POSTER: Passive Drone Localization Using LTE Signals

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ABSTRACT

Drones raise significant privacy and security threats, by intruding into the airspace of private properties or unauthorized regions. Being able to detect and localize the encroaching drones is essential to build geofencing systems to prevent drone misuse. While most existing approaches focus on detecting and localizing active drones, passive drones that do not emit signals are particularly challenging to localize, without requiring advanced hardware. In this work, we propose a novel, low-cost passive drone localization approach, by leveraging opportunistic environmental RF signals (e.g., LTE or WiFi) that reflect off the target drone, with only a single wireless receiver. We implement a prototype system on a USRP-device based testbed, with standard LTE signals emitted by multiple distributed transmitters, and conduct experiments on top of a campus building to evaluate its performance. We also perform a drone detection range analysis to extrapolate the real-world applicability of our scheme.

CCS CONCEPTS

• **General and reference** → **Measurement**; • **Hardware** → **Digital signal processing**; • **Security and privacy** → **Intrusion detection systems**; **Mobile and wireless security**.

KEYWORDS

Passive Drone Localization, LTE, OFDM Radar Processing

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1 INTRODUCTION

The surging prevalence of drone applications also brings privacy and security/safety threats. Malicious users can leverage drones to surveil or track other people with an on-board camera (e.g., recording videos of residents). Therefore, being able to detect and locate drones is essential for preventing and mitigating drone misuse.

Detecting and localizing active drones are relatively easier, since they actively transmit signals which provide abundant features for analysis, such as Doppler shift, packet inter-arrival timing patterns, signal Direction-of-Arrival, etc. However, passive drones are harder to detect and localize, since they are usually non-cooperative (especially malicious ones), and do not actively transmit messages (or infrequently do so). Existing works that focus on passive drone localization and tracking mainly adopt costly sensors such as radars, Lidars, or high-resolution cameras. On the other hand, passive wireless tracking methods can be cost-effective but are challenging to be applied to detect and localize drones with small radar cross sections.

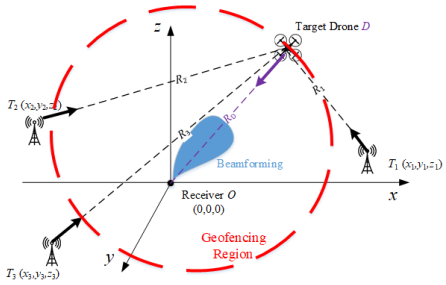


Figure 1: System model. O **stands for a wireless receiver;** T_i, $i = 1, 2, 3$ **is wireless signal transmitter, Dashed circle is geofencing region.**

In this poster, we propose the first practical RF-based passive drone localization scheme, exploiting the environmental LTE signals reflected by drones. Our scheme requires only a single wireless receiver, and at least three transmitters to successfully locate a drone. We implement a proof-of-concept prototype on a USRP-device based testbed, and carry out real-world experiments on the top of a campus building to evaluate its performance.

2 PROBLEM STATEMENT

We consider a stationary wireless receiver O (equipped with beamforming or directional antennas), deployed within or at the boundary of a geofencing region, that aims to determine the position of (and track) an encroaching target drone D, under the presence of N existing stationary wireless transmitters (e.g., cellular base stations). The latter are non-cooperative, in the sense that they use their own protocols and transmission schedules. The receiver O is equipped with the same wireless technology used by the transmitters (e.g., LTE), which gives it the capability of detecting and decoding the wireless packets/frames received from them. The target drone remains passive, i.e., it neither broadcasts any wireless signal actively nor communicates with its controllers during the period of encroaching. In general, we consider a multi-static passive localization setting in a 3-D Cartesian coordinate system.

3 DRONE DETECTION AND LOCALIZATION

Fig. 2 gives an overview of our LTE-signal based passive drone detection and localization scheme. The wireless receiver scans different spatial regions using beamforming, listens to the LTE downlink channels, and detects the presence of an unknown drone by observing changes in the power spectrum density which indicates reflected LTE signals (similar to [2]). After that, the receiver points

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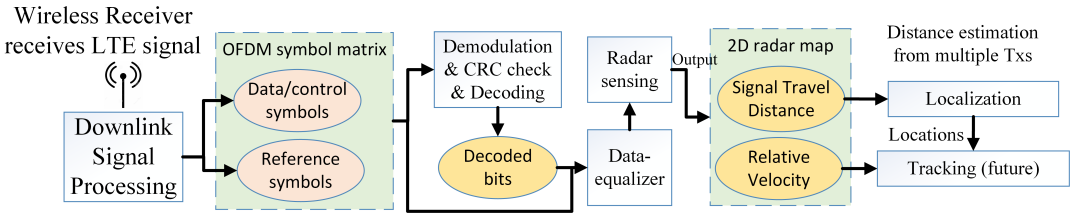


