

# Stevens Drone Detection Acoustic System and Experiments in Acoustics UAV Tracking

Alexander Sedunov  
STAR Center  
Stevens Institute of Technology  
Hoboken, NJ  
asedunov@stevens.edu

Darren Haddad  
AFRL  
Rome, NJ

Hady Salloum  
STAR Center  
Stevens Institute of Technology  
Hoboken, NJ  
hsalloum@stevens.edu

Alexander Sutin  
STAR Center  
Stevens Institute of Technology  
Hoboken, NJ  
asutin@stevens.edu

Nikolay Sedunov  
STAR Center  
Stevens Institute of Technology  
Hoboken, NJ  
nsednov@stevens.edu

Alexander Yakubovskiy  
STAR Center  
Stevens Institute of Technology  
Hoboken, NJ  
ayakubov@stevens.edu

**Abstract**— Concerns about improper use of Unmanned Aerial Vehicles (UAVs, also unmanned aerial systems or UAS) led to the development of various methods for their detection, tracking, and classification. One of the methods is using acoustics. Advantages of passive acoustics include the low cost of acoustic systems, finding of the Direction of Arrival (DOA) and localization by simple means; and classification of UAV sounds by acoustic signature. Stevens Institute of Technology has developed and built the Drone Acoustic Detection System (DADS) that can detect, track and classify UAVs based on the propeller noise. The system consists of three or more microphone nodes. The microphones in each node are arranged in a tetrahedron with configurable size. The microphone data is transferred over WiFi in real-time to a central computer, where it is processed. The Stevens DADS system was investigated in numerous field tests together with several other directional arrays including a 16-channel two-tier cross array, the OptiNav 40-microphone phased array, and parabolic and shot gun microphones. Multirotor UAVs of different sizes were employed in testing, including DJI models Phantom 4, M600 and S1000. The test results of the different systems were compared.

**Keywords**— *signal processing, passive acoustics, UAV detection tracking, and classification.*

## I. INTRODUCTION

In this paper, we consider acoustic methods for detection, tracking and classification of Unmanned Aerial Vehicles (UAV). In many cases, the term Unmanned Aerial System (UAS) is used, but this term is used to describe the whole system including the UAV and ground controller.

Improper use of UASs leads to many potential concerns: collisions with other aircraft, invasion of privacy, and delivery of harmful payloads. As a result, methods and systems to monitor the aerial activity of small aerial vehicles are needed. Among the explored approaches are visible light and infrared

sensors, radar-based sensors, radio frequency monitoring and acoustic methods [1], [2].

There is a significant number of papers investigating UAV acoustic signatures and various aspects of UAV acoustic detection [1]–[10].

Passive acoustics systems in this application have several advantages, mainly the low cost that could be several orders of magnitude less than radar and RF-based systems currently used. Acoustic systems are passive and do not radiate any RF signals; they can be used for UAV classification; and recorded acoustic signatures can be used for the identification of a specific UAV. Acoustic systems allow finding the Direction of Arrival (DOA) and UAV localization by simple means.

The disadvantages of acoustic counter UAV systems include lower detection distances in comparison with other systems. For the majority of COTS counter UAV acoustic systems, the detection range of small UAV does not exceed 300 m, longer detection ranges can be reached using highly directive acoustic arrays that are large and more expensive than systems with few microphones. Detection distances strongly depend on ambient noise and environmental conditions.

This paper presents a description of the Drone Acoustic Detection System (DADS) developed by Stevens Institute of Technology and displays results of UAV acoustic detection tests conducted using various acoustic arrays and directional microphones.

## II. TESTS CONDUCTED

Two field tests for UAV acoustic detection and acoustic signature measurements were conducted at the Stockbridge, NY test facility in June and October 2018 and another test was conducted in Lincoln Park, NJ on June 2019. Recorded data allows extensive study of the UAV sound during flight as well as a demonstration of the DADS capability. The recording was

conducted using multiple passive acoustic sensors exemplifying different approaches to passive acoustic detection of a UAV.

Different UAVs used in the testing included small consumer UAVs: Phantom 4 (1.3 kg), Intel Falcon 8+ (1.2 kg) and the larger filming DJI S1000 (9.6 kg) and M600 (9.6 kg), and the Inspire 2 (3.4 kg). Multiple tests were conducted demonstrating different target motion and exploring distances. Noise levels were measured in-between tests.

We also conducted tests with simulated UAV sounds using an acoustic emitter radiating real UAV sounds decreasing with time that imitates the UAV flying away from the detection system. The collected acoustic signatures combined with emitted sound level measurements conducted in the anechoic chamber [10] have been applied to create a realistic UAV sound simulator based on the emission of the sound from a speaker raised on a mast, thus replicating levels and propagation geometry.

