FALCON: a Networked Drone System for Sensing, Localizing, and Approaching RF targets

Zhambyl Shaikhanov, Ahmed Boubrima, and Edward W. Knightly

***Abstract*—We present FALCON, a novel autonomous drone network system for sensing, localizing, and approaching RF targets/sources such as smartphone devices. Potential applications of our system include disaster relief missions 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 and the target approaching process, 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*—Fine Time Measurement sensor network, autonomous flight planning, networked drone system, localization and approaching**

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 [2], and require significant time to compute AoA, e.g., 45 sec per observation [3]. Likewise, prior on-drone methods employing a *single* antenna per drone sensed RSSI to localize targets, e.g., [4]. However, as RSSI is only coarsely related to distance, [4] 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 [4] 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., [5] mimics the flocking behavior to approach a target whereas [6] 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, leveraging the ubiquity of Wi-Fi [7]–[10], we realize on-drone target-to-drone ranging estimates via Wi-Fi Fine Time Measurement (FTM) and integrate this capability with networked sensing and mission planning. Standardized in 2016 [11], 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., [12]. 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. We begin with a controlled experiment in which we analyze target-to-drone ranging error by performing on-drone distance estimation from predefined locations. The results indicate that a 95-percentile error is approximately ± 2m. Moreover, errors are consistent for different ranges due to the dominant line-of-sight (LoS) property of air-to-ground channels and the linear relationship of ToF measurements and distances. To understand the impact of λ on the trade-offs between accuracy gains due to diverse observations from angular spread vs. increased travel distance to reach a target, we perform missions with a known target position and different λ values. As a baseline, we consider a flocking scheme that navigates drones to flock and move directly towards the

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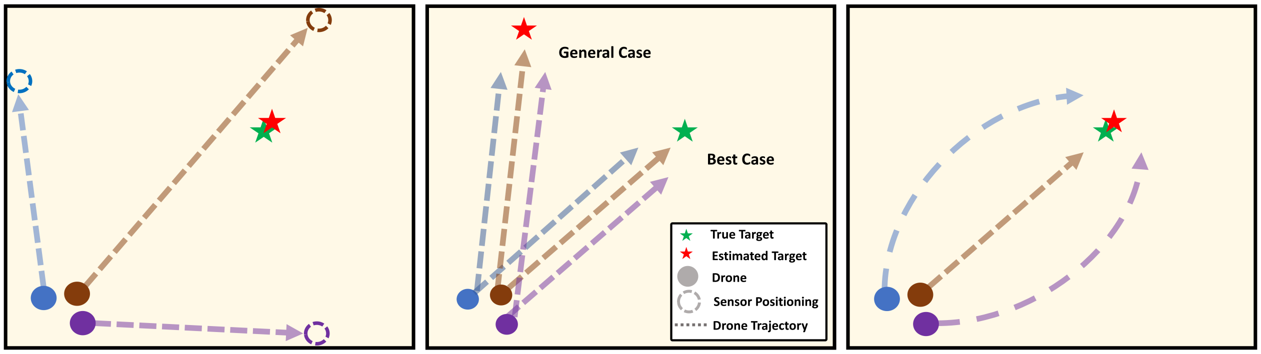


(a) (b) (c)

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

latest estimated target location. We find that, with two drones in the network and $\lambda = 2$, FALCON can increase average angular spread by $2.2\times$ at the expense of only 27% additional average travel distance when compared to the flocking scheme. Moreover, as λ increases beyond fourteen, FALCON mimics the flocking scheme by heavily focusing on approaching.

Next, we perform missions where two drones actively sense and continually reposition to localize and approach an unknown target. Our findings reveal that, compared to the flocking scheme, FALCON consistently and rapidly acquires information about the target position because of its diverse observation feature. Consequently, FALCON localizes a target $2\times$ more accurately and in 30% less time. Likewise, we show that even a single FALCON 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 to improve accuracy whereas FALCON exploits informative locations to achieve better results with fewer drones.

The remainder of this paper is organized as follows. In Section II, we present the FALCON framework, analyze one-shot sensor positioning and, building on that, describe our flight planning strategy. In Section III, we present the design of the on-drone FTM sensing mechanism and describe our multi-drone platform. In Section IV, we present the key results from our experimental evaluation of FALCON as well as the benchmarking baselines. In Section V, we provide an overview of the related work. Finally, we provide a discussion of potential extensions in Section VI and conclude the paper in Section VII.

