Towards RF-based Localization of a Drone and Its Controller

Phuc Nguyen, Taeho Kim, Jinpeng Miao, Daniel Hesselius,
Erin Kenneally*, Daniel Massey, Eric Frew, Richard Han and Tam Vu
[vp.nguyen,taeho.kim,jinpeng.miao,daniel.hesselius]@colorado.edu
[daniel.massey,eric.frew,richard.han,tam.vu]@colorado.edu
University of Colorado Boulder, *United States Department of Homeland Security

ABSTRACT

Drones are increasingly disrupting sensitive airspace around airports, as evidenced by the recent shutdown of Gatwick Airport for over a day by a drone incursion, as well as other incidents at Dubai airport, one of the busiest airports in the world. As a result, there is heightened interest in being able to detect and track drones. This paper explores a system that can use a cost-effective passive RF-based approach to determine from which direction a drone is approaching as well as its location, and also determine from which direction its controller is transmitting and the controller's location. The system combines angle of arrival (AoA) techniques with RF-based signal analysis to determine whether a peak in incoming RF signal strength at a given direction corresponds to a drone or its controller, and utilizes triangulation to estimate their locations. Our experiments demonstrate that a system consisting of inexpensive software defined radios (SDRs) and rotating antennas can effectively estimate the angle of arrival and location of both a drone and its controller.

CCS CONCEPTS

• **Networks** → **Mobile and wireless security**; • **Hardware** → **Wireless integrated network sensors**; • **Security and privacy** → *Usability in security and privacy*; • **Applied computing** → *Aerospace*.

KEYWORDS

drones/UAVs/UASs localization, wireless technology, passive RF

ACM Reference Format:

Phuc Nguyen, Taeho Kim, Jinpeng Miao, Daniel Hesselius, and Erin Kenneally*, Daniel Massey, Eric Frew, Richard Han and Tam Vu. 2019. Towards RF-based Localization of a Drone and Its Controller. In *The 5th Workshop on Micro Aerial Vehicle Networks, Systems, and Applications (DroNet'19), June 21, 2019, Seoul, Republic of Korea.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3325421.3329766

1 INTRODUCTION

Drones are increasingly posing a threat to the airspace around airports due to the threat of collisions with aircraft. Gatwick Airport in late 2018 was shut down for more than 24 hours due to a drone incursion [8]. Just a month later, flights at Newark Liberty International Airport were delayed for an hour due to a drone sighting [6]. In 2016, Dubai airport, the third busiest airport in the world, was shut down three times due to drone incursions [7].

These examples illustrate the need for cost-effective, timely, accurate, and robust detection, tracking and interdiction of drones. This paper focuses on the related problems of detection and tracking of drones, that is, drones must first be identified as drones before they can be tracked. Recent work has shown that passive RF sensing can cost-effectively detect the presence of a drone [20]. However, that work ignores the problem of tracking drones and cannot for example determine from which direction the drone is coming nor its location. In the past, audio and video approaches have been used to try to localize the drones. However, such methods suffer from acoustic noise in the environment as well as increasingly quiet drones, while camera-based techniques require line of sight conditions that preclude operation at night or when buildings/trees obstruct the view, and have difficulty differentiating between drones and birds at a distance.

Recently, much effort on RF/Wi-Fi localization has been presented. RF-emitter localization techniques are often based on the received signal strength (RSS) [13, 31], measured time of flight (ToF) [18, 22, 25], time difference of arrival (TDoA) [19, 28–30], and measured angle of signal arrival (AoA) [14, 17, 24, 27] to localize the RF-emitter. However, applying such systems for drone localization faces a number of challenges. RSS-based approaches would need to know the drone's transmitted power, gain, and orientation of the drone, and in our scenarios the drone may not cooperatively provide such information, i.e., drones may be oblivious to the tracking system. RSS measurements can also be quite noisy and subject to multipath. ToF-based approaches typically require a highly accurate sampling rate, common clock and strict time synchronization between a transmitter and receiver, which we cannot assume from uncooperative drones. TDoA does not require synchronization between a transmitter (drone) and receiver (sensing station) but does require strict time synchronization between receivers. AoA-based approaches are attractive because they don't require cooperation from drones nor any tight synchronization among system components. However, they must be augmented with drone detection because by themselves they don't identify whether the signal whose direction of arrival is being estimated arises from a drone or another RF-emitter.

