Autonomous Drone Networks for Sensing, Localizing and Approaching RF Targets

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***Abstract*—We present FALCON, a novel autonomous drone network system for sensing, localizing, and approaching RF targets/sources such as smartphone devices. A potential application of our system includes a disaster relief mission in which networked drones sense the Wi-Fi signal emitted from a victim's smartphone and dynamically navigate to accurately localize and quickly approach the victim, for instance, to deliver the time-critical first-aid kits. For that, we exploit Wi-Fi's recent Fine Time Measurement (FTM) protocol to realize the first on-drone FTM sensor network that enables accurate and dynamic ranging of targets in a mission. We propose a flight planning strategy that adapts the trajectory of the drones to concurrently favor localizing and approaching the target. Namely, our approach jointly optimizes the drones' diversity of observations while also approaching the target, while flexibly trading off the intensities of the potentially conflicting objectives. We implement FALCON via a custom-designed multi-drone platform and demonstrate up to $2\times$ localization accuracy compared to a baseline flocking approach, while spending 30% less time localizing targets.**

***Index Terms*—networked drones, flight planning, Wi-Fi, FTM.**

I. Introduction

In this paper, we design, implement and experimentally evaluate FALCON. Prior work in drone-network *localization* has employed on-drone *antenna arrays* to sense angle of arrival (AoA) from a target. Unfortunately, antenna arrays have large physical size, e.g., nearly a meter scale [1], and require significant time to compute AoA, e.g., 45 sec per observation [2]. Likewise, prior on-drone methods employing a *single* antenna per drone sensed RSSI to localize targets, e.g., [3]. However, as RSSI is only coarsely related to distance, [3] had localization errors as high as 10 meters. In contrast, we design FALCON as a single-antenna system with nearly an order of magnitude better accuracy than [3] and with computational times in the msec scale.

In addition, in time-critical drone missions such as disaster relief and emergency scenarios, *approaching* is of great value as it enables important services such as fast delivery of life-saving first-aid kits and immediate close-in inspection of the situation for an effective rescue plan. Moreover, approaching targets is beneficial as measurement fidelity is typically improved at a closer range and faster data exchange can be achieved when the drones need to communicate with the target. Unfortunately, prior work has decoupled the approaching problem from localizing. For example, e.g., [4] mimics the flocking behavior to approach a target whereas [5] considers optimal sensor placement to localize a target. In contrast, because approaching and localizing can be conflicting objectives, we incorporate both, which we will show has a profound effect on system dynamics and performance.

To realize FALCON, we make the following three contributions. First, we realize on-drone target-to-drone ranging estimates via Fine Time Measurement (FTM) and integrate this capability with networked sensing and mission planning. Standardized in 2016 [6], FTM measures the time of flight (ToF) of Wi-Fi signal traveling from a client to a Wi-Fi access point. Prior work has employed the protocol to self-position a client, with the client performing multi-lateration to localize itself in the indoor environment with many stationary access points distributed in space, e.g., [7]. In contrast, we, for the first time, use FTM as a mechanism to actively sense target-to-drone range estimates, which we employ to dynamically navigate a network of drones in a mission.

Second, we propose a flight planning strategy to simultaneously approach, localize, and track targets. We tackle these objectives concurrently by jointly exploiting drones' diversity of observation and dynamics of approaching in a mission. We provide a tunable parameter λ that allows modification of flight patterns to weight the mission-planner's objectives for localization accuracy and approaching dynamics. This enables FALCON drones to be flexible and adjust to a range of behaviors in a mission in addition to improving measurement resolution and realizing approaching-critical tasks. Likewise, our flight strategy is agnostic to sensing technology and can be generalized to fit different range sensing mechanisms.

Third, we implement FALCON on a custom-designed multi-drone platform and perform an extensive experimental evaluation. Our findings reveal that, compared to the baseline flocking scheme (coordinated flight with the leader-follower formation [4]), FALCON consistently and rapidly acquires information about the target position because of its diverse observation feature. Consequently, our system localizes a target $2\times$ more accurately and in 30% less time. Likewise, we show that even a single drone can exploit diverse observations throughout a mission, achieving 2.3m mean localization accuracy and spending only around a minute localizing a non-mobile target. To understand the contribution of additional drones on localization accuracy and localization time, we perform missions with up to four networked drones and demonstrate that the flocking approach needs more drones