II. FALCON Framework

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

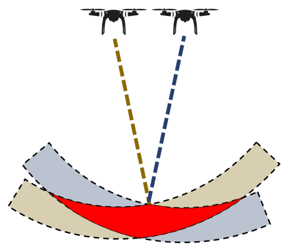
A. Design Overview

On-drone Sensing: In the design of FALCON, 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 via FTM. We discuss our on-drone target-to-drone ranging mechanism in Section III-B.

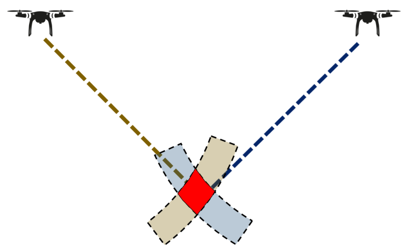
Flight Planning: Next, we design a flight planning strategy that navigates networked drones to approach, localize, and track targets in a mission. For the first time, we consider these objectives concurrently so that drones can improve measurement resolution and realize approaching-critical tasks in addition to localization and tracking. For that, we propose to jointly exploit diverse observation of drones and their dynamics of approaching targets.

To illustrate FALCON's design principles, Fig. 1 shows a simplified example of FALCON compared to two fundamental classes of prior approaches. We consider that networked drones launch a mission from nearly co-located positions, from the bottom-left side of the search area in this example. The drones could have been transported to the area as a group, for instance, on a first responder vehicle, or they might have already been positioned there, possibly at a charging station. We consider that the drones perform a mission as a team, cooperating and coordinating.

In the sensor positioning strategy shown in Fig. 1(a), drones 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. In FALCON, we design



(a) Observing a target from similar locations



(b) Observing a target from diverse locations

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

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 as it provides spatially independent samples, 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* [6]. 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 averages of the measurements are depicted as dotted lines, while standard deviations are shown as blue and brown segment areas for the respective drones. 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, demonstrated as a shrinking confusion area.

Before characterizing the confusion area, we first 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 $U = (x_u, y_u)$. 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

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

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.

Therefore, 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 [6] as

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

where $\nabla_U \log L_d$ is the gradient of the log likelihood function with respect to the source location. 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 [13]

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

Applying trigonometric substitution, it can then be simplified to

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

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

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

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.

First, notice that with one sensor and $N = 1$, D in Eq. (5) equals zero for any source location; therefore, at least $N \geq 2$

sensors are required for the technique. Next, observe that the total information is described by the angular spread between neighboring sensors, $sin^2(\phi(S_i) - \phi(S_j))$. 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. When more than two sensors are involved in positioning a target, the technique takes into account the angular spread of all two-pair combinations of the sensors.

C. Flight Planning

In contrast to the 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 waypoint to best 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, the drones have constrained initial position which may be nearly co-located starting location in a mission. 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:

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

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

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 the objective function 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. To do so, at each epoch, each drone k for $\forall k \in N$ first shares its individual target-to-drone 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 networked drones start a mission and no prior target estimation is available, they 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., [14]–[16]. Following the predict and update phases of the filter, drones revise their estimate of the location of the target 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 in FALCON can 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

$$\hat{\phi}_t(S_{k,t+1}) = tan^{-1}(\frac{y_{k,t+1} - y_{\hat{u},t}}{x_{k,t+1} - x_{\hat{u},t}}). \tag{7}$$

When focusing on the diverse observation aspect of the strategy, the expression

$$\frac{sin^2(\hat{\phi}_t(S_{i,t+1}) - \hat{\phi}_t(S_{j,t+1}))}{\sigma_i^2 \sigma_j^2} \tag{8}$$

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 $\hat{d}_t(S_{i,t+1})$ in the objective function in which

$$\hat{d}_t(S_{i,t+1}) = ||\hat{U}_t - S_{i,t+1}||. \tag{9}$$

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. We experimentally explore these tradeoffs in Section IV.

D. FTM-based on-drone sensing

The Wi-Fi FTM protocol provides a time of flight estimate (ToF) between an FTM initiator (client) and an FTM responder (Wi-Fi access point) with nanosecond resolution [17], [18]. Considering transmission frequency and the speed of light, FTM enables meter-level ranging accuracy between the client and the access point [11], [19]. We leverage the ToF data that is collected by our on-drone FTM devices in order to obtain distance values d_i from each drone i. We then use Eq. (5) to estimate the target location as previously discussed in this section.