Further, none of the prior work considers the scenario of identifying and tracking both the drone and its controller. In discussions with our local police team who both fly and seek to interdict drones for various missions, including observing a criminal or stopping an errant drone, we have found that police are as interested in identifying the location of the drone controller as the drone itself. This

DroNet'19, June 21, 2019, Seoul, Republic of Korea

ACM ISBN 978-1-4503-6772-1/19/06…$15.00
https://doi.org/10.1145/3325421.3329766

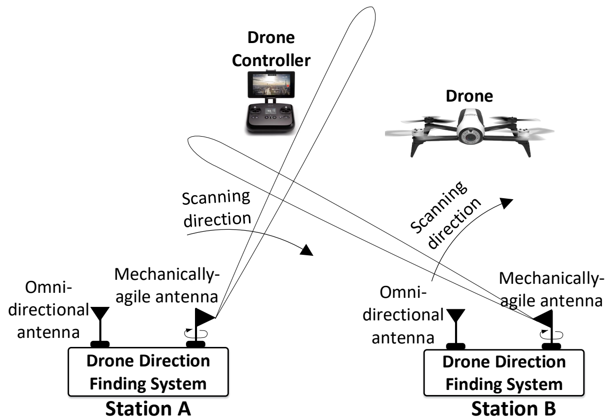

Figure 1: Finding directions of drone and its controller

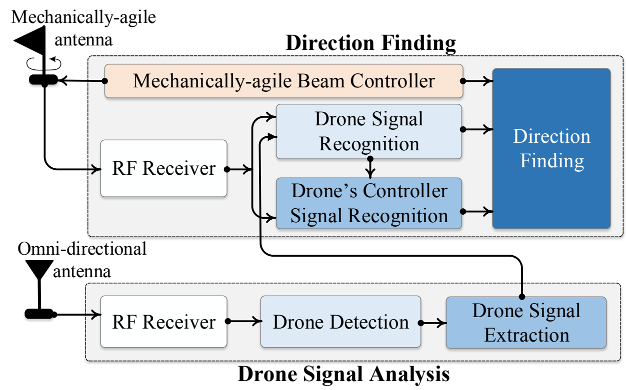

Figure 2: System architecture of a sensing station

is because identifying from where the drone is being controlled allows authorities to find the human operator who may be violating sensitive airspace.

In this paper we investigate the drone localization problem, and explore a first-of-a-kind system that is able to identify not only a drone's location, but also where its associated controller is located. Our work combines RF-based detection of the presence of a drone with AoA-based triangulation to identify the drone's location. In addition, our system identifies the location of the controller associated with a drone. The system is implemented with SDR stations and rotating antennas and evaluated with multiple drones and their controllers.

In this work, we make the following contributions:

- We implement what we believe is a first-of-a-kind RF-based location finding system for both drones and their controllers, consisting of SDRs and rotating antennas that combine passive RF-based drone detection with AoA triangulation.
- We devise a solution to identify the signature of a drone's controller through analysis of unique features in its low frequency profile.
- We experimentally evaluate the system and show that it can identify the direction of arrival of a drone, achieving an accuracy within an average of 12.2 degrees of error, as well as the location of the drone within an average estimation error of 12.71 meters.
- We show that the system can identify both the direction of the drone's controller within an average accuracy of 9.9 degrees of error and its location within 11.36 meters of error.

The following section discusses the system architecture for tracking the location and direction of the drone and its controller. Next, we present our preliminary results on identifying the drone and its controller's direction and location. We follow with a discussion of remaining challenges and future work. We then present related work and conclude the paper.

2 SYSTEM ARCHITECTURE

■ **System overview.** We design a cost-effective and passive system to localize the drone and its controller based on the arrived angles of their signals as illustrated in Figure 1. The system includes two direction finding systems to identify the directions at which the drone and its controller signals are coming. Each direction finding system includes an omnidirectional antenna to detect the presence of the drone signals, and a mechanically-agile directional antenna to identify the directions of the drone and its controller signals.

The key challenge is to differentiate the drone/its controller signal with signals from other RF-emitters in the environment. Leveraging previous studies on building a drone detection system [20, 21], we overcome the challenge by designing a drone direction finding system as shown in Figure 2. Each direction finding station extracts the features from the detected drone signal and uses mechanical steering antenna to identify the upcoming angles. Combining angles obtained from each station and their known coordinates, the drone and its controller locations are computed. In particular, each station includes two modules: (1) *Drone Signal Analysis* module and (2) *Direction Finding*.

