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UAV detection from acoustic signature: requirements and state of the art

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Summary

The detection, identification and classification of micro-Unmanned Aerial Vehicles (UAVs) using their acoustic signature is at an early stage where the current performances do not meet the market requirements. They are targeted to complete electro-optical and radio frequency sensors acting in short distances (between 200 and 500 meters). This study firstly defines the detailed requirements to develop effective and affordable countermeasures to report of UAV flying over critical areas, especially in urban areas. It concerns Signal-to-Noise Ratio (SNR) required by the environment and UAV type/distance, the operational frequency domain with the best SNR, the localization accuracy required for neutralization, the real time capabilities to act as soon as possible…

The sound landscape observation is a complex task which has to isolate the noise sources of interest in short delay. The second part of the study establishes a state of the art of the available technologies on the market and the academic works addressing this topic and details how the current solutions cover the complete procedure from detection to classification. For the detection, the system tries to measure the acoustic signature using a single microphone or more complex sensors for a better directivity. For the identification and classification, a Machine Learning procedure is well-suited to recognize UAV audio fingerprint. For now, many academic papers demonstrate the low maturity of the procedure and the need to improve its reliability.

1. Introduction

The detection, identification and classification of micro-Unmanned Aerial Vehicles (UAVs) requires the combination of different sensors to generate low levels of false negatives and false positives. The use of multiple detection modalities is intended to increase the probability of a successful detection, given that no individual detection method is entirely fail proof. This is difficult to achieve. A detailed study [1] counted in February 2018 155 counter-drone products either on the market or under active development for detection. Those systems rely on a variety of techniques for detecting drones: Radar, Radio Frequency (RF), Electro-optical (EO), Infrared (IR), Acoustic. 95 appear to employ a single sensor type, while at least 60 employ a combination of several sensor types. Roughly an equal number of systems employ radar, RF detection, IR and EO sensors while only 21 systems employ an acoustic sensor. The acoustic sensor detects drones by recognizing the unique sounds produced by their propulsion system. The limited number of solution based on acoustic may points out the low effectiveness of such a sensor in many situations. The first part of this paper analyses the requirements and foreseen limitations of the use of acoustic sensor, especially in urban area. Then a second part lists the current technology based on acoustic sensors with their adequacy to those requirements.

2. Requirements for effective acoustic UAV detection

2.1 UAV none covered by usual detection system

UAVs group a numerous variety of flying autonomous systems from small ones of few centimetres to the largest ones of real plane size. As traditional surveillance systems cope with the largest objects, the ones of interest are "*small UAVs, including cheap Commercial off the Shelf (COTS) and easy to assemble UAS components"* as described in the recent last H2020 call "Capabilities to detect, classify, track, identify and/or counter UASs in defence scenarios ID: EDIDP-CUAS-2020 (European Defence Industrial Development Programme)" (https://ec.europa.eu/info/funding-tenders/opportunities/portal/screen/opportunities/topic-details/edidp-cuas-2020). The below Table 1 extracted from the call lists them with their characteristics.

TAXONOMY (coherent with NATO)	**Reference information regarding UAV threats**	**Reference information regarding UAV threats**	**Reference information regarding UAV threats**	**Reference information regarding UAV threats**	**Reference information regarding UAV threats**
Threat	**Weight [kg]**	**Reference size [cm³]**	**Max speed [km/h]**	**Typical altitude [m]**	**Typical RCS** *(Radar Cross Section)* **[dBm²]**
Class I (a) and (b) - micro	< 2 kg	25 x 25 x 30	80	100	-20 (objective -30) *(Human in the loop)*
Class I (c) - mini	> 2 & < 20	40 x 40 x 30	100	1 000	-13 (objective -20)
Class I (d) - small	> 20 & < 150	200 x 150 x 50	150	1 500	-10
Class II - tactical	> 150 & < 600	1 000 x 700 x 100	300	3 000	-3

Table 1 : UAV classification from H2020 call "Capabilities to detect, classify, track, identify and/or counter UASs in defence scenarios ID: EDIDP-CUAS-2020.

The Class I micro UAV are flying at low altitude and are very small compared to other ones, permitting them to evolve in urban area, hardly detected by conventional radars. Their very low RF, thermal and acoustic signatures make them difficult to also detect by other sensors. The acoustic sensor can help in detecting and identifying those Class I UAV with typical distance from 100 to 1000 m for which one they are sensitive.

