

A Study on the Methods and Technologies Used for Detection, Localization, and Tracking of LSS UASs

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Abstract—The current paper presents a study on the methods and technologies used for detection, localization and tracking of LSS (low, slow and small) UASs (unmanned aerial systems). Due to the increasing number of incidents with such threats, different approaches have been studied and implemented in the last few years. This paper aims to review current methods and technologies used.

Index Terms—UAS detection, localization and tracking, LSS UASs.

I. INTRODUCTION

Drones, known as unmanned aerial vehicles (UAVs), are aircraft without a human pilot aboard.

“UAVs are a component of an unmanned aircraft system (UAS); which include a UAV, a ground-based controller, and a system of communications between the two. The flight of UAVs may operate with various degrees of autonomy: either under remote control by a human operator or autonomously by onboard computers” [1].

The devices – which are both readily available and easy to fly – provide ample opportunity for misuse.

The rapid evolution of low-cost, highly capable drones presents a new set of challenges. Whether the operator is a negligent hobbyist or an agent intent on a malevolent act, an undetected drone can pose a significant safety or security threat [2].

Detection of LSSUAS is quickly becoming an important capability for the maintenance of security. Consumer grade LSS UASs are becoming increasingly complex, and represent a diverse new threat which must be addressed by physical security systems of the future. This report surveys the existing landscape of technological solutions developed, or currently in development, to address the safety and security risks posed by LSS UASs [3].

“In recent years there have been numerous safety and security incidents with UAVs which prompted an increase in research of surveillance and interdiction methods tailored for UAVs” [4].

Being hard to detect and capable of carrying payloads up to a few kilograms, drones can represent a real threat. “Safety and efficiency of future air traffic management relies on adapting to major emerging challenges that small UASs pose. Small UAS have developed to the point that they can carry several pound payloads automatically to any destination within ranges up to 10 miles, at the push of a button, out of the box” [5].

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Figure 1. Different payloads that can be mounted on a drone [6]

Recent work has sought to develop drone detection systems that include microphone, camera, or radar to sense the presence of drones. Each approach has its own limitations.

II. DETECTION TECHNOLOGIES

At the moment there is no such system which could offer a 100% detection and protection against drones. In order to increase the rate of detection different detection techniques have to be implemented simultaneously in the same system.

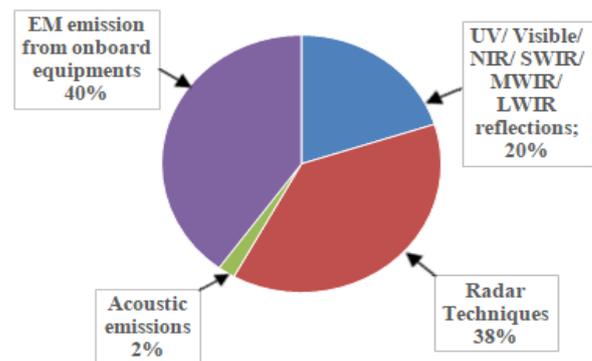


Figure 2. Popularity of techniques and approaches used for detection and tracking [3]

Several phenomenology can be used to detect and identify a LSS UAS [3]. These include:

- Reflectance of UV/Visible/NIR/SWIR/MWIR/LWIR photons;
- Reflectance of a particular photon polarization state;
- Radar reflectance;
- Acoustic emission;
- Electromagnetic emission from onboard radios, WiFi, altimeters, radar, or other communication links;
- Induced magnetic field.

Commercially available UAVs continue to grow in capability, with a variety of systems available for purchase from consumer RC aircraft sites.

Three types of UAVs are taken into consideration when talking about LSS targets. The three types are presented below. Each type present different characteristics in respect with detection and tracking.