### III. DRONE ACOUSTIC DETECTION SYSTEM

Stevens Institute of Technology developed and built the Drone Acoustic Detection System. Fig. 1a shows a single node DADS that can detect and find the direction towards a UAV based on the propeller noise. Audio data can be used to classify the signature, and multiple nodes provide localization of a UAV in real-time. The system consists of three nodes. The digitized acoustic signals from all microphones are wirelessly sent to the central computer where the signal processing for UAV detection, tracking and classification is conducted.

The portable DADS node providing real-time signal processing is shown in Fig. 1a. This system has custom-built microphones that internally consist of 15 microphone capsules (Fig. 1b). Similar construction was previously developed at Stevens for reliable and sensitive microphones that were used in the acoustic system for low flying aircraft detection [11]. The portable DADS acoustic node was designed to be compact and have low power consumption to allow the use of solar panels. It collects data from 4 microphones with custom preamplifiers using NI-9238 module in NI cDAQ-9191 chassis capable of 24 bit and up to 50 kS/s. The data is transferred to a processing computer where the data is processed, displayed and stored. Long-range communication is enabled by a high-power radio link such as Ubiquity NanoStation AC loco 5 GHz. The microphones are arranged in a tetrahedron with configurable size (during the tests, the side of the array was chosen to be 53 cm).

The average distance between nodes is 80-120 m. A special program was developed for the prediction of the system performance depending on the node placement configuration (see section III.D). During the initial tests, the DADS was supplemented by recorder nodes, to demonstrate localization in post-processing and what may be possible with multiple DADS nodes in real-time. The real-time processing was demonstrated in recent tests with three DADS nodes.

A Google-Earth-based GUI was developed and employed (see Fig. 2), that put the results of processing into a common operating picture: momentary directions were found with acoustic tracks and classification. This display also shows UAV GPS ground truth from trackers attached to the tested UAV.



Fig. 1. Single node of Drone Acoustic Detection System (DADS) deployed in the field - a, drawing of DADS microphone construction -b. The system consists of three or more nodes.

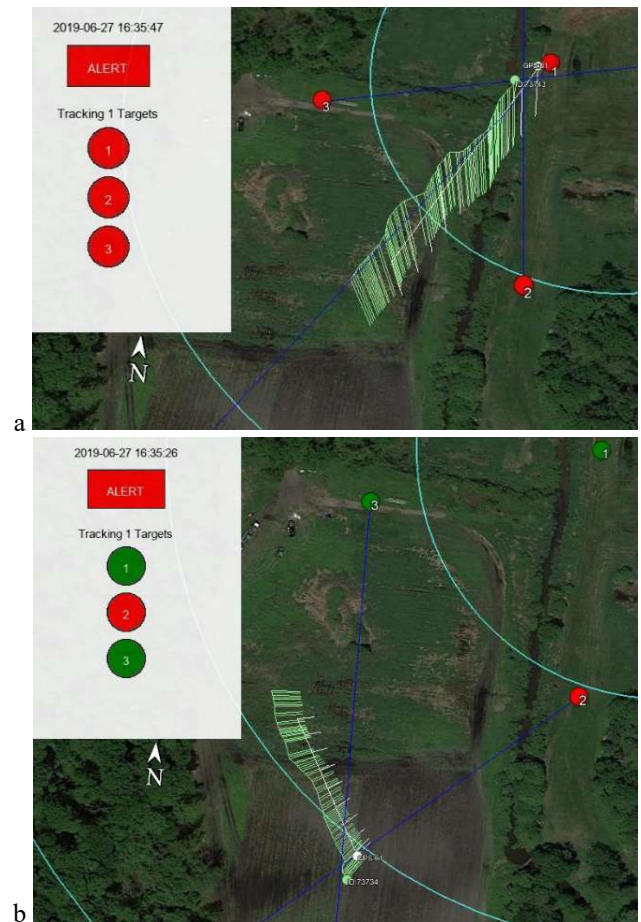


Fig. 2. Drone Acoustic Detection System (DADS) GUI showing common operating picture during the test: 100m range circles – cyan circles, momentary DOA - blue lines, GPS track – white line, acoustic track (target is Inspire 2) – green track, classification shown as circles :red (UAV present) and green (no UAV) labeled as 1,2,3, at DADS location and on dashboard on the left. a- snapshot of GUI, side view, target close, b – target at 200m

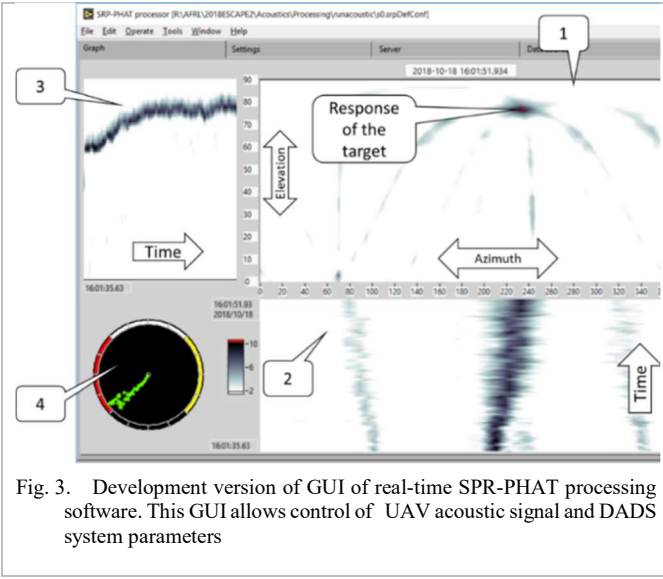


Fig. 3. Development version of GUI of real-time SPR-PHAT processing software. This GUI allows control of UAV acoustic signal and DADS system parameters