2.2 UAV acoustic signature

Class I UAS group a numerous variety of flying autonomous systems with multi-rotor or fixed-wings, electric or thermic propulsion. As a consequence, their acoustic fingerprint can be very different, without prior knowledge of their frequency content and noise level.
One of the primary applications of unmanned aerial vehicles is surveillance. As surveillance often needs to be quietly conducted, the capability of silent flight has led to very low noise system with preferable electric propulsion systems but usually reserved to professional with expensive costs. Most of the systems are COTS but those systems can also be home made with unpredictable acoustic signature but keeping some of the characteristics of usual technology and noise level. The picture below gives some averaged sound pressure level for DJI quadricopters (from https://www.airbornedrones.co/drone-noise-levels/). This range is close to the European Aviation Safety Agency drone regulations published in their Easy Access Rules for Unmanned Aircraft Systems (Regulations (EU) 2019/947 and (EU) 2019/945). These do mention maximum sound power L_{WA} at 85 dB with a future target to 81 dB.

Table 2 : DJI sound power level

There are two different UAV types: the fixed-wings or multi-propellers. The measured noise of those vehicles is dominated by propeller-related noise, including narrowband deterministic noise and broadband noise. Both are characterized by prominent tonal components . The multicopter spectra have significant noise at higher harmonics of the blade passing frequency (BPF), and in some cases the levels at higher harmonics exceeds levels at the BPF compared to fixed-wings [4].
Multi-copter drone flyovers noise emission have been conducted in many studies [2,3,4] including the basic manoeuvers of hover and forward flight. Three distinct frequency regions are identified in the sound spectra as illustrated on Figure 1 for DJI Matrice 600 Pro or Figure 2 for home-made Quad-rotor MUAS. Below 2 000 Hz, tones at harmonics of the BPF correspond to the narrowband peaks in the spectra. Broadband noise between 2 000 and 5 000 Hz is also an important noise source for these vehicles, including noise caused by unsteady pressure fluctuations due to turbulence and boundary layer interactions with the edges of the blade broadband. Over and up to 10 kHz the rotor self-noise is also very typical. It is caused by the electric motors with force pulses as the magnets and armature interact, and variations in forces caused by phase changes in the motor drive signal. Although atmospheric absorption at these high frequencies will attenuate such noise, it could still be an important part of the emission at closer distance.

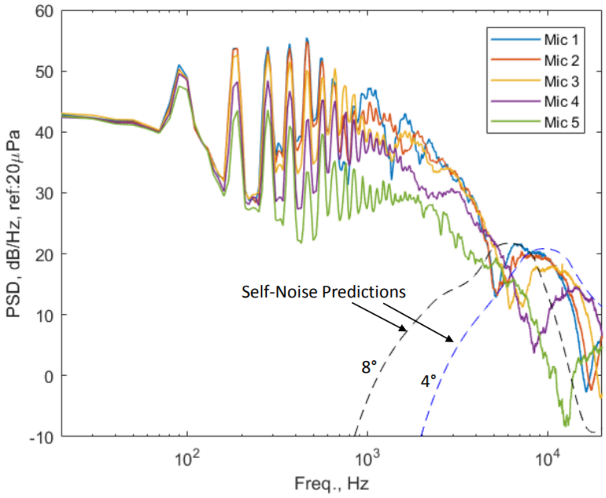


Figure 9. Acoustic frequency spectra for the five microphone positions during hover above Mic 1 at an altitude of 9.18 m

Figure 1: UAV spectrum DJI Matrice 600 Pro from [2]

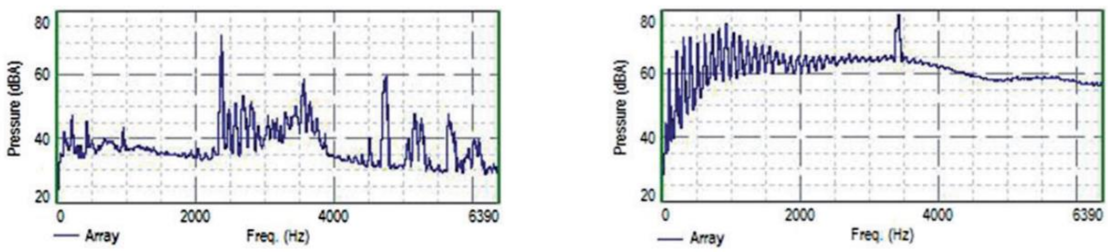


Figure 16. Frequency levels for test with all motors running but no propellers. Top of MUAS facing array.

Figure 18. Frequency levels for test with all motors and propellers running. Top of MUAS facing array.