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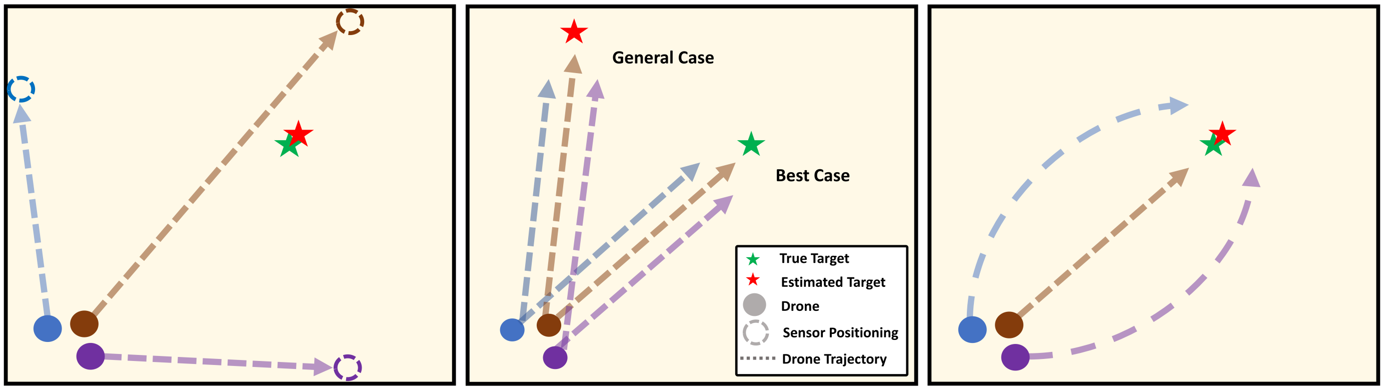


(a) (b) (c)

Fig. 1: Flight planning following (a) the sensors positioning strategy, (b) the flocking scheme and (c) FALCON

to improve accuracy whereas FALCON exploits informative locations to achieve better results with fewer drones.

II. FALCON Framework

Here we first provide an overview of the FALCON design. Next, we analyze one-shot positioning of sensors, and building on that, we then present FALCON flight planning strategy.

A. Design Overview

On-drone Sensing: First, we realize target-to-drone range sensing for networked drones. Unlike existing on-drone sensing systems that either require bulky antenna arrays and perform time-consuming AoA computation or employ RSSI which is only coarsely related to distance, drones in FALCON accurately and quickly range targets by sensing ToF of Wi-Fi signals. We discuss our ranging mechanism in Section III.

Flight Planning: Next, we design a flight planning strategy that navigates networked drones to concurrently approach, localize, and track targets in a mission. We propose to jointly exploit diverse observation of drones and their dynamics of approaching targets. To illustrate the design principles, Fig. 1 shows a simplified example of FALCON compared to two fundamental classes of prior approaches. Once transported to the mission area, e.g., on a first responder vehicle, drones take off and start sensing the target. If they lack initial sensing, e.g., outside RF sensing range, they can employ well-studied divide and conquer search algorithms, e.g., [8], to efficiently search for the target. Otherwise, they navigate to localize, approach, and track the target, working cooperatively in a mission.

Following optimal sensor positioning strategy [5], drones in Fig. 1(a) spread out around the target, to different sides of the area. Spreading enables drones to view the target from diverse locations and collect statistically independent samples, which is favorable for localization accuracy. However, the problem with this approach is the extra distance travelled for severely battery-constrained drones. Even worse, since this extra distance increases with search area, such an approach increasingly risks mission failure (inability to approach, localize, and track) in larger areas. On the other hand, drones realizing a flocking scheme, shown in Fig. 1(b), fly directly to the latest estimated target position in the formation of a flock. In the best-case scenario, when drones sense the target precisely throughout a mission, the scheme helps to get to the target quickly. However, we will show that flocking drones often navigate in the wrong direction due to imperfect sensor measurements and thus the entire flock goes off course. We design a flight strategy in which drones dynamically spread out and approach while they actively sense the target. As shown in Fig. 1(c), spreading out ensures accurate localization while approaching enables fast advancement to the target. In addition, we provide flexibility to configure the intensity of spreading and approaching which allows drones to adjust to different mission requirements and conditions.

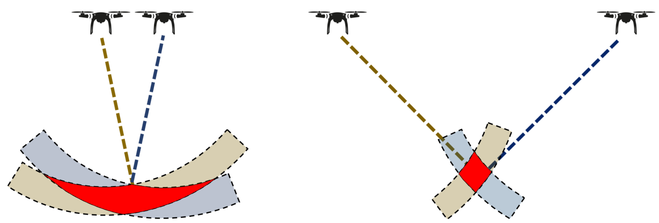
In addition to multiple drones, we will show that FALCON can perform a mission even with a single drone, provided the drone speed is sufficiently greater than the target's speed. Namely, during the flight, even a single drone is collecting ranging samples at different spatial locations. With the proper flight pattern to collect sufficiently independent samples, these single-drone measurements can be used for multi-lateration.

B. One-shot Positioning of Sensors For a Known Source

Diversity of observation is a critical aspect of FALCON flight planning. To characterize and quantify it, we first analyze *one-shot positioning* of sensors for a *known source* [5]. With this foundation, we develop a strategy to address our problem of unknown target location and mobile drones.

To demonstrate the significance of diverse observation, consider Fig. 2 in which two drones range a target and then fuse their measurements to gain information about the target location. The means of the measurements are depicted as dotted lines, while standard deviations are shown as blue and brown segment areas. Once information is fused, the red area indicates the most likely location of the target. We designate it as the *confusion area.* Notice that as drones get close to each other, as in Fig. 2(a), the confusion area expands, indicating poor observation diversity and hence limited information about target location. On the other hand, spreading out and observing the target from different views, as in Fig. 2(b), provides a more focused estimate of the target location.

