+0.04640957j,-0.00310373+0.06243946j],
[0.0448803 -0.03258401j, 0.06619568+0.j,
0.04492317+0.0363746j, 0.02826974+0.04641909j],
[0.02869024-0.04640957j, 0.04492317-0.0363746j,
0.06661629+0.j, 0.04488532+0.03302857j],
[-0.00310373-0.06243946j, 0.02826974-0.04641909j,
0.04488532-0.03302857j, 0.06265865+0.j]]),
(4, 4)).

The use of these beamforming methods made it possible to determine accurately the angles of arrival of the sounds of the UAV engines (Fig. 8).

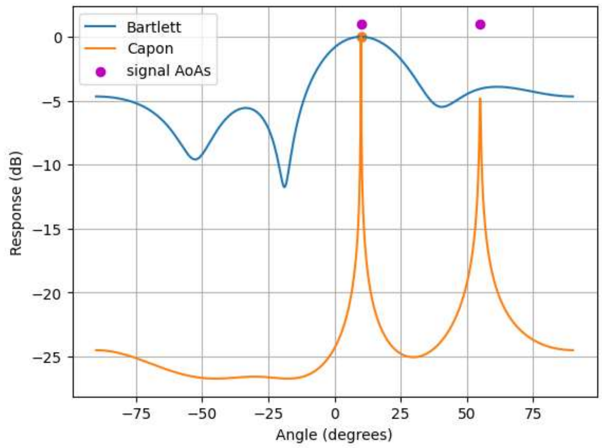


Figure 8. AoAs of two input signals (10 and 55 degrees)

The analysis of Figure 8 also confirms the different power levels of the signals, since the signal that arrived at an angle of 10 degrees was more powerful, we can observe a higher peak on the graph than the signal that arrived at an angle of 55 degrees.

IV. CONCLUSIONS

The results of the research and calculations carried out within the framework of the goals and objectives allow us to draw the following conclusions:

1. Current acoustic detection methods effectively detect specific types of UAVs with a high degree of accuracy. The distinct sound spectrum produced by the MD 550 engine enables the detection of Shahed-136 UAVs in dry, calm conditions with high probability.
2. The sound beamforming techniques, specifically the Bartlett Beamformer and Capon Beamformer, facilitate the calculation of both the azimuth and altitude of targets. These methods also allow for the simultaneous tracking of multiple targets.
3. The effectiveness of acoustic detection is influenced by several critical factors, including the distance between microphones. This distance is determined by the design of the array, and in the case of an array mounted on a UAV interceptor; it is also constrained by the UAV's design.
4. Improving the quality of UAV classification based on the sound patterns of their engine operation will require a significant increase in the training dataset.
5. Further research is needed in the area of acoustic detection and classification, particularly for scenarios involving multiple UAV attacks, where it is essential to allocate targets among UAV interceptors effectively.
6. The research confirms the possibility of building interceptor UAVs with microphones on board in terms of the geometric constraints imposed by existing prototypes. The practical modeling results obtained and the approaches considered are also a good starting point for the further development of combined UAV intercept systems.
7. Obviously, anti-drone systems for the considered class of UAVs will implement the following algorithm:
   - Detection and identification of the UAV class using machine learning methods.
   - Calculating the height and azimuth of an enemy UAV.
   - Bringing the interceptor UAV to the target at a distance that allows the infrared camera to work.
   - Capturing the enemy UAV with an infrared camera.
   - Tracking the UAV and subsequent destruction.
8. Further research is needed on the issue of guiding the UAV interceptor to the enemy drone using an infrared camera. The issue is quite promising in terms of using second-class UAVs with appropriate gasoline engines with a characteristic spectrum of thermal radiation, in which even inexpensive cameras available today work very well.

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Oleh V. Zaritskyi, *Doctor of Engineering Science, an Associate Professor at Department of Management Technologies Information Technologies Faculty of Taras Shevchenko National University of Kyiv. Scientific interests: data science, AI, machine learning, AI programming languages.*

OLEKSANDER V. PONOMARENKO, *PhD, Associate Professor, an senior researcher at Department of monitoring and diagnostics of energy facilities, General Energy Institute of National Academy of Sciences of Ukraine, Scientific interests: data science, AI, processes in the energy sector.*