Drone Signal Analysis module is used to detect the drone presence and extract the drone and controller signatures. It includes an *RF receiver* that is connected to an omnidirectional antenna and passively listens to the drone and its controller communication channel. When RF samples are collected, *Drone Detection* function analyzes the signals using Fast Fourier Transform Analysis [20, 21] to identify whether the drone signal is detected or not. When a drone is detected, the FFT output contains the physical signature of the drone and its controller which are then used as templates for recognizing the drones and its controller signal by the *Direction Finding* module.

Direction Finding module is used to identify the directions at which the drone and controller are located. It includes multiple functions: a *RF receiver*, a *Drone Signal Recognition*, a *Drone's Controller Recognition*, *Mechanically-agile Beam Controller* and a *Direction Finding*. RF Receiver captures the wireless samples at the drone communication frequency. Drone Signal Recognition and Drone's Controller Recognition functions analyze the received signal using FFT and identify whether that signal is from the detected drone or its transmitter. Mechanically-agile Beam Controller control the antenna beam to steer 360^o to different directions around the sensing station. During scanning, Direction Function Finding looks for the matched patterns to confirm the arrival angles of the drone and its controller signals.

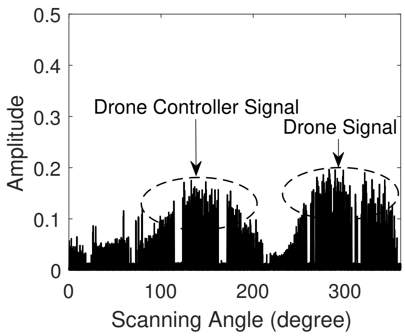

Figure 3: An example raw signal captured from a Bebop drone and its controller

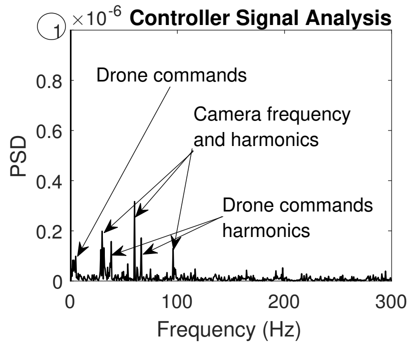

Figure 4: Example FFT analysis of Bebop controller signal

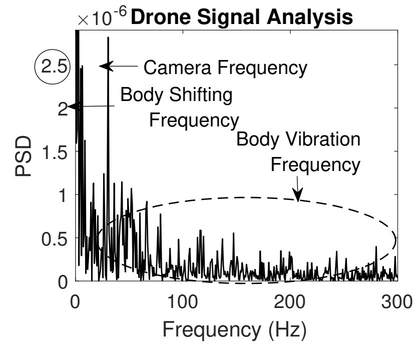

Figure 5: Example FFT analysis of Bebop drone signal

Figure 3 shows the received signal obtained from the directional antenna as the sensing station scans through different angles. By looking at only received signal strength, the system cannot tell the difference between the signal from the drone, its controller and other RF transmitters that are operating at the same frequency. However, the FFT analysis of the incoming signals during scanning have different patterns when the receiver beam sweeps through the drone and controller locations as shown in Figure 4 and 5.

In particular, Figure 5 shows the FFT analysis of the received signal captured from the drone at frequencies from 0Hz to 300Hz. In this Figure, there are three main frequency components that can be used to identify the drone signal including the body shifting frequency (< 5Hz), the camera streaming frequency (30Hz with Bebop 2 and 70 Hz with DJI Phantom 4 Pro), and the vibration frequencies (50Hz-200Hz). The vibration frequency of the Bebop is obtained from our in-lab experiment by attaching a high quality IMU sensor MicroStrain LORD 2DM-GX5-25 [16] to the drone body when it is flying. The drone creates different vibration frequencies ranging from 50Hz to 200 Hz. Also observed from this experiment, the drone controller signal exhibits some similar patterns with the drone signals as shown in Figure 4. The drone and controller communication packet rates including camera streaming, drone commands and their strong harmonics are currently used as the drone controller signatures.