Here we introduce some notation. For ease of exposition, we consider a search area P in $2D$ which is discretized into a grid such that algorithms can perform operations on it. N sensors (drones in the context of flight planning) and a source are positioned in that area. We denote the location of sensor i as $S_i = (x_i, y_i)$ and the location of the source as $U = (x_u, y_u)$.



(a) Similar observation (b) Diverse observation

Fig. 2: Two target-to-drone range sensing drones

Each sensor i ranges the source as $d_i = r_i + \epsilon_i$ where $r_i = ||S_i - U||$ and ϵ is a standard Gaussian noise with zero mean and σ_i^2 variance. Then, sensors can share their data, forming vectors of ranges $\boldsymbol{d} = [d_1, ..., d_N]$ and $\boldsymbol{r} = [r_1, ..., r_N]$ as well as a covariance matrix, which we denote by Σ .

To characterize the confusion area, likelihood information of finding the source can be retrieved from $\boldsymbol{d}$ and expressed as

$$L_d = \frac{1}{(2\pi)^{N/2}|\boldsymbol{\Sigma}|^{1/2}} e^{-\frac{1}{2}(\boldsymbol{d}-\boldsymbol{r})^T \boldsymbol{\Sigma}^{-1}(\boldsymbol{d}-\boldsymbol{r})} , \quad (1)$$

where $|\boldsymbol{\Sigma}|$ is the determinant of Σ. When L_d is flat, there is less information about the source location, whereas an abundance of information is characterized by L_d being sharply peaked.

To quantify the source location information contained in the confusion area, a common method is to measure sharpness of the likelihood via Fisher Information Matrix [5] as

$$F = E\{(\nabla_U \log L_d)(\nabla_U \log L_d)^T\} , \quad (2)$$

The matrix F can be interpreted as the curvature of the log-likelihood function and indicates how well U can be estimated from $\boldsymbol{d}$. In our example, F can also be expanded as [9]

$$F = \sum_{i=1}^{N} \begin{bmatrix} \frac{(x_u - x_i)^2}{\sigma_i^2 r_i^2} & \frac{(x_u - x_i)(y_u - y_i)}{\sigma_i^2 r_i^2} \\ \frac{(x_u - x_i)(y_u - y_i)}{\sigma_i^2 r_i^2} & \frac{(y_u - y_i)^2}{\sigma_i^2 r_i^2} \end{bmatrix} . \quad (3)$$

Applying trigonometric substitution, it can be simplified to

$$F = \sum_{i=1}^{N} \begin{bmatrix} \frac{sin^2(\phi(S_i))}{\sigma_i^2} & \frac{sin(2\phi(S_i))}{\sigma_i^2} \\ \frac{sin(2\phi(S_i))}{\sigma_i^2} & \frac{cos^2(\phi(S_i))}{\sigma_i^2} \end{bmatrix} , \quad (4)$$

where $\phi(S_i) = tan^{-1}(\frac{y_i - y_u}{x_i - x_u})$ and denotes the angle between S_i and U with reference to the global X coordinate. Observe that in Eq. (3), the confusion area is a function of the locations of the sensors, and it is further expressed by the angular placement of the sensors in Eq. (4). To quantify the source location information with a single scalar value, we use the determinant of F, which can be computed as

$$D = \sum_{i=1}^{N} \sum_{j>i}^{N} \frac{sin^2(\phi(S_i) - \phi(S_j))}{\sigma_i^2 \sigma_j^2} . \quad (5)$$

We refer to D as *total information* as it quantifies the source location information contained in the confusion area, with a smaller confusion area indicating greater total information. For given sensor range measurements, the sensor placement technique aims to achieve the highest possible D by maximizing angular spread between all neighboring sensors in the network. Considering Fig. 2 with range measurements of equal mean and the same variances, positioning drones 90° with respect to the target results in the maximum total information. For $N > 2$, the technique takes into account the angular spread of all two-pair combinations of the sensors.

C. Flight Planning

Unlike one-shot framework above, here we remove the assumption of a known target; instead, a network of drones actively sense and autonomously navigate to localize, approach, and track a target. To do so, each drone estimates a range to target. Next, the drones share their estimates along with their current GPS coordinates, each of which represents a different perspective on the target position. The drones then update their target estimation by fusing their own range estimate with the newly received information from other drones along with past information. Subsequently, each drone computes its next best waypoint to enable both accurate localization and fast advancement to the target, by flying to the most informative waypoint for the mission objective. To consistently improve the accuracy of the target estimation as well as approach it at the same time, the networked drones continually execute these steps as they progress in a mission.

We extend the notation from Section II-B to incorporate temporal information such that $S_{i,t} = (x_{i,t}, y_{i,t})$ denotes the location of drone i at a discrete time t as observed via GPS while $\hat{U}_{i,t} = (x_{\hat{u},t}, y_{\hat{u},t})$ represents the latest estimated location of the target at time t. For ease of exposition, we consider a search area P of rectangular shape that has (x_{min}, y_{min}) and (x_{max}, y_{max}) waypoints, fixed drones velocity v, and fixed update frequency f for exchanging range estimates and GPS data and updating their reposition waypoint decisions. To avoid collision, drones keep a minimum distance c_{th} between each other and a_{th} designates the desired target-approach threshold as specified by the mission. It can be set to zero to indicate that the drones should get as close to the target as possible without colliding.