#### A. Signal processing for DOA finding

Steered-Response Phase Transform (SRP-PHAT) [12] was used for direction finding. It is based on computing and adding up the GCC-PHAT (Generalized Cross-Correlation Phase Transform) output [13]. It is equivalent to finding steered response power (SRP) in a wide band of traditional filter-and-sum beamformer.

The SRP-PHAT algorithm was implemented in LabVIEW-based software, that permitted real-time processing. The software permits integration by transmitting momentary detections and DOA measurements over TCP/IP.

For visualization and control of UAV acoustic signal and DADS system parameters, we used the version of the DADS GUI shown in Fig.3. The figure displays an example of GUI screenshot showing the angular spectra and current snapshot of the steered response over azimuth and elevation. In Fig. 3. the momentary angular power spectrum (1) shows the steered power response over the range of azimuth and elevation angles for the latest portion of data. Azimuth slice power spectrum (2) shows the history of steered power response SRP over time around the global maximum response for each time, while elevation slice power spectrum (3) shows the SRP history over azimuth (4).

Mathematically, the SRP-PHAT algorithm can be expressed as follows:

$$P(\mathbf{q}) = \sum_{l=1}^N \sum_{k=1}^N R_{l,k}(\Delta_{k,l}),$$

where  $\mathbf{q}$  is the steering vector toward a chosen DOA,  $N$  is the number of microphones,  $R_{l,k}(\cdot)$  is the GCC computed between channels  $l$  and  $k$  and  $\Delta_{k,l}$  is the expected time difference of arrival for a plane wave along the steering vector  $\mathbf{q}$ .

For a few sensors, a wide frequency band and many directions computed, it proves computationally advantageous, as after GCC-PHAT computation it only requires an addition for every possible pair. For DADS it is 6 additions per direction.

#### B. Microphone array orientation calibration

The orientation calibration for the DADS system is performed by emitting white noise from a speaker with a known GPS position for a few minutes, then correcting the orientation based on the difference between the detected direction and one computed from the surveyed GPS locations. This method is more reliable than a magnetic compass in the presence of metal or a strong magnetic field.

#### C. UAV localization and tracking

The placement of the DADS node and the two recorder nodes, separated by 60-120 meters allowed localization of the UAV by triangulation.

Results of tracking a maneuvering target (DJI S1000) during the October 2018 test are shown in Fig. 4. Tracking in 3D demonstrated up to 250 m (limited by the sensor placement geometry) from the furthest sensor and demonstrated good correspondence to the predicted tracking area (blue area in Fig. 4 and Fig. 4). The track in Fig. 4 was acquired in post-processing using data from a DADS node and 2 recorders. The noise level during the test was low (45-50 dBA)

In the June 2019 test, the tracking was demonstrated in real-time using three DADS nodes, as shown in Fig. 5. The target tracked in Fig. 5a is Inspire 2, portions of the same track were shown previously in Fig. 2 demonstrating how it looks in the real-time GUI.

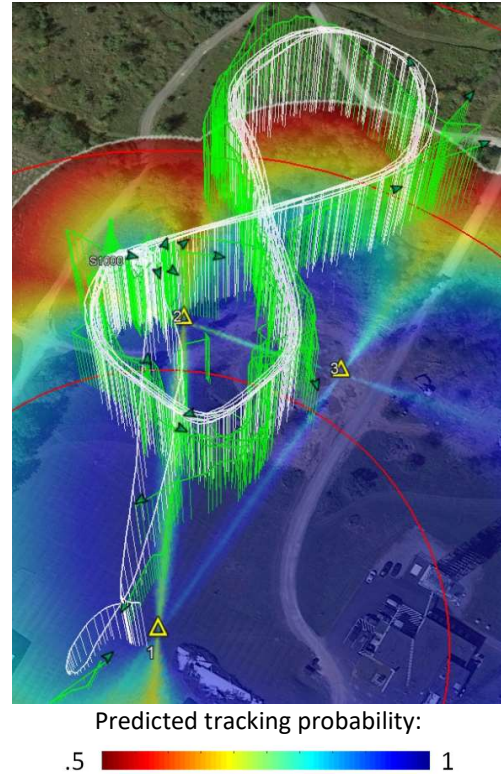


Fig. 4. Deployment schema of the three nodes for tracking, predicted probability of tracking maneuvering UAS (DJI S1000) using multiple nodes, side view. White line – GPS track, green line – acoustic track, yellow triangles- node locations (1- DADS, 2,3 are recorder nodes)