Figure 2 : home-made Quad-rotor UAS from [3]

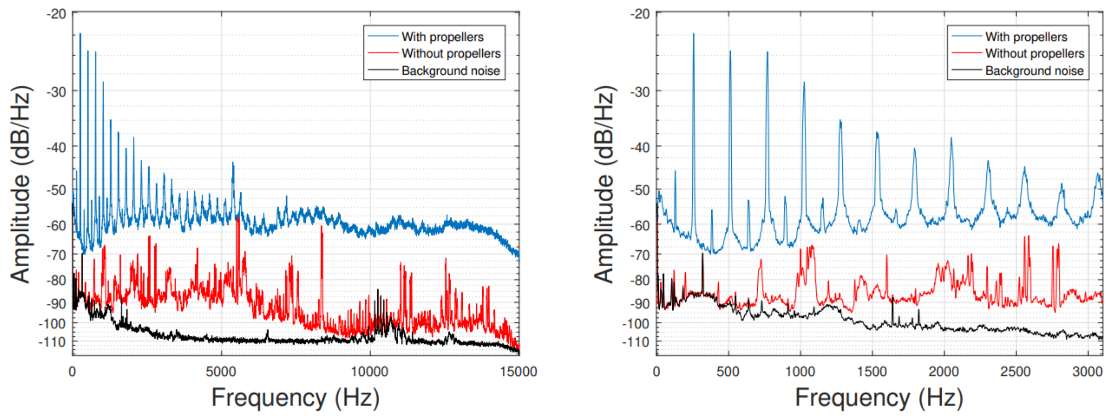


Figure 2: (left) Power Spectral Densities of the sound emitted by the drone with propellers (blue), without (red) and the background noise (black) of the anechoïc room and (right) a zoom up to 3 kHz.

Figure 3: DJI Phantom IV acoustic signature from [6]

2.3 Signal-to-noise ratio

For acoustic detection, the own UAV emission cannot be considered as a single source of noise because it usually flies over noisy environment. For VIP events or in urban site the threat can act at short distance but usually with high background noise level. On the opposite, sensitive site protection requires middle range detection but in usual less noisy environment with constant and

regular levels. At last in military operational theatres or airports, the background noise can be at a large scale with unpredictable additive noisy events of different nature. So the signal-to-noise ratio is a parameter to consider to isolate the UAV acoustic signature from the other noise sources of an acoustic scene.
The Figure 4 superimposes on the same graph the environment background level and the Sound Pressure Level of UAVs with decreasing distance. This estimation is given from average DJI sound power level with a decrease of 6 dB per doubling of distance. Those approximations are confirmed in [3] and [4] whose some results are presented in Figure 5. It points out that a negative SNR is mostly envisaged for short distances and quickly below – 25 dB over 500 m. From usual microphone sensitivity, the maximum audible distance with acoustic sensors would be 1 km.

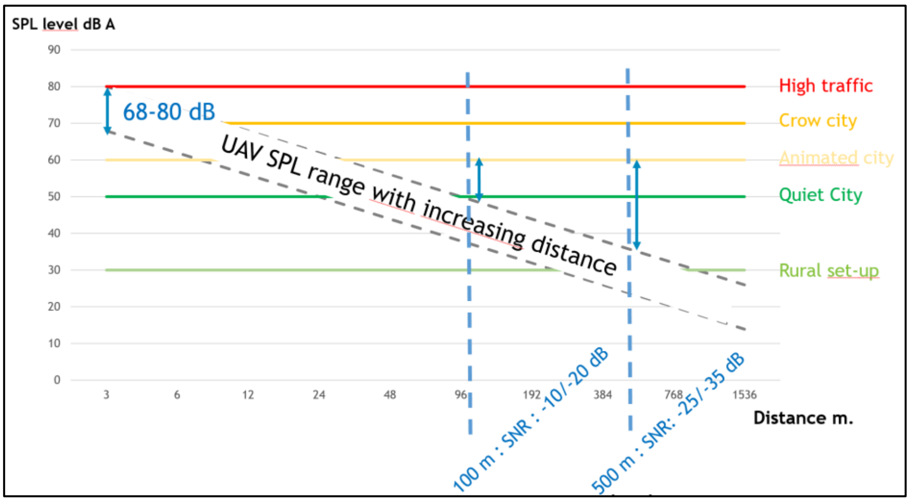
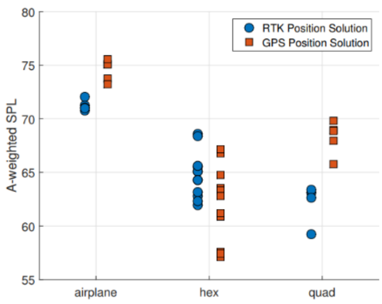


Figure 4 : superimposition of usual UAV sound emission with distance and typical background noise level



(a) LAmax normalized to 15 m from microphone.