■ **Finding the directions.** The directional antenna is configured to point to 0^0 North when it starts scanning. The angle of the drone is identified as the angle where the FFT signal is strongly matched, that is the cross-correlation is the highest. The accuracy of the direction function finding depends on (1) the ratio between the drone velocity and scanning velocity, (2) the beam width of the directional antenna, and (3) the antenna gain. If the scanning velocity is much faster than the drone velocity, the drone will always be in the coverage area of the system. However, the captured wireless samples from the drone might not provide sufficient data to extract the drone signature. If the scanning velocity is much slower than the drone velocity, the drone might be out of the coverage area of the directional antenna, which makes direction finding unusable. The scanning velocity needs to be designed to make sure that it slow enough to capture the drone signature and fast enough to always capture the drone in one scan. The beam-width is also affected by the direction finding performance. If the beam width is too small, the scanning delay will be increased in order to capture the whole surrounding area. If the beam width is too large, it is challenging to identify the exact angle of arrival because the drone signal is captured even when the directional antenna is not directly steered to the drone. Last but not least, the antenna gain will define the distance that the system is supported.

Identifying the drone's controller signal is more challenging because it does not include the unique physical signature such as body shifting or body vibration. The controller signature has to be obtained through the drone's signal signatures. We propose to utilize two following features to detect the drone controller (1) the drone and its controller communicate at the same communication channel (same frequency), (2) the power intensity of the signal from the drone controller can be as strong as that of the drone, (3) the drone and its controller have similar patterns in communication (packet rates). The captured signals are separated into different groups, the output FFT of the group that has the strongest cross-correlation results with the detected signature from *Drone Signal Analysis* module (excepting the drone's group) is the drone's controller signal.

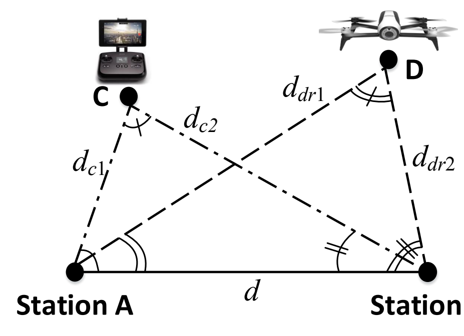

Figure 6: Localizing the drone and its controller

■ **Identifying the locations using two sensing stations.** Given two estimated angles of arrival from two sensing stations, we apply the angle-side-angle solution to calculate the location of the drone and its controller, as shown in Figure 6. We now discuss how to compute the distance from the drone (i.e., drone location). A similar approach is used to identify the drone's controller location. Let's assume that the location of station A, that of station B, and the distance between them (d) are known. The location of the drone D can be calculated from the distance between the drone to each station A and B (d_{dr1}, d_{dr2}, respectively). Hence, we have the following system of equations:

$$\begin{aligned} &\frac{d_{dr1}}{sin(\widehat{DBA})} = \frac{d_{dr2}}{sin(\widehat{DAB})} = \frac{d}{sin(\widehat{ADB})} \\ &\widehat{DAB} + \widehat{DBA} + \widehat{ADB} = 180^o \end{aligned} \tag{1}$$

The direction finding technique mentioned above will give us the two angles $\widehat{DAB}$ and $\widehat{DBA}$. Solving the above equations, d_{dr1}, d_{dr2} are obtained.

This current design exhibits a number of advantages when it comes to realizing drone localization. First, the system is completely passive and consists of inexpensive RF WiFi/SDR components and antennas, and hence is easy and cheap to build and deploy. Second, the system does not require any coordination or information from the drone such as its transmitted signal power, gain, modulation type, etc. The system also works independently of the orientation of the drone.

3 EXPERIMENTAL VALIDATION

3.1 Experiment setup

We conducted an experiment at a flying area in our university campus to validate the feasibility of the approach. There are two stations that are deployed during the experiment 50m away from each other. Each sensing station setup is illustrated in Fig. 7. It includes two laptops, two USRP B210 boards, one directional antenna controller (PE51019 (9dBi)), one omnidirectional antenna (9dBi), and one mechanically-agile antenna. Laptops with core i7 running Ubuntu 16.04 LTS and GNURadio 3.7.12 are used during the experiment. The directional antenna is controlled by a motorized module (PT785-S Pan & Tilt System from Servo City [23]) to steer the antenna to different directions to find the drone and controller signal. The GPS locations of the drones and detected system are used as ground-truth. The drone is flying at 20m altitude and 30-150m away from the sensing station. We flew Bebop 2 and DJI Phantom 4 Pro drones for this experiment. The drone is controlled by a Samsung Galaxy S9, Samsung Galaxy S8+ plus, and iPhone 7. The Bebop drone and its controller are operated at a predefined 2.4 GHz Wi-Fi frequency channel. The DJI drone and its controller are pre-configured to operate at 2.4065 GHz frequency. Since the experiments were conducted at an area that is close to a residential area, the Wi-Fi interference were also experiences at the tested location.