Then, the problem of flight planning is to compute mission waypoints $S_{k,t+1}$ for all networked drone $\forall k \in N$ for the duration of the mission, as long as drones have sufficient energy to operate.

Challenges: The first challenge is a reciprocal effect in which flight planning impacts target estimation while target estimation influences flight planning decisions. Specifically, networked drones account for their current location at t to estimate the target location $\hat{U}_t$, while $\hat{U}_t$, on its turn, defines the drones next reposition waypoints. This suggests that drones should consistently reposition to informative waypoints in order to enable accurate target estimation and approaching. Second, drones might have a similar starting position in a mission (launched from their transported location). This condition is highly unfavorable for target localization as it initially yields extremely inaccurate target estimation due to poor observation diversity. Consequently, drones should start realizing diverse observations as soon as the mission begins.

Optimization: In FALCON, we propose a distributed and real-time flight planning strategy where each networked drone k computes its next reposition waypoint $S_{k,t+1}$ by performing the following optimization:

$$S_{k,t+1} = \underset{\{S_{i,t+1}\}_{i=1}^{i=N}}{\text{argmax}} \quad \sum_{i=1}^{N} \sum_{j>i}^{N} \frac{sin^2(\hat{\phi}_t(S_{i,t+1}) - \hat{\phi}_t(S_{j,t+1}))}{\sigma_i^2 \sigma_j^2 \hat{d}_t(S_{i,t+1})^{\lambda} \hat{d}_t(S_{j,t+1})^{\lambda}} \tag{6a}$$

$$\begin{aligned}
\text{subject to} \quad & \text{if } k = i \text{ (or } k = j\text{), then} && \text{(6b)}\\
& S_{k,t+1} = (x_{k,t+1}, y_{k,t+1}) && \text{(6c)}\\
& x_{min} \leq x_{k,t+1} \leq x_{max} && \text{(6d)}\\
& y_{min} \leq y_{k,t+1} \leq y_{max} && \text{(6e)}\\
& ||S_{k,t+1} - S_{k,t}|| \leq v/f && \text{(6f)}\\
& \text{otherwise} && \text{(6g)}\\
& S_{i,t+1} = S_{i,t} && \text{(6h)}
\end{aligned}$$

In other words, at each epoch, each drone k considers its speed v, update frequency f, and current position $S_{k,t}$ to obtain a set of candidate reposition waypoints in P indicated in Eq. (6b-6f). Taking into account neighboring networked drones and their recent GPS coordinates in Eq. (6g-6h), the drone computes its next best reposition waypoint by maximizing angular spread $sin^2(\hat{\phi}_t(S_{i,t+1}) - \hat{\phi}_t(S_{j,t+1}))$ between drones, while also minimizing the distance, $\hat{d}_t(S_{i,t+1})$ to the target in Eq. (6a). We describe the algorithm's key aspects as follows.

1) Unknown Target Location: In FALCON, drones estimate the location of the target and continually improve those estimations as a mission progresses. For that, at each epoch, each drone k for $\forall k \in N$ first shares its individual range estimate $d_{k,t}$ and current GPS coordinate $S_{k,t}$ with other drones in the network. Then, they use all the data to estimate the target $\hat{U}_t$.

Initially, when a mission just started and no prior target estimation is available, drones employ a least-squares filter to develop an initial estimate of the target's location, thereby minimizing estimation error in a least-squares sense. As they progress in a mission and obtain more diverse observations, the drones employ both the new and previous target location estimates. For that, we implement an Extended Kalman Filter, a well-known approach for many analogous problems, e.g., [10]. Following the predict and update phases of the filter, drones revise their estimate leveraging both the current and past range estimates of all drones. Hence, the flight planning strategy combined with filter-based measurement fusing enables accurate target localization. As more drones are involved in a mission, FALCON further improves the localization accuracy and localization convergence time by taking advantage of an increasing number of measurements in a given epoch.

2) Flight Planning over Time: Unlike static sensors in one-shot sensors positioning, drones take advantage of their mobility and reposition to more informative locations throughout a mission. For that, a drone computes a set of physically reachable candidate reposition waypoints at each epoch by taking into account its speed, update frequency and current location. To have a different perspective of the target position, each drone considers all other drones in the network and their current locations as indicated by Eq. (6g-6h). Then, to decide on the best next reposition waypoint at $t+1$, drone k computes the total target information by considering the angular spread between each of its candidate reposition waypoints $S_{k,t+1} = (x_{k,t+1}, y_{k,t+1})$ and the latest estimated target position $\hat{U}_t = (x_{\hat{u},t}, y_{\hat{u},t})$ as $\hat{\phi}_t(S_{k,t+1}) = tan^{-1}(y_{k,t+1} - y_{\hat{u},t}/x_{k,t+1} - x_{\hat{u},t})$

When focusing on the diverse observation aspect of the strategy, the expression $sin^2(\hat{\phi}_t(S_{i,t+1}) - \hat{\phi}_t(S_{j,t+1}))/(\sigma_i^2 \sigma_j^2)$ provides incentive to maximally spread drones out over time as indicated in the objective function in Eq. (6a). This feature is particularly important in flight navigation as it enables localization accuracy improvement as the mission progresses. This is especially critical when drones just started a mission and their estimated target position may be far away from the true target location. However, as drones actively sense and spread out, their belief about the target location more accurately reflects the true target location.