Vehicle Name	Type	Flight Weight (kg)	Max Speed (m/s)	Power	Location
Edge 540[1]	fixed-wing	~11.3	27	gas engine	42VA
DJI Phantom 2[2]	quadcopter	1.6	15	electric motor	42VA
3DR Y6[3]	tricopter	2.5	15	electric motor	42VA
Prioria Hex[4]	hexcopter	7.3	15	electric motor	AP Hill

Figure 5 : interpolated noise level from [4]

2.4 Implementation requirements regarding acoustic sensor and processing

One point of interest which is to consider in the development of methodology is real time processing. As much as possible, the system has to deliver the results of detection/identification in real time. The state of the art will prove that this constraint limits the fitting processing and implies optimization in those last ones. The Table 1 indicates speed of 100 km/h, 27 m/s for UAVs class I (c) mini. It means that with the previous analysis indicating that UAV could be detected from 500 meters, it remains 18 seconds to act for neutralization.
The system must cover a 3D sound landscape without prior knowledge of any privileged direction. In some cases like VIP events, the system has to be easily deployed on the field. It implies low power consumer, easy positioning to communicate the drone position in GPS coordinate system,

low cumbersome and handled hardware, and robustness regarding harsh environmental exposition.

3. State of the art for UAV detection/identification from their acoustic signature

3.1 Actors and history

The first publication referring drone detection dates from 2004 [23] with the TTCP-AG6 mission leaded by United States US to explore the use of acoustic sensor technology against UAVs. Although the first good results they present and claim, no further work from this group could be founded later about acoustic sensor. Besides, only one publication could be founded until 2015 also in US [7].

But most of the work were done after 2015. UAV detection/identification is therefore a recent topics of interest with mainly academic publications and theoretical experiments. Only two commercialized solutions can be found with brochures and associated patent in US and Norway [25, 26, 27] indicating performances which do not completely answer to the previous requirements.

Area	Objectives/methods	Publication date	Ref.
US	Mission to explore the use of acoustic sensor technology (Music) Beamforming for tracking with low cost array Droneshield patented solution (parabolic antenna / ML) Patent : Delta signature from different UAV manoeuvre Patent for system with audio/video/RF detection from multi-arrays Detection and Acoustic Scene Classification with Deep Learning	2004 2008 2017 2016 2018 2018	23 7 24,25 20 26 14
China	Patent for wearable system with audio/video/ultrasonic detection Patent :UAV identification with ML and vibration velocity vector signal TDOA and tracking with Kalman filter Doppler effect and the matching method for UAV straight line flying	2019 2019 2018 2016	21 19 8 9
Europe	Beamforming and Tracking with Kalman filter Beamforming TDOA comparison Acoustic/video based detection/identification solution with micro array Patent for audio/video detection/identification system with micro array Micro Array Methodology coupling beamforming and SVM Identification/classification with SVM Correlation first approach Identification/classification with ML (LPC & freq spec slope) Beamforming for noise source tracking	2020 2019 2018 2017 2019 2017 2016 2015 2015	18 6 17,10 27 16 15 12 13 5
Korea	Identification and classification with Deep Learning	2017	28
Australia	laboratory prototype for embedded flying system to detect and avoid UAV (TDOA)	2011	22

Figure 6 : list of main publications relating UAV detection, identification and classification

3.2 Detection

In most of the publications, the detection consists of locating in the space the UAV as a source of noise. The methodology is based on microphone array measurement and processing. There are three categories of algorithm which allow to localize the source.

The first one is TDOA (Time Direction Of Arrival) or goniometry. It is usually calculated through the generalized cross-correlation function between two microphones. But four microphones or more are required to localize a sound source in 3D with better accuracy. They are arranged over a tetrahedral shape. This processing is interesting for its low computational complexity and time domain, large frequency range using low cost microphone array. This method is already used in gunshot detection with usually good signal-to-noise ratio and one or few noise sources.

The experimental tests carried out in laboratory-like conditions with determined and controlled sound scape [11] show good results. But its application for UAV detection meets the difficulties of multi-path effect, multi drone and the low signal-to-noise ratio (SNR) condition in complex environment (e.g. presence of buildings in city scape).
TDOA method for UAV detection is detailed by Martin in 3D [11] with two to four microphones. The Phase transform function (GCC-PHAT) is usually applied as a window to attenuate the effects of the intensity difference in the generalized cross-correlation function.