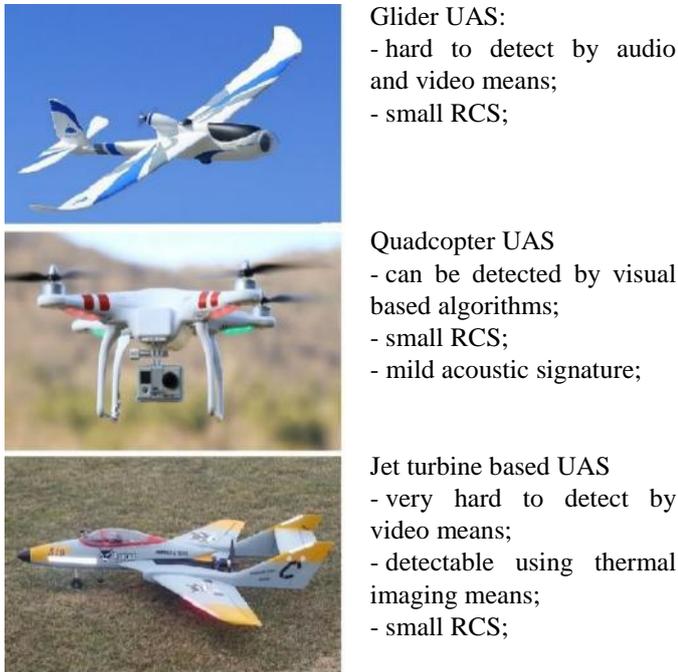


Figure 3. Glider, quadcopter, and Jet turbine UAVs [3]

The ability to detect these UASs with conventional technologies is summarized in Table I, where green, yellow, and red indicators represent good, mild, and poor detection performance, respectively [3].

TABLE I. ABILITY TO DETECT TYPICAL UAS TYPES BASED ON CONVENTIONAL [3]

Detection scheme	Glider	Quadcopter	Jet
Radar	Red	Yellow	Red
Passive optics (i.e., cameras)	Yellow	Yellow	Red
Active optics (i.e., LIDAR)	Yellow	Yellow	Red
Acoustics	Red	Yellow	Yellow
EM emissions	Yellow	Yellow	Red
B-field detection	Red	Red	Red

The lack of green indicators for all UAS types is supported by the findings of the NATO studies, namely that multiple detection technologies must be integrated or fused into a single detection/classification architecture to ensure higher probability of detection. [3]

A. Visual means for detection and tracking

The detection and tracking of UAVs can be made either using video cameras or using equipment that do not use video processing algorithms (techniques that use laser diffusion, etc.). Up next, only the first category is analyzed.

The most advanced video processing techniques that use frames of images utilise algorithms of detection for interest points that are invariant when different transformation is applied (scaling transformation, etc.).

Interest point is a recent terminology in computer vision that refers to finding the points in an image that can be detected and are relevant for higher level processing [6].

Scale invariant image descriptions have been studied since the late 1970s. Burt [8] proposed a rapid algorithm to compute a multi-scale Laplacian pyramid. Crowley [9] proposed a scale invariant algorithm for the Laplacian pyramid and showed that such representations could be used to compute scale invariant image descriptions composed of peaks (scale invariant interest points) and ridges. Lowe adopted scale invariant peaks in the Laplacian Pyramid as the basis for a Scale Invariant Feature Transform (SIFT) [10]. This operation is now widely used in image matching, tracking and object categorization [11].

Another way to do this is using HOG descriptors. “The technique counts occurrences of gradient orientation in localized portions of an image. This method is similar to that of edge orientation histograms, scale-invariant feature transform descriptors, and shape contexts” [12].

Convolutional neural networks are also used as classifiers. “CNN are deep artificial neural networks that are used primarily to classify images (e.g. name what they see), cluster them by similarity (photo search), and perform object recognition within scenes. They are algorithms that can identify faces, individuals, street signs, tumors, platypuses and many other aspects of visual data. Convolutional networks perform optical character recognition (OCR) to digitize text and make natural-language processing possible on analog and hand-written documents, where the images are symbols to be transcribed. CNNs can also be applied to sound when it is represented visually as a spectrogram. More recently, convolutional networks have been applied directly to text analytics as well as graph data with graph convolutional networks. The efficacy of convolutional nets (ConvNets or CNNs) in image recognition is one of the main reasons why the world has woken up to the efficacy of deep learning. They are powering major advances in computer vision (CV), which has obvious applications for self-driving cars, robotics, drones, security, medical diagnoses, and treatments for the visually impaired” [13].

As an alternative (to not face the problem of working with such large number of regions), Ross Girshick et al. proposed a new method called R-CNN (regional-CNN) [14].

Same authors from [14] managed to build a faster detection algorithm called Fast R-CNN [15].