3) Dynamics of Approaching: Another important aspect of the proposed flight strategy is the approaching feature which is represented as an inverse of $\hat{d}_t(S_{i,t+1}) = ||\hat{U}_t - S_{i,t+1}||$.

Due to symmetry stemming from two-pair neighboring drones, there is also $\hat{d}_t(S_{j,t+1})$ with index j in the function. We provide the mission planner with the flexibility to control the rate of approaching a target via a parameter λ. Serving a key role in the objective function, λ balances the importance of approaching vs. diverse observation. In return, diversity of observation impacts localization accuracy while dynamics of approaching impacts total travel distance in a mission.

In one extreme, when λ is chosen to be large, drones will fly nearly directly towards the estimated target with almost no spreading. Provided they are traveling in the correct direction, this would yield minimal total travel distance. However, this may not be the case as if λ is too large, localization accuracy may suffer due to lack of diverse observation. On the other extreme, when λ is very small, drones focus on diverse observation and will localize a target as accurately as possible. In this case, the distance traveled would be increased as the drones would fly to spread out in the search area, and would not have incentive to approach the target. Thus, in FALCON, λ provides the flexibility to choose between these trade-offs based on the mission requirements.

Lastly, we remark that the drones can potentially dynamically adjust λ during a mission based on, for instance, the quality of the sensory data. If measurements are too noisy or estimation error is high, drones can tune λ to a lower value to focus more on spreading. Conversely, if measurements are of high quality and drones need to reach the target quickly, then λ can be adjusted to a higher value to emphasize approaching. Nonetheless, such dynamic adaptation of λ is beyond the scope of this paper.

III. Evaluation Setup: Multi-drone System

We design FALCON to comprise of three main components.

Drone Platform: As shown in Fig. 3, in addition to essential navigation sensors such as GPS and gyroscope, each drone

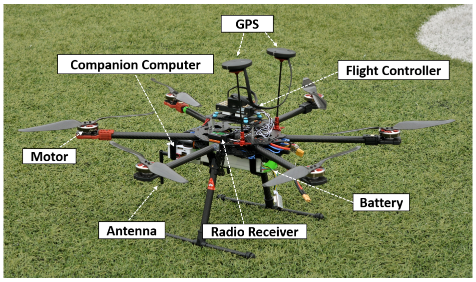


Fig. 3: FALCON drone platform

has two main control blocks, Flight Controller (FC) and Companion Computer (CC), that assist it in navigation. The FC is resource-constrained embedded hardware that focuses on communicating with on-board sensors and managing dynamics of the flight as directed by mission logic. The CC is a more powerful embedded computer that executes the mission logic. We employ an UP-Board running on Linux OS as our CC.

Software and Communication: FALCON integrates a custom designed API that abstracts out underlying complexities of avionics in the system. It provides convenient methods for coordinating and sharing sensory data between drones in a mission. In addition, our drones are tetherless and do not require a ground control station for communication and data sharing. They establish an ad hoc network amongst each other and maintain continuous communication throughout a mission.

On-drone Sensing: We leverage the ubiquity of Wi-Fi technology and its recent FTM protocol to realize target-to-drone ranging mechanism. First, we integrate a miniature IoT device by CompuLab with IEEE 802.11mc supporting chipset to our drones. Next, we establish a connection between the IoT device and the drone's CC to enable data exchange between the IoT device that houses FTM specific hardware and firmware and the CC that runs the mission logic. Then, we provide software that can (1) initiate an FTM scan, (2) configure FTM parameters based on mission requirements, and (3) process received FTM measurements on the CC.

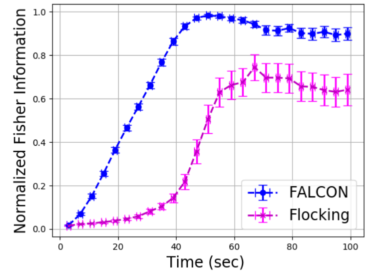
IV. Experimental Evaluation

In this paper, we explore target localization, an increasing number of drones, and the computational complexity of FALCON. Due to limited space, we refer the reader to [11] to provide more details on how to determine target-to-drone ranging error and how to choose λ that offers trade-offs between localization accuracy gains due to diversity of observations from angular spread vs. increased travel distance (highly correlated with energy consumption) to reach a target.

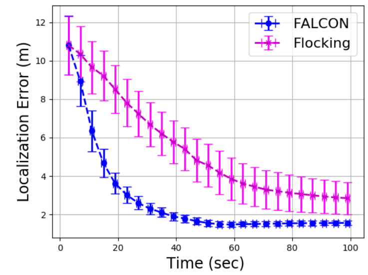
A. Target Localization

In this experiment, we set two networked drones on a mission to localize the target such that spreading out can now impact localization accuracy alongside sensor measurement errors from FTM and GPS.

Setup: Experiments are performed at Rice Stadium. Drones start a mission from the upper region of the stadium and the target is positioned in the lower center of the stadium as shown in Fig. 6. We set λ to 2 and configure the remaining parameters of the experiment based on Table I. A mission is considered completed when the target estimation converges and drones are within distance a_{th} of the target.