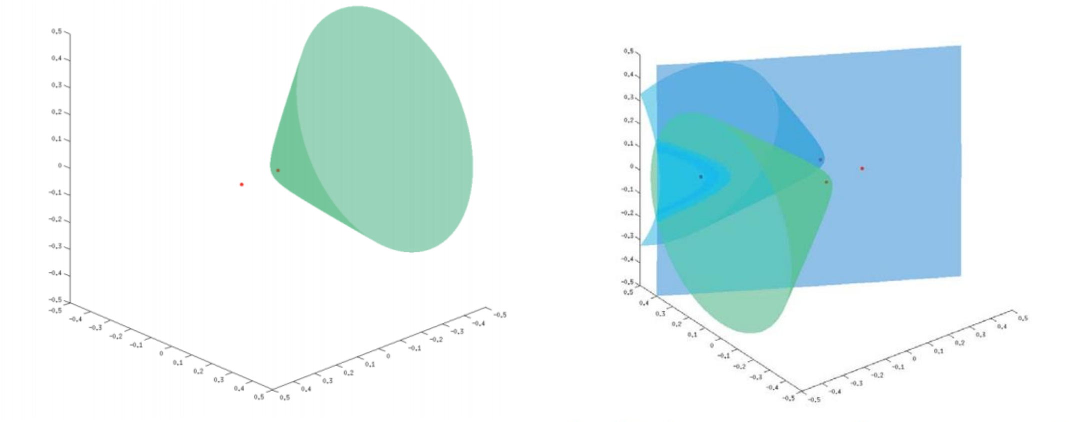


Figure 2.3: Solution space in $\mathbb{R}^3$ (green), for two microphones (red)   Figure 6.1: Array microphones in red, intersection point in blue

Figure 7 : sound source localization with TDOA methods from [11]

In [10], the tetrahedral shape acoustic array is upgraded to seven microphones to increase the frequency range and localization accuracy. In [8] two arrays of tetrahedron-shaped microphones are used to ensure accurate localization in 3D space.
The regular movement of the UAV can also be used to improve its localization knowing that at succeeding time window analysis, the localization is close. [8] proposes a new TDOA algorithm based on the Gaussian prior probability density function which mainly makes use of the relevance of the TDOA estimation results for a flying drone between time k and time k−1 with the peak of cross-correlation function at time k will appear near the peak of one at time k − 1. The results are improved but at larger distance (80-100 m) and on large incident angle, the error range is quickly increasing.
The second family groups maximum energy methods with mainly the usual beamforming method. It can be applied in time or frequency domains. The second one is at higher computation cost with Fast Fourier Transformations but allows a frequency selection where the source of interest emits noise. Thus, the energy of undesirable frequencies coming from other sources is attenuated and therefore the Signal-to-Noise Ratio (SNR) is improved. The method to select the frequency range of interest is manually set-up in most of the experiments. [23,6] propose to identify the harmonics of the rotor blades and focuses localization algorithms on those ones.
In [17], localization is performed with an original method estimating the pressure and the particle velocity components on two orthogonal axis at the center of the microphone array from multiple microphone pairs. A Chinese patent from its abstract seems to use the same approach [19].
Blanchard in [6] compares beamforming to the previous TDOA methods using a dedicated ten microphone array distributed over three arms. The low accuracy of the GPS for the outdoor case did not allow to evaluate the actual performances of the methods while the results are good consistent between TDOA (goniometry) and beamforming (namded “TFDSB”) referring Figure 8.

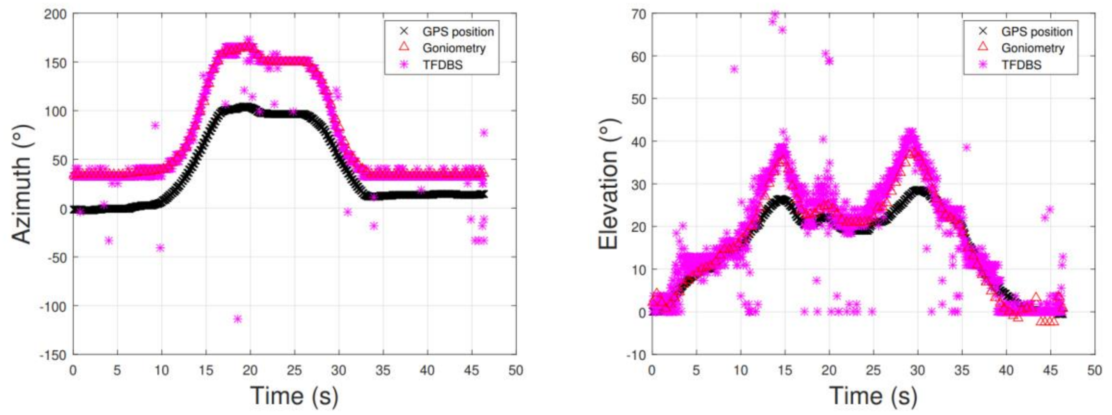


Figure 11: Results of the localization estimation of the drone using the TFDSB algorithm (magenta) with 4 harmonics selected and the acoustic goniometry method (red) for the outdoor measurement conditions in azimuth (left) and elevation (right).

Figure 8 : trajectory comparison between TDOA (goniometry) and beamforming (TFDSB) from [6]

Beamforming is also successfully used in [5] determining that drones can be tracked from 160 to 250 meters.

The last category groups high resolution methods. MUSIC (MUltiple SIgnal Classification) has been early applied in [23] with good results. But those methods are sensitive to correlated sources and low Signal-to-noise ratio. In the publication they indicate that wind speed is below 5 knots. [8] criticizes this method with "*very low accuracy and fails to track the target*". No other publication refers to this type of method.