Figure 2: Overview of our proposed LTE-signal based passive drone localization scheme.

the beam at the direction of the detected drone, demodulates and decodes the LTE data symbols (separated by different transmit cell tower IDs). Then the receiver adopts an OFDM-based passive radar sensing technique [4] to estimate the signal travel distance from each transmitter (bi-static range) and relative speed of the drone. A data-equalizing re-encoder strategy [3] is used to eliminate the impact of unknown transmitted OFDM symbols (with only known reference symbols). Finally, bi-static range estimations from at least 3 transmitters are used to estimate the position of the drone, using a localization algorithm based on intersection of ellipsoids [1].

4 EXPERIMENTAL EVALUATION

We implement our scheme on a testbed consisting of multiple USRP N210 (as LTE transmitters) and 1 USRP-2921 (as LTE receiver) devices, and conduct experiments in a rectangular balcony on a building's roof. Fig. 3a shows the top view of the half-open balcony. A small drone hovers in the air outside the edge of the balcony, which is designated as a warning zone for unknown drone monitoring and localization. Each USRP is equipped with a directional antenna which points toward the warning zone. There are no other obstacles/reflectors at the edges of the top and right sides. We test 3 transmitter location settings (Tab. 1), where settings 1 and 2 are for 2D localization, setting 3 is for 3D. The target drone is a DJI Mavic Air 2, which has a very small radar cross section (RCS). Thus we attach an extra load under the drone (an aluminum-wrapped plastic bottle (190 mm × 190 mm × 250 mm)) to increase the RCS, and add two RF amplifiers to the transmitters to increase the signal power. We use the MATLAB LTE toolbox for LTE signal generation and reception.

Table 1: Transmitters and drone position settings

Setting Number	1 (No amplifier)	2 (No amplifier)	3 (With amplifier)
Transmitter positions (m)	(−11.62, 0) (0,−9) (5, −7.91)	(−8.5, 0) (0, −3) (5, −2.5) (7, −0.5) (−3, −2) (−6, −2)	(-7, 0, 1) (0, -1.4, 0) (4, -1, 1) (6, -0.5, 0) (-3, -1, 1) (-5,-1, 0)
Drone (m)	(0, 3)	(0, 9.75)	(0, 18.5, 2)

Drone detection: Fig. 4 shows a spectrogram of received LTE frames during a 50 s time window. In this window, the drone flies in and out of the warning zone at 11 s and 40 s respectively. When the drone exists in the warning zone, the receiver receives the reflected LTE signal, which increases the PSD in the baseband (carrier frequency is 2.495 GHz with a 20MHz bandwidth). Note that the controller-to-drone communication channel does not overlap with the monitored channel, and therefore will not affect the drone detection and parameter estimation.

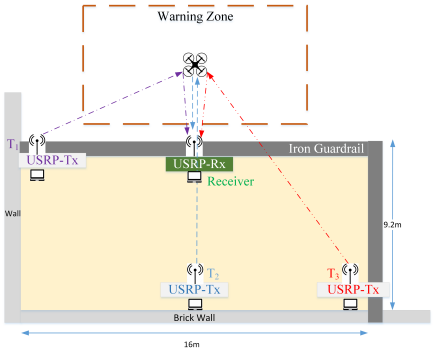
Results of Signal Travel Distance Estimation: Examples of 2D radar maps obtained by the OFDM-based sensing algorithm are shown in Fig. 5. In setting 1, the ground truth signal travel distance is 15 m for all three paths. In setting 2, the average range estimation error is 0.345 m over 6 paths. For setting 3, the average range estimation error is 0.145 m over 6 paths (we change Tx locations). The maximum detectable signal travel distance is around 22.5 m in the first 2 settings (no RF amplifier), which is equivalent to a 11.25 m direct detectable distance from the receiver to the drone (or detection radius). With two RF amplifiers in setting 3, the maximum detectable signal travel distance increases to 37.5 m, suggesting an approximately 20 m detection radius.

Results of Drone Localization: In setting 1, the estimated drone location is (0.33 m, 3.6 m), which is 0.7 m from the real target location (0 m, 3 m). The position estimation results in settings 2 and 3 are shown in Tab. 2, where $\bar{e}_{re}$ is the average range estimation error of all paths in each setting. Since there are 6 possible transmitter locations in each setting, for 3 transmitters' localization, we enumerate all possible combinations of 3 out of 6 transmitters (20 in total), and compute the average localization error. The same is done for 4 and 5 transmitters' localization results. We can see that, as the number of available transmitters increases, the location estimation error decreases. Also, a longer drone-receiver distance leads to a higher localization error since the longer distance scales up the error. Besides, 3D localization has higher average errors than 2D localization.