(a) Normalized FI vs. time



(b) Localization error vs. time

Fig. 4: Two networked drones localizing and approaching a target.

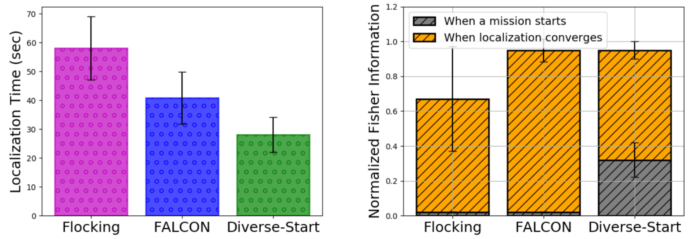
Drone speed (v)	1m/s
Search space resolution	1m
Reposition frequency (f)	4s
Collision threshold (c_{th})	8m
Approaching threshold (a_{th})	10m
Drone altitude	10m

TABLE I: List of important evaluation parameters

As discussed in Section II-C, diversity of observation is a key factor for accurate target localization. We quantify this factor via Fisher Information (FI) following Eq. (5) and normalize it over the maximum achievable information with two drones [5].

Information Gain: Fig. 4(a) shows normalized FI with a 95% confidence interval. It indicates that FALCON and the flocking scheme have similar low information due to the initial nearly co-located position of drones. However, it also suggests that FALCON gains information at a much higher rate compared to the flocking strategy as a mission progresses. For instance, in the first 20 sec of a mission FALCON attains $10\times$ more information compared to the flocking scheme. This is because of the diverse observation feature which allows FALCON drones to spread out as soon as a mission begins. While spreading from their initial positions, drones view the target from increasingly diverse spatial positions. This, in turn, enables FALCON to acquire information at a much faster rate compared to the flocking scheme whereas drones in the flocking scheme stay close to each other as a flock throughout a mission and observe the target from a similar location.

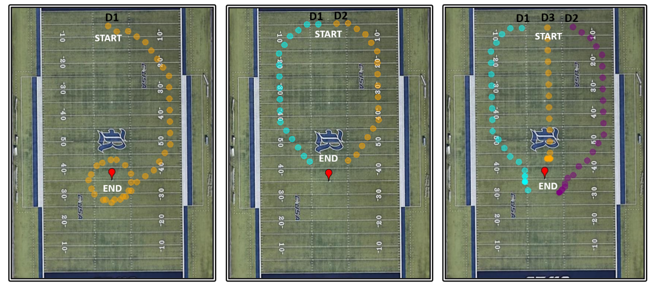
The figure also suggests that FALCON attains more than 90% of achievable information in just 40 sec and maintains it throughout a mission, with slight variation in the information corresponding to continuous estimation and repositioning



(a) Localization convergence time

(b) Information gain

Fig. 5: Flight planning with two networked drones



(a)

(b)

(c)

Fig. 6: FALCON with (a) 1, (b) 2 and (c) 3 drones in a mission.

processes. Unlike FALCON, the flocking scheme is only able to gradually increase its information in the first 40 sec, achieving less than 20% of information. Initially, drones in the flocking scheme are both far away from the target and flying at close proximity; they severely lack diverse observations and therefore experience an extreme scarcity of information. Hence, they inaccurately localize the target and spend some time flying mostly in the wrong direction. As they eventually come closer to the target later in a mission, the angular spread quickly increases because of reduced distance to the target. This raises the average FI from 0.2 to 0.65 during $40 - 60$ sec. However, lack of diverse observation in the process of approaching the target results in inconsistency of acquired information. It is demonstrated as FI standard deviation of ± 0.1 in Fig. 4(a). FALCON, in contrast, consistently acquires almost all information about the target location in a short period and retains it as a mission progresses.

Localization Accuracy: We now explore how the information gain impacts localization accuracy: Fig. 4(b) shows localization error with a 95% confidence interval vs. time. First, both FALCON and the flocking strategy initially localize the target with a high mean error of 11m and a standard deviation of $\pm$2m because a mission just has started and the drones extremely lack information. Then, similar to the gradual and inconsistent information gain, the flocking scheme only gradually improves localization accuracy, with average error converging to 3m and standard deviation always fluctuating in the scale of $\pm$1m. In contrast, through consistent and rapid information gain, FALCON drastically improves the accuracy as drones reposition in a mission. In a short period, it localizes the target $2\times$ more accurately compared to the flocking strategy and reduces the standard deviation of the error to a negligible value. Notice that FI does not necessarily map one-to-one to accuracy due to the target estimation process involving in the mission cycle. However, it demonstrates the impact of information gain on target localization accuracy over time and provides the reasoning behind the performance advantages of FALCON.