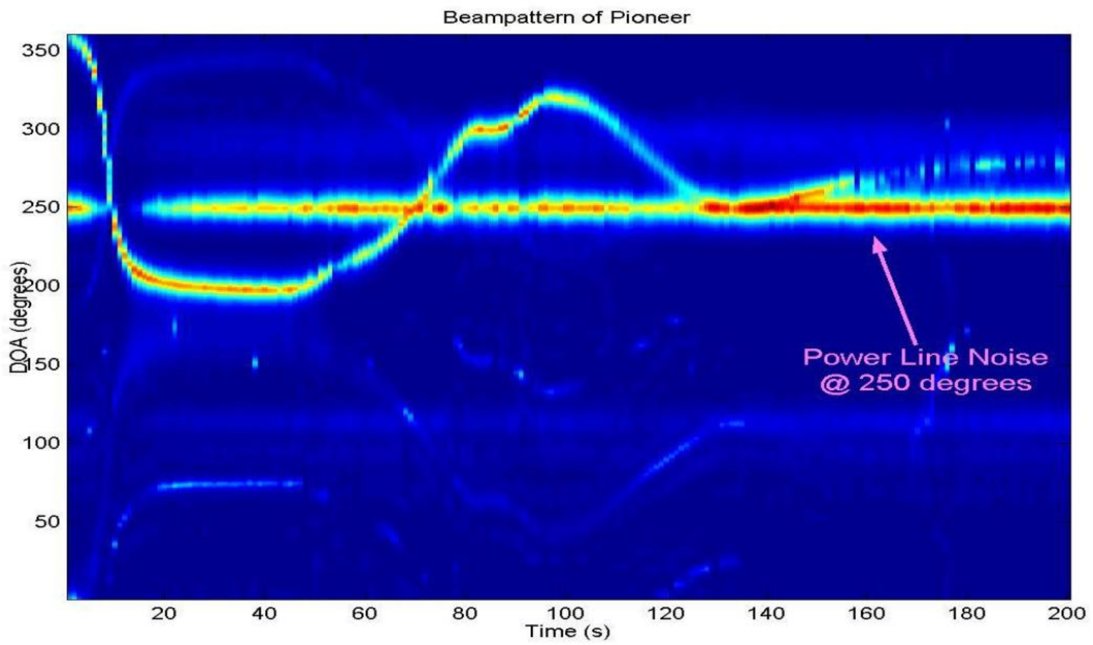


Fig. 4: Pseudo-spectrogram (DOA estimates vs. time) of a low-flying, medium-size, gasoline-engine tactical UAV.

Figure 9 : trajectory with MUSIC method from [23]

3.3 Trajectory

Whereas a microphone array usually provides only angular position, using the combined output of several arrays enables to obtain the source distance. This triangulation problem can be solved by different algorithms. It implies technical constraint to ensure the signal synchronisation between several data recording systems and their accurate relative position. A calibration procedure is proposed in [7] using TDOA.

Kalman filters are used in several publications to reconstruct the drone trajectory to obtain continuous trajectory from discretized position [8, 18]. This filter is widely used in tracking problems because of good real-time and low computational complexity. A method for reconstructing trajectories of multiple simultaneously flying quadcopter drones from microphone array measurements is presented in [18]. The method was tested in an anechoic chamber with up to four UAS flying at the same time in five different flight scenarios.
[9] provides an original algorithm using the total least square estimate of the target trajectory combining beamforming and Doppler effect evolution over harmonics emitted by propellers but under the assumption of constant target height, direction, and speed.