Table 2: Average drone localization error (m) under transmitter location setting 2 and setting 3

Setting	$\bar{e}_{re}$ (m)	3Tx	4Tx	5 Tx	6Tx
2	0.345	0.589	0.551	0.528	0.515
3	0.144	3.59	3.01	2.53	2.14

Drone Detection Range Analysis: In above experiments, we achieved a maximum drone detection radius of 20 m. This would be sufficient for some applications (e.g., private households), but may not be enough for others (e.g., airport geofencing). Therefore, we analyze the maximum detection range if we adapt our scheme to use a commercial LTE tower's signal with a cellphone as the receiver using a case study. Fig. 6a demonstrates the T-Mobile signal towers' locations in a campus, with a total of 5 towers. The area of this map is 640 m by 427 m. Assume that a cellphone receiver is on



(a) Floor plan



(b) Drone with a reflector

Figure 3: Experimental setup

top of a garage (point R), whose location is set as (0,0). We assume that the transmitters, receiver and drone are at the same height for simplicity. The locations of 5 signal towers, T_1 to T_5, are (−149.33 m, 54.09 m), (−124.95 m, −156.57 m), (−57.90 m, −45.55 m)), (−6.10 m, −227.73 m), (320 m, 47.70 m), respectively.

An LTE cell tower can transmit at a power of 43 dBm (20 Watt). The transmitted antenna gain is around 6 dBd for a directional antenna on the signal tower. For cellphone receiver, a good signal strength on the reference signal received power (RSRP) scale is anything stronger than -90 dBm. The measured RCS of our reflector is about 0.07 m^2. We plot the feasible geofencing zone under this topology in fig 6b based on the bi-static radar signal propagation model [5]. We define the feasible geofencing zone as a set of locations, at which if a drone appears, the reflected signal can be received with a RSRP higher than -90 dBm (detection threshold) from at least 3 LTE cell towers. In other words, if a drone appears inside the geofencing zone, it can be detected and located by the receiver.

From Fig. 6b, we can see that the corresponding geofencing zone has an area of approximately 20 000 m^2 when the RCS is 0.07 m^2. That is, using commercial LTE signal towers and a cellphone receiver can achieve an acceptable geofencing zone for a mid-sized or large drone.

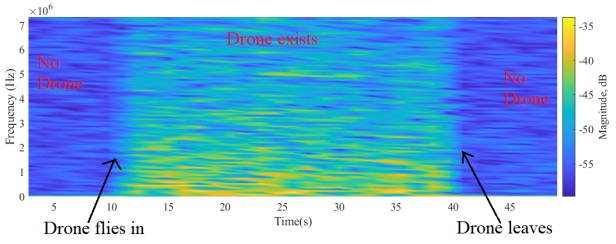
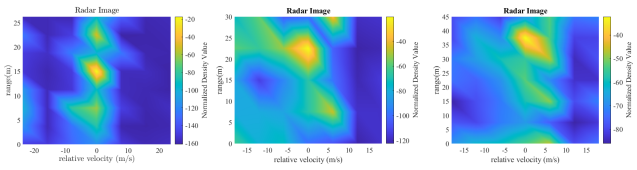
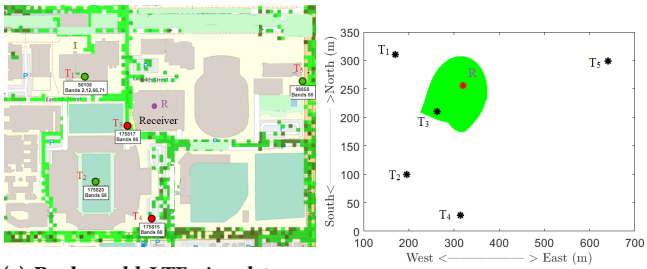


Figure 4: The PSD of received signal, with or without a drone.



(a) Setting 1 (b) Setting 2 (c) Setting 3

Figure 5: Range estimation results of path 1 ($T_1 - Drone - R$ distance) in each setting



(a) Real world LTE signal tower distribution

(b) Geofencing zone

Figure 6: Simulation of real-world drone detection

5 CONCLUSIONS AND FUTURE WORK

We design and implement an RF-based passive drone localization scheme, which exploits the opportunistic LTE signals reflected by drones. Experimental results show that, we can detect and localize a small commercial drone (with an additional reflector) up to 20m away, using a proof-of-concept USRP based testbed. Finally, we analyze the maximum feasible drone detection ranges using commercial signal towers and cellphone receiver settings, to extrapolate the real-world applicability of our approach. Future work include a full-scale implementation of the system with LTE signals from real cell towers to address practical deployment challenges.

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