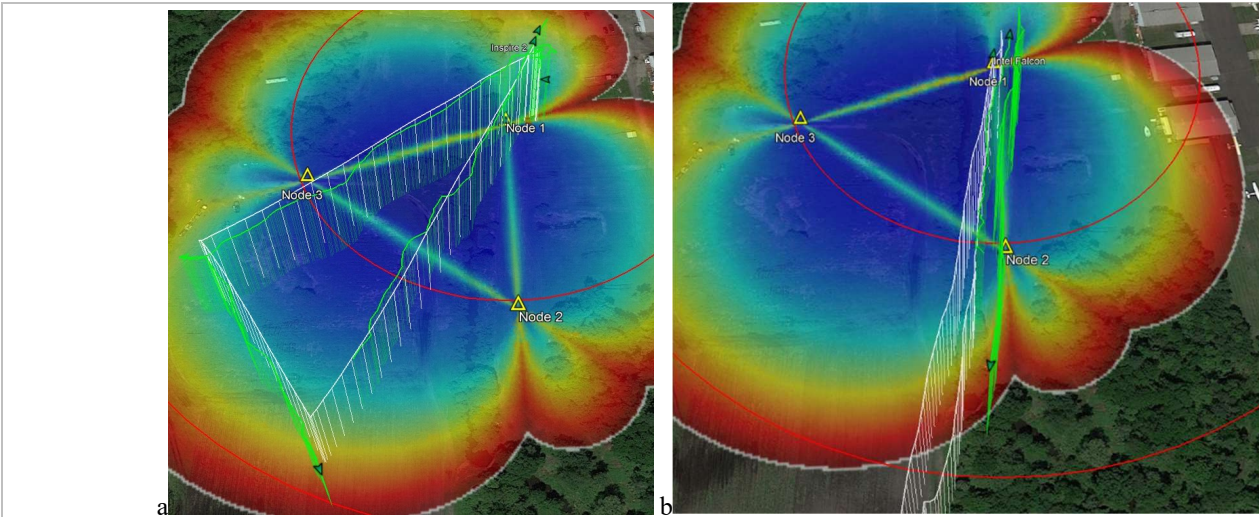


Fig. 5. Tracks during experiment in Lincoln Park airport in June 2019 where the real-time tracking was demonstrated, side view. yellow triangles- node locations (3 DADS nodes)/ White line – GPS track, green line – acoustic track. Tracks shown for Inspire 2 (a) and Intel Falcon 8+ (b).

Tracks are shown up to 200 m, however the noise level during this test was significantly higher (50-60 dBA) due to frequent helicopter activity near.

#### D. Prediction of tracking performance

The principles of localization are analogous to localization of low-flying aircraft as reported in [11], [14], [15]. The probability of establishing a track was predicted based on several parameters: node placement, direction finding probability depending on range and precision for a given target and ambient conditions, and tracker association threshold (set to 30 meters for this application).

The tracking probability distribution is shown in Fig. 5 as a colored overlay, with red showing the probability around 50%, and blue showing probability close to 100%.

#### E. UAV classification

Known published methods of UAS classification [6], [16] are based on the fact that a UAS makes sound with harmonic components (spectral peaks) caused by the motors/propellers rotation.

In real-life scenarios, it is highly likely that other than UAS vehicles (airplanes, helicopters or ground vehicles) may be present on the scene. Such vehicles also have harmonics in the acoustic spectrum, and often with frequencies similar to UAS ones. Another problem is that even a single type of UAS harmonic content of the acoustic signature depends on many factors: speed, maneuvering, load, wind, etc. Thus the known UAS acoustic detection devices with harmonic content-based classification rely on the huge database of acoustic signatures which includes all known types of UAS and all variations of flight regime [8]. That giant database requires constant improvement as new types of UAS come to market, but still cannot guarantee successful discrimination between UAS and non-UAS vehicles [9].

We have developed a novel classification algorithm based on a feature which is unique for the multi-rotor UAS. It is based on the fact that groups of motors in a multi-rotor UAS rotate

with different RPM (Revolutions Per Minute) speed. RPM in UAS' front and rear groups of motors must be different in order to provide a trust force in the horizontal direction. Also, motors RPM has to be different to provide a steady flight or hovering in windy conditions. That feature translates into more than one set of harmonic lines in UAS acoustic signature. On the other hand, the acoustic signature of non-UAS motorized vehicles has only one set of parallel harmonic lines.