3.2 Preliminary results

Figure 8 shows the results of estimating the angles at which the DJI Phantom 4 Pro and Bebop 2 and their controllers are located. This figure shows the average errors obtained from the two stations. The system obtains 9.9^o of error on average when estimating the angle of the DJI drone when it is flying at 30m - 70m from the two stations. The system can find the angle of a Bebop drone flying from 30m to 150m distance with 14.5^o error in average. The system is also able to identify the angles of DJI and Bebop controllers with 15.45^o error, and 4.4^o error, respectively. The results are obtained from the average of 100 measurements. It is less accurate to detect the angles of the DJI drone and its controller due to the impact of peak-to-average-power ratio (PAPR) in signal caused by high order OFDM modulation. The peak to average power ratio of the DJI drone and DJI controller signals are much higher than that of Bebop drone and Bebop controller. We are currently using 1-D median filtering to remove these peaks; we intend to investigate more advanced techniques to remove the peaks more precisely.

When we use two stations to localize the location of the drones and controllers using the technique mentioned in Section 2, the results are presented in Figure 9. The system can localize the DJI drone with 11.8m error, Bebop drone with 13.62m error, DJI controller with 15.21m error, and Bebop controller with 7.5m error on average of 100 measurements. These errors can be reduced significantly by optimizing the following components. First, the antenna beam size can be narrowed down to minimize the angle of arrival detection error thereby reducing distance measurement errors. Second, the mechanical component of the system can be upgraded to be more precise so that the collected wireless signal and corresponding scanning angle are aligned more accurately. Last but not least, the impact of peak-to-average-power ratio could be reduced by using more advanced techniques. The angle of arrival and also localization will also be improved significantly when the peak-to-average power are removed completely. We believe these modifications will result in more accurate angle finding and localization.

Figure 10 shows the example results of 100 angle of arrival measurements from our system compared with the ground-truth angles obtained from GPS coordinates. Our system is able to identify the angle of the drone when it is locating at different locations. This result shows that the system can be potentially used for tracking the trajectories of the drone and its controller. However, as the drone flying speed is often fast, the current motorized module needs to be upgraded to scan at the higher speed so that the drone is always within its coverage area.

4 DISCUSSION AND FUTURE WORK

Although the preliminary results are promising, our work has uncovered a host of exciting research issues that can stimulate future research in drone localization. Moreover, new areas of research can be spurred by this drone localization work, such as prediction of drone trajectories, and perhaps even airtraffic management of drone highways in the future.

■ **Improving drone localization accuracy.** We feel there are a number of opportunities to improve the accuracy of our drone localization system. First, one of the issues is with the relatively wide beam width of our rotating antenna, which smears the peak power signal making it more difficult to estimate the angle of peak power. A narrower beam width would enable tighter estimation of the angle of arrival. A tradeoff may be that our FFT would run more frequently over a smaller data set potentially introducing more noise into the estimation of peak power. Second, we may introduce a larger network of RF sensing stations to provide many more angles of arrival and thereby reduce the error in location estimation.

■ **Improving the drone controller's localization.** Identifying other unique signatures of the drone controller's signal is a next