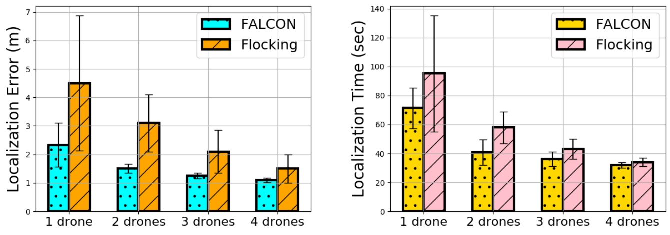
Localization Time: For the different methods, Fig. 5(a) depicts localization convergence time whereas Fig. 5(b) shows normalized FI when a mission starts and when the target localization converges. To analyze the impact of initial diverse observation on the localization time, here we also have Diverse-Start strategy. It considers drones that start a mission from diverse positions, from different corners of the stadium, and otherwise follow FALCON. First, observe that the Diverse-Start strategy is the fastest to localize a target, on average requiring less than 30 sec. This is attributed to the fact that drones in the Diverse-Start strategy are already spread out in the beginning of a mission (viewing the target from different corners of the stadium) and already have approximately one-third of the total information when a mission just begins as indicated in Fig. 5(b); only the remaining information needs to be acquired during a mission to quickly localize a target. However, drones in FALCON and the flocking scheme start a mission from similar positions and their initial information is in the scale of one-fiftieth. To localize a target, the flocking scheme on average requires approximately 1 min, navigating drones to move as a flock. FALCON, in contrast, needs 30% less time compared to the flocking scheme to localize a target by jointly spreading and approaching a target in a mission.

B. Increasing Number of Drones

To yield a unique solution, multi-lateration requires at least three observation points for 2D and four for 3D. Thus far, we have examined FALCON with two drones, seemingly under-constrained for 3D multi-lateration. However, FALCON exploits the mobility of drones to realize multiple spatial observation points with each drone. Consequently, localization and tracking are even possible with a single drone. While increasing the number of drones is advantageous for localization accuracy and localization time, it also increases the total system cost and energy usage.

Single Drone: Following the proposed flight strategy in Eq. (6a - 6g), the drone in this scenario plans its next reposition waypoint with respect to the previous location $S_{k,t-1}$. Fig. 6(a) demonstrates the trajectory of the drone denoted as D1. Notice that the drone navigates in a non-direct, curved pattern before encircling the target. This is because the drone aims to increase FI over time by exploiting lateral observations and obtaining different spatial views of the target. For a single drone, straight-line flight would miss that opportunity and provide only a single-sided view of the target with very limited observability, ultimately degrading localization accuracy.

Once a_{th} distance from the localized target, the drone encircles the target in order to maintain (and if possible, even further improve) observation diversity. This also aligns with prior work [12] in which a drone circles over the target for optimal target localization. Moreover, the FALCON drone also has the flexibility to modify the radius of the circle via simply adjusting approach threshold a_{th}, with larger a_{th}



(a) (b)

Fig. 7: Localization accuracy as the number of drones increase

corresponding to expanded circle. This feature might be of particular use in accommodating different mission scenarios, for instance, dynamically adjusting the radius of the circle to track a mobile target.

Multiple Drones: Unlike the single drone scenario, some missions require multiple drones, for example, to share the workload or decrease localization time. Then, as the number of drones increases, the issue of collision among drones arises. To prevent it, drones maintain collision avoidance distance c_{th} between each other. With two drones in a mission, as shown in Fig. 6(b), the risk of collision is typically low since λ enables sufficient spreading of drones D1 and D2 to two different sides of the stadium to avoid collision (unless λ is sufficiently high that the approaching component of the strategy prevails, in which case the drones move directly to the estimated target keeping c_{th} between each other).

When there are more drones in a mission, e.g., three as shown in Fig. 6(c), the two outermost drones, D1 and D2, approach the target in a spread out pattern while D3 navigates between those drones. An interesting behavior occurs when there is no collision avoidance or if c_{th} is extremely small. Then, D3 tend to fly close to the outermost drones, even following their flight pattern. This is due to the two-pair effect that results from expressing angular spread between drones via the two-pair angular combination. However, adjusted appropriately, e.g., $c_{th} = 8m$ in Fig. 6(c), collision avoidance itself creates a form of diversity that enables all drones in FALCON to navigate towards the target from a diverse perspective.

Localization Accuracy: Fig. 7(a) shows localization error as the number drones increase for FALCON and the baseline flocking strategy. First, notice that FALCON outperforms the flocking strategy for any number of drones. However, the flocking strategy improves its localization accuracy at a much higher rate as more drones join a mission. For example, compared to a single drone mission, the localization error drops to 53% with three drones, and even to 67% with four. The reason this is that adding extra drones increases the ratio of drones per search area and higher overall observation is achieved. To understand the scale, consider four drones positioned ten meters apart from each other ready to start a mission. Then, the drones already cover more than 70% of the search space's width. As they progress in a mission, they potentially create virtual sensors all over the search area, which results in significant improvement of localization accuracy. In contrast, FALCON relies on informative flight decisions to achieve high localization accuracy, even with several drones in a mission. A single drone following FALCON's flight strategy (exploiting diverse observation) can attain the accuracy of 2.3m whereas two drones achieve similar localization accuracy results to that of four drones in the flocking scheme. Being able to acquire most of the informative measurements with a limited number of drones, FALCON can achieve high accuracy with several drones, and the improvement beyond two drones is incremental, at least in this relatively small search area.