Fig. 6 illustrates the aforementioned unique feature. The upper part of the figure shows the propeller RPM variation measured by the UAV controller. There are 2 groups of motors with almost the same RPM as 3 motors within the group, but the RPM is different between the groups. Propellers are two-bladed ( $N_{blades} = 2$ ). Starting from 19:38:10 UTC, the mean RPM in the first group is about 4300, the mean RPM in the second group is about 4700. That corresponds to the fundamental frequencies of

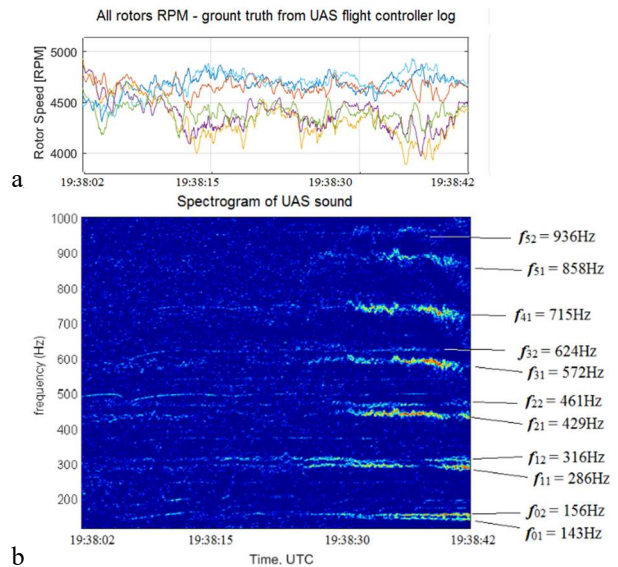


Fig. 6. Alta 6 hexacopter. Rotors RPM (a) and corresponding sound spectrogram (b).

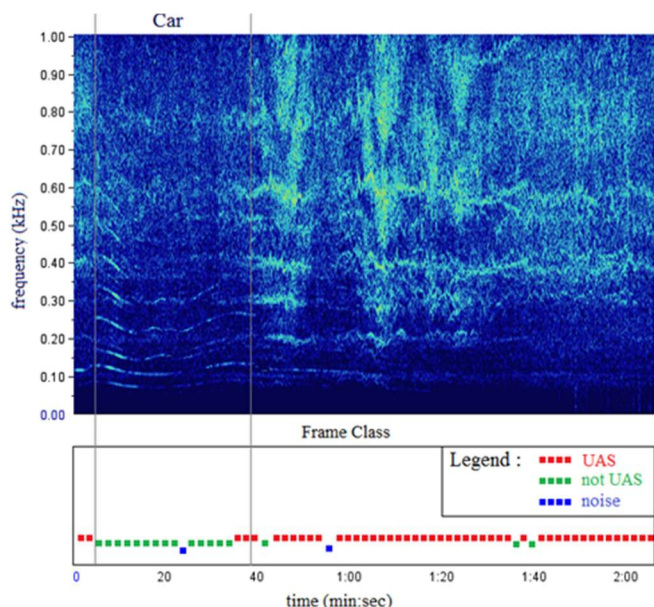


Fig. 7. Results of automatic classification in “UAS and car” scenario.

two sets of harmonics:  $\text{RPM} \cdot N_{\text{blades}} / 60 = f_{01} = 143\text{Hz}$  and  $f_{02} = 156\text{Hz}$  – exactly what we can see in the spectrogram of the acoustic signal.

Our algorithm does not need a database at all. The algorithm detects and traces harmonics in a spectrogram and evaluates if there is more than one set of harmonics. As implemented in software, the algorithm processes an acoustic signal captured into 4-second-long time frames, with 50% frame overlap, and makes an automatic decision for every frame, so that classification decision is updated every 2 seconds. For every time frame, it classifies the detected target into 3 classes: UAS/not UAS/noise. Fig. 7 illustrates the result for the scenario similar to the one shown in Fig. 4: DJI M600 making a figure-eight maneuver near the sensors. Unlike in scenario Fig. 4, a car (F250 pickup truck) is driving close by the acoustic sensor while a UAS is in the air. The algorithm correctly recognized a car as “not UAS”, and recognized the UAS in 47 of 51 time-frames (92%) where a UAS was detectable.

The classification algorithm was tested using acoustic records for scenarios with different types of multi-rotor UAS, small airplanes (Cessna), helicopters (Choucas and Dragon), cars and lawnmowers. Statistically, the algorithm showed 74%

to 97% (depending on Signal-to-Noise Ratio) probability of correct discrimination between the UAS and other vehicles.

#### IV. TEST OF OTHER ACOUSTIC DIRECTIONAL ARRAYS

Several other acoustic systems were used in the conducted tests. The tested equipment consisted of multiple acoustic sensors, including several types of devices: a DADS node, a 16-channel cross two-tier array, acoustic recorder nodes equipped with clusters of five microphones, directional acoustic microphones (parabolic microphones and shotgun microphones), and an acoustic array based on 40 mems microphones.