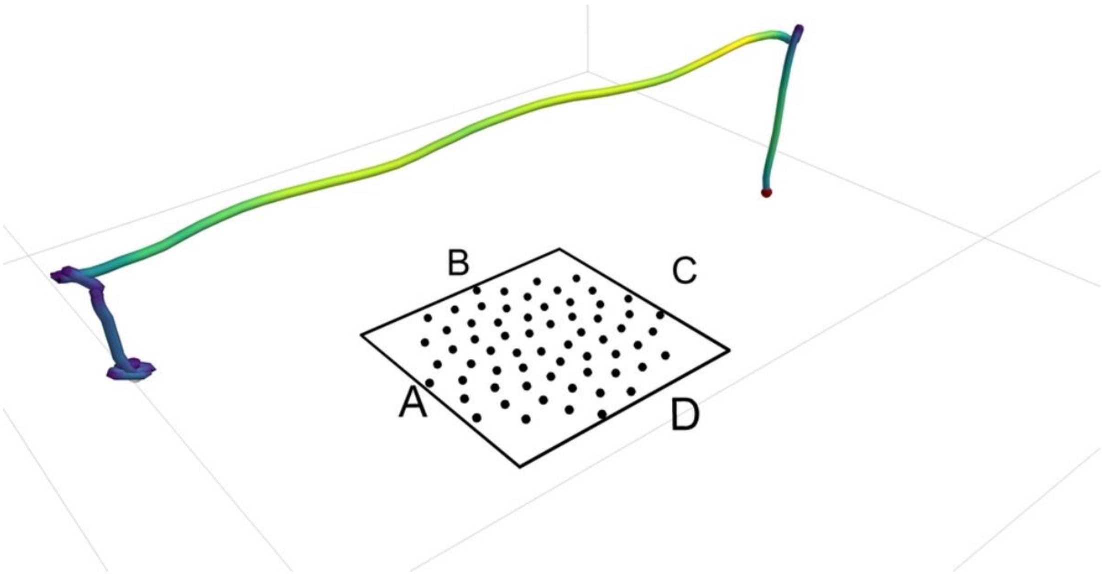


Figure 7: Scenario 1: Single drone flying from FATO A to FATO C.

Figure 10 : trajectory reconstruction with speed level indicating by colours from [18]

The output of the sound source localization algorithm can be processed exactly as traditional mono-channel signals for the case of beamforming. This class of algorithm presents an advantage compared to other ones which cannot reconstruct the “denoised” acoustic signature of the UAV acoustic source. The focused signal presents better signal-to-noise ratio than single microphone recording and as a consequence it will bring better performance in the identification step.

3.4 Identification

Features for acoustic characteristics

While the previous “detection” processing allows to localize a moving sound source like a UAV, the identification processing recognizes this sound source in the audio scene as a UAV by its acoustic signature. The identification is performed by comparing the similarities on selected features between the detected sound source and values in a database from UAV recording and other environmental noises in training stage. The intelligent machine listening systems identifies acoustic sources similar to human listeners. This technology has been widely used for speech recognition based on machine learning well known as Automatic Speech Recognition (ASR). Many academic works try to apply similar methodologies for acoustic scene classification, with among them an application for drone identification [12,13].
When detecting human speech the three most used techniques are linear predictive coding (LPC), Mel-Frequency Cepstral Coefficients (MFCCs) and perceptual linear predictive (PLP) analysis. MFCC and PLP analysis are both based on how humans perceive sound. The methods could therefore be unsuitable for identifying UAV. LPC requires the analysed sounds to have spikes in the spectral envelop as human speech does. The acoustic signature of UAV presented

in the first chapter showed similarities to human speech with harmonics, which made LPC a possibility used in [13]. The zero crossing rate which counts the average number of times where the audio signal changes its sign within the short-time window useful for voiced sub-frame has not met the same efficiency for UAV identification.
Among features based on the spectral content of the UAV signature, it is also commonly used Spectral Centroid and Spectral roll-off which represent the balancing point of audio spectrum and the frequency below which a certain amount of the spectral energy is concentrated, respectively [15].
Other features relate to the energy of the signal. The slope of the frequency spectrum is used in [13]. In [15], the Short Time Energy provides a measure of the energy variations of the environmental sound over time.
In [16], 32 features are computed over three different domains: the temporal, spectral and cepstral domains. They describe the input signals by means of statistical oriented, entropy oriented or shape oriented descriptors maximising the success of classification.
[12] introduces the use of correlation to identify a drone from its sound emission. With the help of correlation, the tightness of the relationship between two sets of data can be given.
Those previously described features are calculated on small time window describing the perceptual physical property of the audio frame for UAV source of interest and other environmental sources. Then those ones can directly be aggregated into global vector or statistically processed on a mid-term time window to reduce variability sensitivity [15]. This task allows to look into long-term dependencies with statistical, polynomial, regression and transformations functions applied to the instantaneous features. For example in [14], to classify an acoustic scene, the model needs to initially compute all the events happening during the scene, followed by identifying the relationship between those events to make the final prediction.
An original approach of machine learning has been patented [20] working on the difference of acoustic signature between two manoeuvres (stationary, moving, changing direction) types to identify the UAV. The acoustic signature delta may be correlated with acoustic signature deltas of various types of UAVs.