They suggested a similar approach like the one presented in [14]. Both algorithms presented in [14-15] use selective search to find out the region proposals. A common drawback of both algorithms is that this search is slow and is time-consuming process affecting the performance of the system. Therefore, Shaoqing Ren et al. [16] came up with an object detection algorithm that eliminates the selective search algorithm and lets the network learn the region proposals [17].

Multi-Domain Networks (MDNet) are also used for detection.

The performances of systems that use Faster R-CNN and MDNet can be seen in Fig. 3.

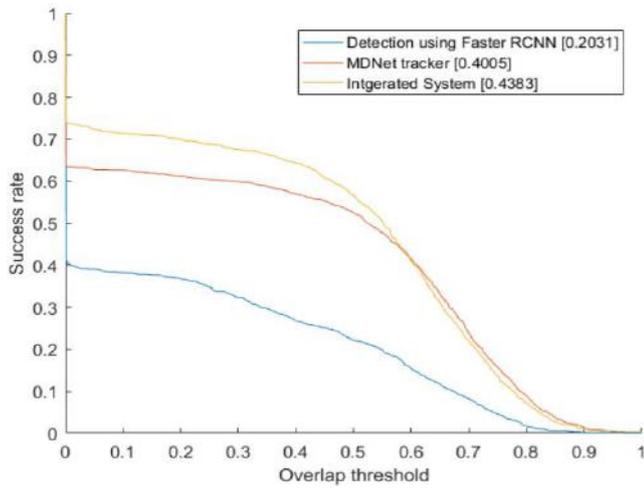


Figure 3. Performances of systems that use Faster R-CNN vs MDNet [16]

The authors from [18] demonstrated the possibilities of using thermal cameras for detection and tracking.

They concluded that:

- small electrically powered multirotor UAVs can be detected with low-cost thermal sensor in some conditions;
- main source of heat are batteries, not motors;
- maximum range of detection is shorter than calculations assume.

B. Radar based techniques

The radar-based techniques and technologies will be analyzed in this part of the article.

In order to be detected by the radar, the signals have to be strong enough comparing to the noise. The signal to noise-ratio (SNR) is a key factor when talking about LSS targets detection. This is illustrated in Fig. 4.

For UAV detection and tracking, the SNR needs to be greater than 15 dB in order to provide detection with acceptable false alarm rate.

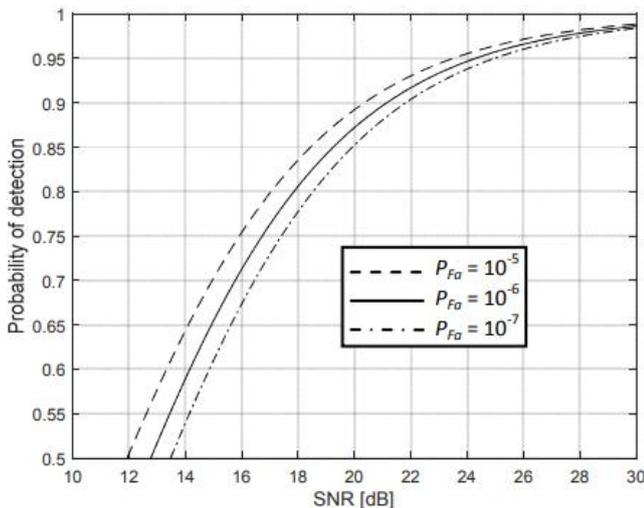


Figure 4. Probability of detection in respect to signal to noise ratio [19]

Among the studies presented at the specialist conferences we can find:

- the analysis of small RCS target detection in primary radar system; [20]
- a probabilistic early collision warning scheme for UAVs in 3D space; [21]

- a ground-based multi-sensor system for autonomous landing of a fixed wing UAV; [22]
- 35 GHz FMCW drone detection system; [23]
- NLOS radars;
- etc.

Millimetric wave radars are ideal for close range detection when visibility is low. Large bandwidths ensure good range resolution. The majority of millimetric wave radars use the frequency-modulated continuous-wave technique (FMCW).

In [23] is presented a detection based on FMCW radars.

The results of the systems presented in [23] can be seen in Table II and Fig. 5.