The acoustic recorders (Fig. 8b) setup consisted of 5 COTS Behringer B-5 microphones, in a pyramid configuration. The sensitivity of the B-5 microphone flat frequency response is between 300Hz and 16 kHz of -40 dBV/Pa within 2 dB. Windscreens were placed on the outside of the microphones. The data was recorded by a Zoom F8 recorder, using the sampling rate of 48 kS/s.

The acoustic two-tier cross array (Fig. 8a) provided the recording of 16 channels for audio from the array elements and an additional channel for GPS signal recorded as an audio. The array had a shape of a two-tier cross, with each tier spanning 3 meters, with pseudo-logarithmic spacing between elements.

A shotgun microphone (Rode NTG8) was connected to a 4K camera and provided a simultaneous sound recording and video from a given direction (Fig. 8d). It was a convenient tool for the UAV acoustic signature recording.

Two parabolic directional microphones were tested: COTS parabolic microphone dish (JonyShot 24") and an in-house made parabolic microphone dish made from an RF antenna (Fig. 8e).

The OptiNav ACAM 120 acoustic camera (Fig. 8c) has 40 digital microphones on a 40 cm x 40 cm plate. It was fitted with a windshield and an interface to the raw data was developed using the provided API. The data was not processed using the software provided by the manufacturer, but rather by in-house developed software, relying on the SRP-PHAT algorithm.

The algorithm used only 10 microphones out of the 40 for direction finding. The identified direction could also be used for steering a conventional beamformer using all 40 microphones (see Fig. 9e).

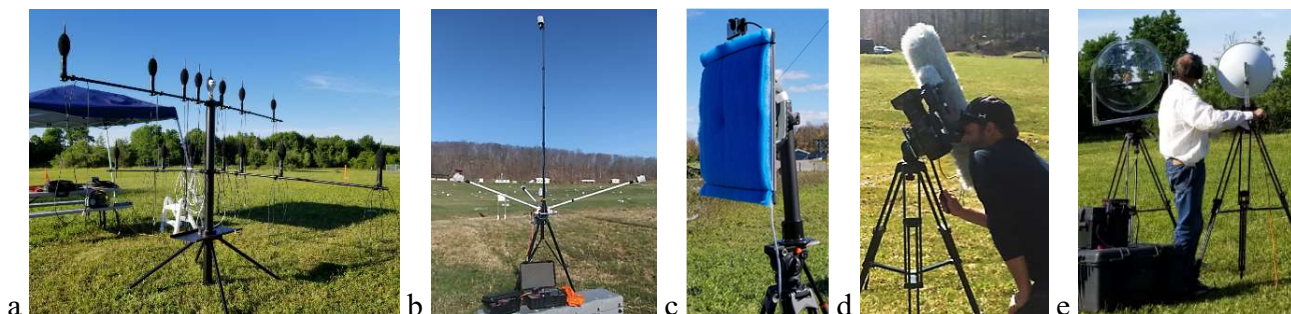


Fig. 8. Tested acoustic system: a-cross array, b- acoustic recorder node, c- OptiNav array, d- camera with a shotgun microphone, e- parabolic microphones.



## V. COMPARISON OF DIRECTIONAL AND OMNIDIRECTIONAL SENSORS

The UAV signature has been observed at a variety of ranges and during the maneuvers. The directional sensors were compared to the collocated omnidirectional microphones as shown in Fig. 9.

The results of using the shotgun microphone are shown in Fig. 9b. This demonstrates improvement relative to the omnidirectional microphone (Fig. 9a). The parabolic dish also shows improvement of the signal to noise ratio Fig. 9b).

Conventional beamforming was tested as a way of enhancing the discernible features of the UAV signature at a longer distance. The results for the cross two-tier array are shown in Fig. 9d.

The directional processing has led to modest gains of  $\approx 3$  dB around 500 Hz. Larger arrays are limited by decorrelation due to turbulence and grating lobes in beam pattern due to the not fully populated microphone array. The smaller arrays have lower directivity in the relevant frequency range (200 Hz-1.7 kHz), while higher frequencies do not propagate far enough due to atmospheric absorption of sound above 1 kHz.

## VI. UAV DETECTION AND DIRECTION-FINDING RESULTS

The detection of a UAV was performed on each node by finding the direction to the UAV using the SRP-PHAT method [12] as previously reported in [10]. The conducted tests allow to