Classifier for UAV

The UAV classification problem can be addressed formulating a multiclass environmental audio recognition problem using preceding features. A SVM (Support Vector Machine) based classifier is usually trained for estimating the multidimensional audio descriptors [15,16]. The "one against all" and the "one against one" are the two most popular strategies for multi-class SVM. The first one consists of building one SVM per class, trained to distinguish the samples in a single class from the samples in all remaining classes while the "one against one" builds one SVM for each pair of classes. In any case, a labelled training data set is required to implement a SVM. In [16], two different learning models are tested: the first one uses two classes : UAV and noise, with a classic SVM model while the second one is based on an One Class Support Vector Machine algorithm where only the UAV class is learned. In [15], the "one against one" strategy is adopted. A boundary is defined by the hyperplan that separates the two classes with a maximum margin. The classification accuracy is given by the ratio of number of correct predictions to the total number of samples in the dataset. Identification results on the tested database in [15,16] give accuracies over 95 % for the two or one classes approaches. It is also pointed out that this high accuracy is reached thanks to the intrinsic separability of the created data obtained by the different features that have been chosen to compute.
[14,28] explore the use of Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) to detect the presence of multi-drone. [14] uses hand engineered features extracted from large-scale feature extraction schemes as inputs to Deep Neural Networks. [28] uses the most popular combination of feature and classification Mel-frequency Cepstrum Coefficients (MFCC) with the Gaussian Mixture Model (GMM). In both works, custom datasets were collected for different classes: multiple drone detection which includes background noise, a single drone in

the scene and two drones in the scene. The results in [14] prove that large-scale extraction schemes with Deep Neural Network or CNN with Spectrograms are possible with limited availability of data. [28] concludes from their experiments that the RNN model showed the best score. Both agree with the use of data augmentation to synthesize raw drone sound with diverse background sounds to alleviate the shortage of drone training data

In the state of the art, a Chinese patent [19] also relates to “a UAV positioning system based on a vector detecting unit”, with “*the following steps: training a UAV recognition model to obtain a trained UAV recognition model; allowing a vector detecting unit to acquire an ambient sound vector signal of a detection area; preprocessing the sound vector signal acquired by the vector detecting unit*.”

3.5 Strategy

This section is interested into the implementation of the preceding technologies into industrial tools.

Some patents relate to the use of acoustic sensor for UAV detection combined with other sensors without detailing the technology envisaged with acoustic sensors [21, 26].

In [22], they apply the TDOA using a small array of microphones located on board an UAV or aircraft to characterise the temporal variation of the received tone of an approaching aircraft/UAV and estimate its propeller blade rate (and hence type), together with its speed, time and distance to the point of closest approach. This work is interesting by the fact that the acoustic sensors and processing are envisaged to be embedded on UAV but requiring to maximise effectiveness of the adaptive cancellation techniques of the own UAV noise embedded the array.

In [17] and [10], a network of compact microphone arrays is used to detect and localize a potential target in real time, and the 3D DOA of this potential target is then transferred to an optical system for a multi-modal audio/video accurate identification. First, spatial filtering is achieved using differential beamforming to focus the array on four principal directions in order to enhance the initial detection. Then, the video system with a limited view angle is oriented towards the target before triggering the tracking.

In [24], DroneShield details their patented technology based on audio. They use the difference of spectral content between time sample with and without flying UAV to detect a drone. They identify it using matching between background/UAV combination database from the spectral density. This company commercializes their solution with an acoustic sensor which is an omnidirectional microphone or one mounted on parabolic structure to focus on target and to improve SNR. With this last solution, [25] indicates detection for distance up to 100-250 m in Urban environment, 250-500 m in Suburban environment, and 500-1000 m in rural environment which coincide with the signal-to-noise analysis done in section 1.

In [27], SquareHead technology details their patented technology associating video and audio sensors with a commercialized solution named “Discovair”. They use differential beamforming map associated to video for detection and machine learning for identification/classification.

4. Conclusions

Many academics works are dealing with UAV detection/identification and classification from acoustic sensors since 2015. China, Europe, US mostly published. The maturity of the published technologies does not permit to have commercial solutions answering to the complete market requirements defined in the first chapter.

The foreseen solution is based on a first detection stage which would localize the sound sources in 360° soundscape. It requires multi-microphone arrays of few sensors if TDOA processing is applied or more microphones if other methods are preferred. The processing has to be real time, preferably without human actions. Nevertheless, the automatization of the source extraction in the space and in the frequency spectrum with the best SNR needs to develop artificial intelligence on that topics. First approaches have been investigated with harmonics extraction, trajectory coherence. The second stage is to apply machine learning for UAV sound recognition. The selection of the right features and good training are the success keys before any neural network methodology. The SVM is preferred to deep neural network due to the few available data. There are few academic works working on both stage detection/identification processing. Anyway the complete processing has to be evaluated together to optimize it.

The experiments meet several difficulties. The GPS technology is not an easy task to retrieve the right trajectory limiting the evaluation of results. UAV flying requires authorization, and large area for test over 200 m. The UAV database are usually limited to few quadcopters. It leads to limited experiments usually not realistic. When system are then tested with true scenario, they failed to cope with the customer requirements. UAS detection must be sensitive enough to detect all drones operating within the area of use, but systems that are too sensitive may create an overwhelming number of false positives, rendering the system unusable. Systems that aren't sensitive enough might generate false negatives, which is even less desirable from the operator's standpoint.

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