TABLE II. 35 GHz FMCW RADAR PERFORMANCES [23]

P [W]	τ [s]	R [m]	Vmax [m/s]
0.02	0.1	8.1	15
0.02	0.04	6.4	37.5
2	0.1	25.5	15
2	0.04	20.3	37.5

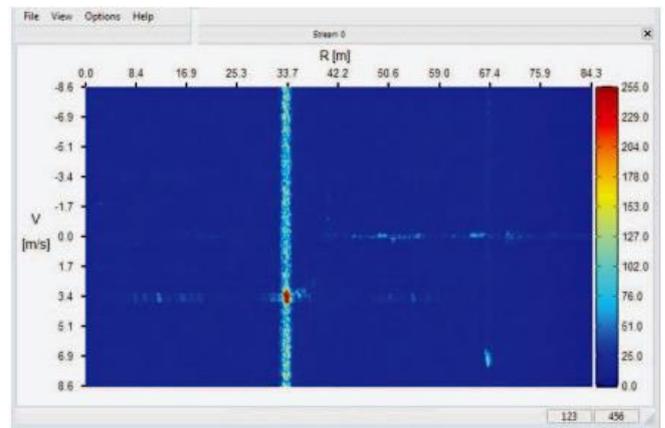


Figure 5. 35 GHz FMCW radar performances [23]

Another millimetric wave radar was presented in [24]. Here, the authors used a W-band radar for detection of small UASs.

In [25] the authors studied the possibility of using UWB radars in C band.

The authors from [26] demonstrated that is possible to detect small UAVs with payload from 300 g and above from distances between 1 and 2 kilometers using a Ku band radar.

C. Acoustic emissions for detection and tracking

Another way of detecting and classifying UASs can be made by using acoustic sensors that can detect a UAV from 20 m up to 600 m.

The main sources of acoustic waves are the propellers and the motors.

Acoustic detection can be completely passive and relatively cheap. The detection can be influenced by bad weather conditions such as strong wind or noisy areas.

In [27-28] arrays of microphones were used to detect drones. In [28], the authors studied the performances of a 120 microphones array. Different types of drones were tested. The range of detection was reported to be between 150 and 290 meters.

Acoustic cameras are also used for detecting small UAVs. An example of acoustic image can be seen in Fig. 6.

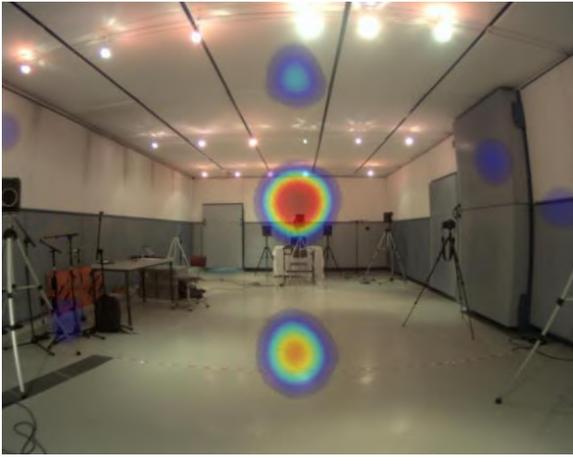


Figure 6. Acoustic image example [28]

The performances of the system presented in [28] can be seen in Table III.

TABLE III. ACOUSTIC CAMERAS PERFORMANCES PRESENTED IN [28]

Drone model	Maximum range of detection
Parrot AR Drone 2.0	150 m
DJI Phantom2	290 m
DJI Flamewheel F450	160 m

The precision of the system is represented in Fig. 7.

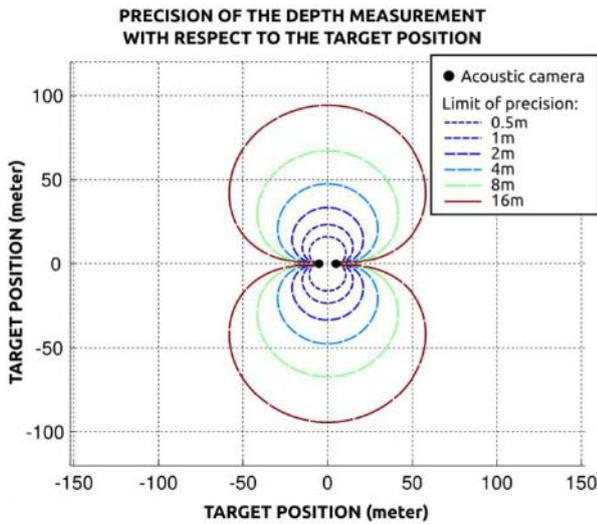


Figure 7. Acoustic camera precision [28]



Figure 8. Detecting a drone [28]

Authors of [29] implemented machine learning techniques alongside acoustic sensors.