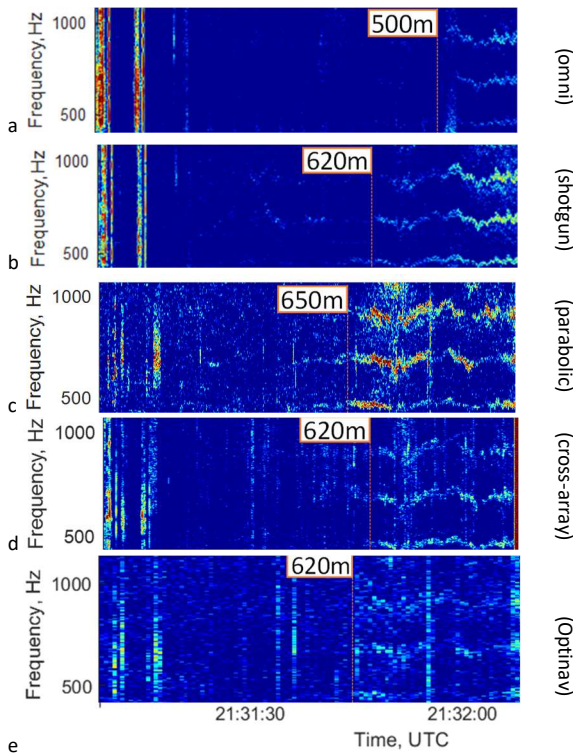


Fig. 9. Spectrograms of Phantom 4 UAV run, normalized by average noise: a- omnidirectional microphone, directional shotgun microphone –b, parabolic dish –c, beamforming using 16 channel array –d, OptiNav ACAM 120 –e.

practically test the distance at which direction finding is possible for different sizes of UAV.

DADS has been shown to find direction to the Phantom 4 UAV up to 360 m in quiet conditions. Results for different tests are summarized in Table I.

TABLE I. SUMMARY OF DETECTION RESULTS FOR DADS AND OPTI NAV WITH STEVENS PROCESSING

Test	Conditions	System	UAV	Precision [deg]	DOA finding range [m]
June 2018, NY	Wind 2-5 m/s, Temp. 25 °C, Quiet (45-50 dBA)	DADS	Phantom	3.4	360
Oct. 2018, NY	Wind 5-15 m/s, Temp: 4 °C, Quiet (45-50 dBA)	DADS	M600	4.8	265
		DADS	S1000	4.1	265
June 2019, NJ	Wind 2-5 m/s, Temp.: 32 °C, Sunny, Noisy (52-60 dBA)	DADS	Inspire	5.5	150
		OptiNav	Inspire	5.5	135
		DADS	Falcon	4.5	145
		OptiNav	Falcon	5.3	135

## VII. FIELD TEST WITH SIMULATED UAV SOUND

The sound of UAV was radiated by an acoustic emitter, elevated using a FireCo mast to a height of 12 meters. Such tests allow for testing various acoustic UAV detection systems with raw acoustics without employing practical UAV flights. This test emulates the signal strength varying range. The elevated source simulates the propagation geometry. The repetitions of the same run can be added easily, pauses in emission can be incorporated for sampling the background noise or resetting the state of the tested systems.

The limitations of this method are the inability to test rapid changes of the angle as with a maneuvering target, or the effects of atmospheric turbulence. Thus, while comparison may hold for between systems, the precision of direction finding and range may be exaggerated by comparison with practical long-range propagation.

The emitter was as speaker Pyle Boom Rock PWMAB250, modified to accept external Li-Ion 18650 3.7V batteries. The simulated samples of a UAV for radiation by a speaker accounts for the sensitivity of the emitting speaker and the distance of the speaker. To simulate the signal of an airborne target, a speaker is placed at a distance so that it is in the far-field of the receiving arrays. In the experiment, the emitter was placed at approximately 35 meters so that the signal was propagating that distance and incurring losses due to spherical spreading and atmospheric absorption. The signal propagation from a further distance was simulated by additionally reducing the amplitude of the signal, in accordance with atmospheric attenuation and spherical spreading. To create a signal that retains the properties in flight, the signal of the UAV in flight with good SNR was taken, then the signal amplitude was corrected to achieve the average power expected from the UAV at a given range. The speaker was emitting a signal based on its built-in player that reproduces digital signals in WAV format. The approximate

sensitivity of the speaker (on-axis) was obtained to be 118 dB re 20  $\mu$ Pa/Full Scale.

The additional absorption of sound was simulated for a relative humidity (RH) of 50%, atmospheric pressure of 29.92 inHg, and air temperature of 24 degrees Celsius. For each type of UAV, the target was simulated first hovering at a fixed 35-meter distance, then traveling at a constant speed to a distance of 400 meters, then returning back to 35 meters.

The target OSPL for the synthesized signal is based on the characteristics of the signal established in the anechoic chamber tests [10].

The results of testing a DADS node and OptiNav are shown in Table II. Due to extremely noisy conditions, the ranges for direction finding the ranges were short, however, the OptiNav array has shown some advantage over the DADS in detection distance, likely due to a smaller field of regard as the plate physically blocks propagation from behind the array. In the setup in Lincoln Park Airport the results were not replicated, likely since the background noise is not isotropic and whether the interfering noise is blocked depends on the spatial distribution of noise sources.