Localization Time: Fig. 7(b) presents converged localization time that FALCON and the flocking strategy incur for a different number of drones. Similar to the localization accuracy analysis, having more drones in a mission significantly helps the flocking scheme to more quickly localize the target due to extra observations that each drone contributes to a mission. In particular, compared to a single drone, two drones can decrease localization time by 37% whereas three drones improve localization by more than half. Also, notice that FALCON sharply decreases localization time when two drones are involved in a mission in contrast to one drone. This is because the additional drone navigates to exploit the second half part of the view (right-hand side of the stadium in Fig. 6(b)) of the target position, which is critical for boosting the information gain. Overall, FALCON is effective in quickly acquiring target location information, and always outperforms the flocking scheme as shown in Fig. 7(b).

C. Computational Complexity

We develop a distributed and computationally light-weight flight planning strategy that provides real-time flight decisions on resource-constrained drone platforms. For that, each drone k takes into account its speed v, reposition update frequency f and search space grid resolution r to construct a set of W candidate reposition waypoints that are physically reachable until the next reposition instance. Next, it considers each of the waypoints in the set and the current location of the $N-1$ neighboring drones in the network to performs $W \times (N-1)$ angular spread and distance to target computation. Then, it selects the best waypoint from that set that maximizes the angular spread of the networked drones relative to the estimated target and minimizes the distance towards it. Although increasing drone velocity, update frequency, search area, or spatial resolution also increases W, such increases have a linear impact on the overall complexity of the strategy. Given the search area of $50m \times 100m$ and the grid size of $\times$ 1m, in the experiments, it takes just several milliseconds for two drones flying at 1m/s and $f = 0.25$Hz to compute their next best reposition waypoints on UP-Board companion computer.

D. Discussion

Leveraging $3D$ mobility of drones, FALCON takes advantage of the dominant LoS property of air-to-ground channel. In some environments with blocked LoS signals, ranging quality will likely to decrease (up to several meters [6]), yet accurate localization can still be achieved by repositioning drones for a better view and/or applying spatio-temporal filters to smooth out errors. Also, FALCON can be extended to multiple target missions. The flight strategy could be adapted in a divide-and-conquer fashion, assigning different drones to different targets, or it could also be formulated as a joint optimization problem, exploiting cumulative informative locations.

V. Related Work

Flocking Approach: Cooperative behavior of birds has inspired, perhaps, the most well-known and well-understood flocking approach [4], which later has been employed by many multi-robot systems for target tracking, e.g., [13], [14]. In such work, robots follow 3 basic rules for repositioning: *cohesion* rule to stay close to nearby robots, *separation* rule to avoid a collision between robots, and *alignment* rule to match velocity and heading of robots. It also adheres to the leader-follower hierarchy [15]; a more experienced bird (more advanced robot) takes the lead while other members join as followers. Unlike the flocking approach, FALCON navigates drones to simultaneously to localize, approach, and track a target by jointly optimizing for diverse of observation and dynamic approaching. While the leader-follower hierarchy and simple rules of the flocking approach can potentially enable better scaling to swarms of 100's, FALCON allows for more advanced on-board processing with drones of equal standing.

Fine Time Measurement (FTM): Wi-Fi FTM provides an estimate of ToF between an FTM initiator, a client, and an FTM responder, an Wi-Fi access point, with nanosecond resolution [16]. Existing implementations of the protocol focus on self-positioning the client in an indoor environment, e.g., self-localizing a client inside a building [7]. For that, the client usually performs multilateration in an environment that has multiple distributed APs deployed. Recently, [17] proposed to complement existing GPS and odometry systems by jointly fusing FTM, GPS, and odometry information in vehicle self-positioning. It has shown to achieve lane-level positioning accuracy in urban canyons. Unlike any prior work, FALCON is the first system to realize the on-drone target-to-drone range sensing mechanism via FTM and to propose a flight planning strategy to autonomously navigate a network of drones.

Experimental Multi-Drone Systems: While there are many algorithmic prior works, relatively few design a multi-drone system and perform field experiments, e.g., [3], [18], [19]. Moreover, most existing systems are designed with different goals than FALCON. For instance, [19] proposed a software-defined control framework and presented a prototype of a fully reconfigurable drone network. The most relevant work [18] aims to localize VHF radio-collared animals via multiple drones equipped with yagi antennas, capturing bearing information. Unlike autonomous and adaptive flight proposed in FALCON, drones in [18] navigate to pre-defined sample locations that are based on dividing the search space into disks of equal radius. FALCON also takes advantage of ubiquitous Wi-Fi for range sensing. Leveraging the infrastructure of [3], FALCON integrates FTM feature on a multi-drone platform, implements a novel flight planning strategy, and proposes an end-to-end system to approach, localize, and track RF targets.

VI. Conclusion

In this paper, we propose FALCON, an end-to-end system to autonomously approach, localize, and track RF targets via drone networks. We realize the target-to-drone range mechanism and propose a novel flight planning strategy. We implement FALCON on a multi-drone platform and show that, compared to a baseline flocking scheme, FALCON achieves up to twice the localization accuracy and requires 30% less time. The performance improvements can be realized by deploying fewer drones, having faster missions, achieving higher localization accuracy, or any combination of these features.

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