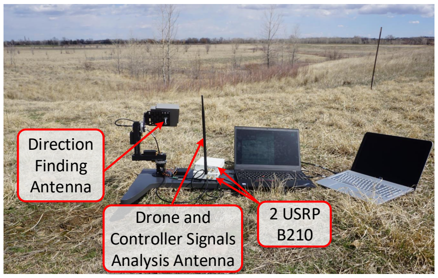

Figure 7: A sensing station during experiment

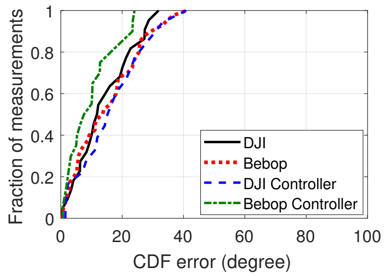

Figure 8: Estimating the angles

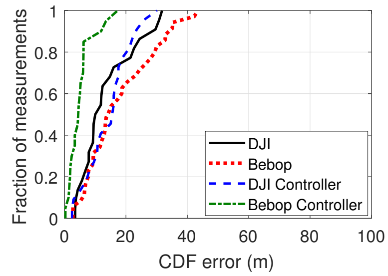

Figure 9: Estimating the locations

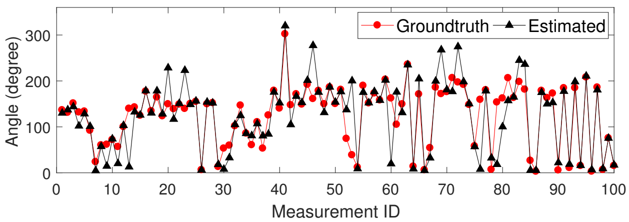

Figure 10: Direction finding results using single station

logical step. The current approach of localizing the drone's controller based on its communication packet rate is not robust when similar video/controllers are nearby. One of the approaches that we are investigating is the potentially stronger association between the drone's movement/trajectory and the controller's command patterns. In particular, what are the command patterns of the signal transmitted from the controller when the drone is turning, rotating, accelerating, and decelerating and so on?

■ **3D localization.** The current system only validates the feasibility of estimating the azimuth angle. A T-shaped antenna array or another vertical mechanically-agile antenna is needed to estimate the elevation angle of the drone (how high the drone is flying). We will need to address the increased sensitivity of measuring the elevation angle, since small errors may result in large errors to the estimated elevation.

■ **Tracking multiple drones simultaneously.** A key area of future work is to address the scenario where multiple drones may be in the same vicinity. We will need to test our system to see if it is capable of differentiating the individual drone signals and tracking multiple drones simultaneously.

■ **Improving the beam-steering mechanism.** Using phased-array antennas will definitely reduce the delay of the current mechanical stirring approach. Electrical beam steering will be a solution for the problem. However, most existing phased-array antennas are not cost-effective. The Stitched Wi-Fi ANtennas (SWAN) [26] approach may be the most suitable solution for designing a low cost and highly accurate system. The antenna array can be controlled using a switch managed by an Arduino. There would be no need to have an SDR board to control each antenna.

■ **Trajectory/speed prediction and airtraffic management** Being able to localize a drone multiple times allows us to plot its trajectory, estimate its speed, and predict its path through an area. This could enable airtraffic management to limit congestion in certain geographic areas and steer drones towards uncongested paths. With sufficient precision, such a system could be used to monitor and enforce that drones follow for example futuristic drone highways in the sky.

■ **Addressing corner cases for localization.** The system has difficulty identifying the drone's location when the drone is collinear with the axis between the two stations. Also, when the drone's controller is collinear, the controller's location is difficult to deduce. In particular, the current localization technique is based on angle-side-angle in a triangulation problem. The drone and two stations need to create a triangle for the system to be able to identify the distance from each station to the drone (two unknown sides of the triangle). By adding more RF AoA sensing stations to the network, we can both address such corner cases and improve the accuracy of localization.

■ **Addressing multi-path effects.** The impact of multipath effects in drone localization have not been studied yet in literature. One of the potential approaches is to attach a programmed RF transmitter on the drone which continuously transmits a single tone signal to the sensing station. We then can analyze the received signal to explore the impact of multipath to the system performance at different distances and environments (city area, urban, and suburban area). The understanding of multipath effects from these studies will help us to optimize the system's performance.

5 RELATED WORK

We next discuss in more detail relevant related work.

Angle of arrival based approaches. AoA approaches can either employ a rotating antenna or a phased array antenna to measure the angle of arrival of the drone's signal. Phased array solutions have the advantage that additional RF stations are not essential to estimate angle of arrival, but are more expensive to implement than mechanical solutions. Phased array solutions can be applied including SpotFi [17] or Phaser [14]. These approaches are often based on well-established methods such as MUSIC or Joint AoA and Delay Estimation (JADE) techniques, which require the system to be equipped with an array of antennas. These methods often need to open the Wi-Fi packets and look for changes in channel state information phase to compute the angle.