TABLE II. RESULTS OF THE TESTS USING SIMULATED UAV

Test conditions	System	Target	Precision [deg]	Estimated Detection range [m]
Stevens Athletic field. Wind 2-6 m/s, Temp.: 24°C, RH: 50% Very noisy (60-71 dBA)	DADS	M600	1.2	130
		Phantom	1.6	85
	OptiNav	M600	1.9	170
		Phantom	1.5	105
Lincoln Park, NJ Wind 2-5 m/s, Temp.: 32 °C Sunny, Noisy (52-60 dBA)	DADS	M600	1	300
		Phantom	3.2	155
	OptiNav	M600	1.5	255
		Phantom	2.2	130

## VIII. CONCLUSION

The Stevens DADS acoustic system has been demonstrated for the detection, tracking, and classification of a UAV in real time. It allows detection and finding the direction towards a Phantom 4 UAV up to 350 m with an average precision of 4 degrees. Tracking a UAV within the predicted coverage (distances around 250m) has been demonstrated, showing the feasibility of tracking a maneuvering UAV using multiple compact acoustic nodes. Real-time tracking capability was demonstrated using multiple DADS nodes. A classification algorithm is presented that is capable to detect a multicopter UAV based on the specifics of sound inherent in the flight control mechanism. Classification distances were lower (on the order of 100m) and we plan to improve the classification algorithm.

The SRP-PHAT software developed by Stevens has been applied to OptiNav ACAM 120 array for real-time direction finding.

Field investigations of various microphone arrays and systems with many microphones did not demonstrate a significant or consistent advantage over systems with DADS with fewer microphones, therefore the latter is more cost-effective.

A method using radiation of simulated UAV sounds for testing acoustical systems without employing practical flights was demonstrated, such method allows fast and low-cost acoustic system parameter measurements and can be employed for both experimental systems and third-party systems.

## ACKNOWLEDGMENT

This work was funded by AFRL Contract Number: FA8750-17-C-0190.

## REFERENCES

- [1] G. C. ; Birch, J. C. ; Griffin, and M. K. Erdman, "UAS Detection Classification and Neutralization: Market Survey 2015," *Sandia Rep.*, p. 74, 2015.
- [2] O. Ozdemir, Y. Yapici, H. Mehrpouyan, and D. Matolak, "Detection , Localization , and Tracking of Unauthorized UAS and Jammers," pp. 1–10, 2019.
- [3] ISL, "Acoustic and optical tracking and identification of Unmanned Aerial Vehicles (UAVs)," 2018. [Online]. Available: <https://www.isl.eu/documents/flyers/EN/isl-drone-detection-EN-nm.pdf>.
- [4] R. Cabell, R. Mcswain, and F. Grosveld, "Measured noise from small unmanned aerial vehicles," *NOISE-CON Pap. 20160010139*, pp. 1–10, 2016.
- [5] B. Harvey and S. O'young, "Acoustic Detection of a Fixed-Wing UAV."
- [6] Z. Kaleem and M. H. Rehmani, "Amateur drone monitoring: State-of-the-art architectures, key enabling technologies, and future research directions," *IEEE Wirel. Commun.*, vol. 25, no. 2, pp. 150–159, 2018.
- [7] L. Shi, I. Ahmad, Y. He, and K. Chang, "Hidden Markov model based drone sound recognition using MFCC technique in practical noisy environments," *J. Commun. Networks*, vol. 20, no. 5, pp. 509–518, 2018.
- [8] B. Hearing and J. Franklin, "Drone detection and classification methods and apparatus," US 9.275,645 B2, 2016.
- [9] L. Hauzenberger and E. H. Ohlsson, "Drone Detection using Audio Analysis," Lund University, 2015.
- [10] A. Sedunov and A. Sutin, "UAV Passive Acoustic Detection," in *IEEE-HST*, 2018, pp. 3–8.
- [11] A. Sedunov, A. Sutin, N. Sedunov, H. Salloum, A. Yakubovskiy, and D. Masters, "Passive acoustic system for tracking low-flying aircraft," *IET Radar, Sonar Navig.*, vol. 10, no. 9, pp. 1561–1568, 2016.
- [12] J. H. DiBiase, H. F. Silverman, and M. S. Brandstein, "Robust Localization in Reverberant Rooms," pp. 157–180, 2001.
- [13] C. H. Knapp and G. C. Carter, "The Generalized Correlation Method for Estimation of Time Delay," *IEEE Trans. Acoust.*, vol. 24, no. 4, pp. 320–327, 1976.
- [14] A. Sedunov, A. Sutin, H. Salloum, N. Sedunov, and D. Masters, "Passive acoustic localization of small aircraft," in *The Journal of the Acoustical Society of America*, 2015, vol. 20, no. 1, p. 055005.
- [15] A. Sedunov, H. Salloum, A. Sutin, and N. Sedunov, "Long-term testing of acoustic system for tracking low-flying aircraft," in *2018 IEEE International Symposium on Technologies for Homeland Security (HST)*, 2018, pp. 1–6.
- [16] L. Shi, I. Ahmad, Y. He, and K. Chang, "Hidden Markov model based drone sound recognition using MFCC technique in practical noisy environments," *J. Commun. Networks*, vol. 20, no. 5, pp. 509–518, 2018.