The performances of the system developed in [27] are represented below.

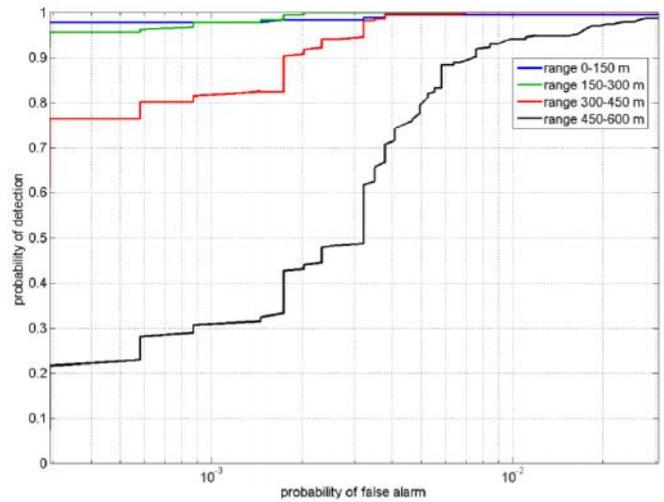


Figure 9. Probability of detection in respect with probability of false alarm [27]

D. Other methods

In this part of the article other methods will be presented.

One method for detecting, locating and tracking UAVs is eavesdropping on the communication between drone and its controller. In order to do this, one needs to fully understand the uplink and download to and from drone.

Another way of detecting drones is by analyzing micro doppler signatures. In [2] is presented a system capable of detecting the presence of a drone by identifying its unique signature in the reflecting signal caused by the body vibration of the drones. The authors demonstrated that every drone's body vibrates with a specific frequency. The vibrations are caused by the rotation of the propellers. The authors demonstrated that the detection is made with high probability of detection. The performances of the system can be seen in Fig. 10 and Fig. 11.

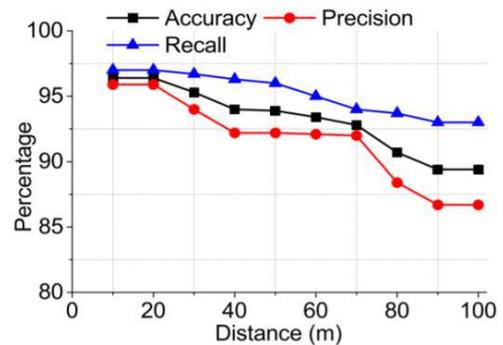


Figure 10. Precision and accuracy for distances up to 100 m [2]

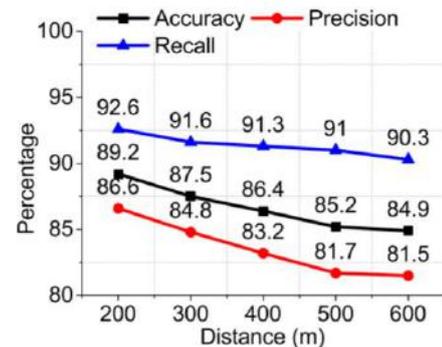


Figure 11. Precision and accuracy for distances from 200 to 600 m [2]

Classification is performed with the percentages presented in Fig. 12.



Figure 12. Classification performances [2]

There are three basic properties of electromagnetic wave propagation that can be measured and used for position estimation: [29]

- the propagation direction, measured as the Angle of Arrival (AOA) at the receiver;
- the propagation attenuation, measured as the Received Signal Strength (RSS);
- the propagation delay, measured as the Time of Arrival (TOA).

The values of these properties as measured by the receiver depend on the position of the receiver relative to the transmitter. This dependency can be used for position estimation. [30]

III. CONCLUSIONS

This paper had the purpose to review the current methods and technologies used for detection, localization and tracking of LSS UAVs.

In order to increase the rate of detection, different techniques and methods need to be implemented simultaneously in the same system.

The results presented in this paper can help scientists in the process of studying and developing drone detection systems.

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