Radar based approach. Radio waves are transmitted, and the reflection from the object is used to verify if it is a drone or not. X-band frequencies have been used for surveillance [10]. Doppler processing of the radar provides the velocity of the target and hence enables the detection of the small moving objects with a low radar cross section. They are passed through a series of electronic filters to distinguish the drone from all the other moving targets [2]. mmW radar has been investigated to localize the drone [15]. The results of using this approach are very promising, but the system will introduce interference to the environments. Passive radar approach was also discussed [12]. The proposed system analyzes the received signal strength of the drone signal and does not explore the physical signatures of the drones to differentiate them from other wireless sources. In addition, the system is not designed to detect and localize the the drone controller.

Camera-based and audio-based approaches. Video-based detection methods require costly compute-intensive hardware and/or high bandwidth network connections to process the camera data. Further, using computer image processing to discriminate between other flying objects, e.g., birds, and drones, is a challenging task [11]. For night detection, infrared sensing via a thermal camera would be needed [1]. The effective range to detect humans is around 300m and vehicles is 600m [9]. However, small drones do not produce a lot of heat and thermal cameras are costly. Acoustic signature-based detection has been employed for drones. The acoustic signatures of the different drones in the market are collected into a database [4, 5] and compared with the recorded signals to find a match. Noisy urban environments with city traffic pose challenges for using audio for drone detection [3, 11].

6 CONCLUSIONS

We have presented an approach to localize the drone and its controller by building a cost-effective and passive tracking system. We present a new solution to identify the drone and its controller angle and location based on the RF signals that they are emitted. Using two sensing stations, our field testing shows the system obtains 12.2 degrees of error in identifying the drones' directions, 12.71 meters error in localizing them. In addition, the system also obtains 9.9 degrees of error in identifying the controllers' directions, and 11.36 meters of accuracy in locating the controllers. While the preliminary results are promising, we identify many exciting remaining challenges and opportunities for research.

ACKNOWLEDGMENTS

This material is based on research sponsored by DHS Science & Technology Directorate agreement number 13012585. The U.S. Government is authorized to reproduce and distribute reprints for Governmental purposes notwithstanding any copyright notation thereon.

The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either expressed or implied, of the DHS S&T or the U.S. Government.

REFERENCES

[1] Dedrone. http://tinyurl.com/ztfl5v6.
[2] Detect inc. http://tinyurl.com/d3jmkys.
[3] Drone detection issues. http://tinyurl.com/gsm4n3t.
[4] Drone detector (orelia). http://tinyurl.com/jcmbmep.
[5] Drone shield. http://tinyurl.com/h4gyahs.
[6] Drone sighting sparks delays at newark liberty international airport. USA Today, January 22, 2019.
[7] Dubai deploys a 'drone hunter' to keep its airport open. CNN, November 4, 2016.
[8] Gatwick airport shut down by 'deliberate' drone incursions. New York Times, December 20, 2018.
[9] IEC infrared systems: Banshee. http://tinyurl.com/zeswc7e.
[10] Kelvin Hughes drone detection. http://tinyurl.com/jvxj4kx.
[11] NCC Group. http://tinyurl.com/j8u44sx.
[12] M. M. Azari, H. Sallouha, A. Chiumento, S. Rajendran, E. Vinogradov, and S. Pollin. Key Technologies and System Trade-offs for Detection and Localization of Amateur Drones. *IEEE Communications Magazine*, 56(1):51–57, Jan. 2018.
[13] E. Elnahrawy and a. R. P. Martin. The limits of localization using signal strength: a comparative study. In *2004 First Annual IEEE Communications Society Conference on Sensor and Ad Hoc Communications and Networks, 2004. IEEE SECON 2004.*, pages 406–414, Oct. 2004.
[14] J. Gjengset, J. Xiong, G. McPhillips, and K. Jamieson. Phaser: Enabling Phased Array Signal Processing on Commodity WiFi Access Points. In *Proceedings of the 20th Annual International Conference on Mobile Computing and Networking*, MobiCom '14, pages 153–164, New York, NY, USA, 2014. ACM. event-place: Maui, Hawaii, USA.
[15] I. Guvenc, O. Ozdemir, Y. Yapici, H. Mehrpouyan, and D. Matolak. Detection, localization, and tracking of unauthorized UAS and Jammers. In *2017 IEEE/AIAA 36th Digital Avionics Systems Conference (DASC)*, pages 1–10, Sept. 2017.
[16] IMU MicroStrain LORD. 3DM-GX5-25. http://tinyurl.com/yxm8bngy. March 26, 2019.
[17] M. Kotaru, K. Joshi, D. Bharadia, and S. Katti. SpotFi: Decimeter Level Localization Using WiFi. In *Proceedings of the 2015 ACM Conference on Special Interest Group on Data Communication*, SIGCOMM '15, pages 269–282, New York, NY, USA, 2015. ACM. event-place: London, United Kingdom.
[18] S. Lanzisera, D. Zats, and K. S. J. Pister. Radio Frequency Time-of-Flight Distance Measurement for Low-Cost Wireless Sensor Localization. *IEEE Sensors Journal*, 11(3):837–845, Mar. 2011.
[19] A. T. Mariakakis, S. Sen, J. Lee, and K.-H. Kim. SAIL: Single Access Point-based Indoor Localization. In *Proceedings of the 12th Annual International Conference on Mobile Systems, Applications, and Services*, MobiSys '14, pages 315–328, New York, NY, USA, 2014. ACM. event-place: Bretton Woods, New Hampshire, USA.
[20] P. Nguyen, H. Truong, M. Ravindranathan, A. Nguyen, R. Han, and T. Vu. Matthan: Drone Presence Detection by Identifying Physical Signatures in the Drone's RF Communication. In *Proceedings of the 15th Annual International Conference on Mobile Systems, Applications, and Services*, MobiSys '17, pages 211–224, New York, NY, USA, 2017. ACM. event-place: Niagara Falls, New York, USA.
[21] P. Nguyen, H. Truong, M. Ravindranathan, A. Nguyen, R. Han, and T. Vu. Cost-Effective and Passive RF-Based Drone Presence Detection and Characterization. *GetMobile: Mobile Comp. and Comm.*, 21(4):30–34, Feb. 2018.
[22] R. O. Schmidt. Multiple emitter location and signal parameter estimation. *IEEE Transactions on Antennas and Propagation*, 34:276–280, Mar. 1986.
[23] ServoCity. Pt785-s pan tilt system. https://www.servocity.com/pt785-s. March 26, 2019.
[24] E. Soltanaghaei, A. Kalyanaraman, and K. Whitehouse. Multipath Triangulation: Decimeter-level WiFi Localization and Orientation with a Single Unaided Receiver. In *Proceedings of the 16th Annual International Conference on Mobile Systems, Applications, and Services*, MobiSys '18, pages 376–388, New York, NY, USA, 2018. ACM. event-place: Munich, Germany.
[25] D. Vasisht, S. Kumar, and D. Katabi. Decimeter-Level Localization with a Single WiFi Access Point. pages 165–178, 2016.
[26] Y. Xie, Y. Zhang, J. C. Liando, and M. Li. SWAN: Stitched Wi-Fi ANtennas. In *Proceedings of the 24th Annual International Conference on Mobile Computing and Networking*, MobiCom '18, pages 51–66, New York, NY, USA, 2018. ACM. event-place: New Delhi, India.
[27] J. Xiong and K. Jamieson. ArrayTrack: A Fine-grained Indoor Location System. In *Proceedings of the 10th USENIX Conference on Networked Systems Design and Implementation*, nsdi'13, pages 71–84, Berkeley, CA, USA, 2013. USENIX Association. event-place: Lombard, IL.
[28] J. Xiong, K. Jamieson, and K. Sundaresan. Synchronicity: Pushing the Envelope of Fine-grained Localization with Distributed Mimo. In *Proceedings of the 1st ACM Workshop on Hot Topics in Wireless*, HotWireless '14, pages 43–48, New York, NY, USA, 2014. ACM. event-place: Maui, Hawaii, USA.
[29] J. Xiong, K. Sundaresan, and K. Jamieson. ToneTrack: Leveraging Frequency-Agile Radios for Time-Based Indoor Wireless Localization. In *Proceedings of the 21st Annual International Conference on Mobile Computing and Networking*, MobiCom '15, pages 537–549, New York, NY, USA, 2015. ACM. event-place: Paris, France.
[30] J. Xu, M. Ma, and C. L. Law. Position Estimation Using UWB TDOA Measurements. In *2006 IEEE International Conference on Ultra-Wideband*, pages 605–610, Sept. 2006.
[31] G. V. Zaruba, M. Huber, F. A. Kamangar, and I. Chlamtac. Indoor Location Tracking Using RSSI Readings from a Single Wi-Fi Access Point. *Wirel. Netw.*, 13(2):221–235, Apr. 2007.