Furthermore, we propose to adjust the λ diversity parameter adequately depending on the quality of the FTM sensor data. Indeed, if measurements are too noisy or the estimation error is high, we 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, we then adjust λ to a higher value to emphasize approaching.

III. Evaluation Setup: FTM-enabled Multi-Drone System and Drone FTM Dataset

FALCON leverages the ubiquity of Wi-Fi technology [7]–[10] and its recent FTM protocol to realize target-to-drone range sensing. We integrate FTM with our drone network infrastructure to enable the networked drones to realize the objectives described in Section II. We create a target-to-drone ranging dataset by ranging a target via FTM-enabled drones in an outdoor environment. We perform in-the-field missions to analyze the impact of various factors on FALCON and other baseline flight planning strategies and also use the dataset to emulate additional scenarios.

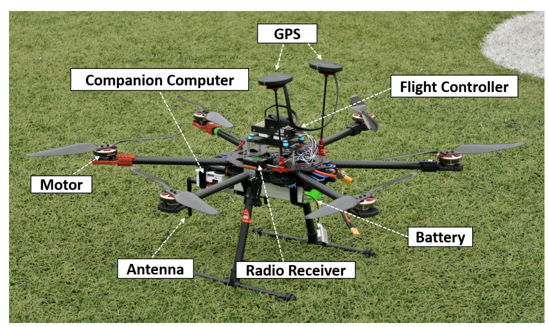


Fig. 3: FALCON drone platform

A. Multi-Drone Infrastructure

To realize FALCON, we extend the open-source multi-drone platform [4], [20] with three main components.

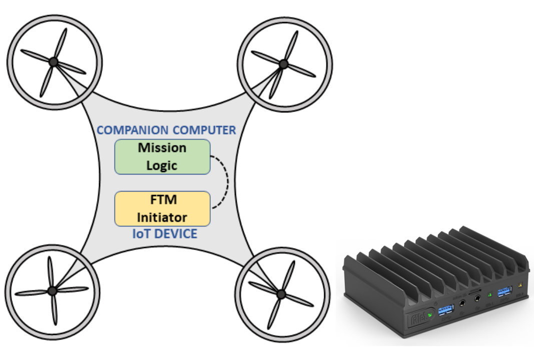
Drone Platform: Our drones are made of durable and lightweight carbon fiber frames and equipped with navigation sensors such as GPS and gyroscope as shown in Fig. 3. Each drone has two main control blocks, Flight Controller and Companion Computer, that assist it in navigation. The Flight Controller is resource-constrained embedded hardware that focuses on communicating with on-board sensors and managing dynamics of the flight as directed by mission logic. The Companion Computer is a more powerful embedded computer that executes the mission logic. We utilize an UP-Board with an Intel Atom x5 Z8350 quad core processor running Linux as our Companion Computer.

Software: FALCON integrates a custom designed API that abstracts underlying complexities of avionics in the system. It provides convenient methods for coordinating and sharing sensory data between drones in a mission. In addition, the API helps to analyze each building block of FALCON separately and to build an emulator that can run a mission on experimental dataset.

Communication: Drones in FALCON 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 with each other throughout a mission via Wi-Fi.

B. FTM On-Drone Platform

To enable on-drone FTM, we first considered different network devices that support IEEE 802.11mc FTM capability. Ideally, we wanted to have a compact and lightweight device like a pocket-sized USB Wi-Fi dongle with a Wi-Fi chipset that supports IEEE 802.11mc FTM protocol so that drones can carry and perform missions with it. Unfortunately, as of this writing, no such device is yet available in the market. Most of the FTM compatible chipsets such as Intel AC8260 are, at this moment, dedicated to large systems like desktop computers and laptops. One available miniature device with IEEE 802.11mc FTM support is an IoT device provided by CompuLab. By modifying the device and leaving only integral components, we integrate it on FALCON drones. At the end, the device adds an extra 200g weight and takes 11cm $\times$ 8.5cm $\times$ 3.5cm space on the drone platform (which fits our drone allowed payload). Next, we establish a connection



(a) (b)

Fig. 4: (a) FALCON with on-drone FTM and (b) IEEE 802.11mc FTM compatible IoT device

between the IoT device and the drone's Companion Computer to enable data exchange between the IoT device that houses FTM specific hardware and firmware and the Companion Computer that runs the mission logic. For that, we first connect those two devices via an Ethernet cable as shown in Fig. 4(a). We implement multiple software routines to (1) initiate the FTM Responder scan, (2) configure the FTM parameters based on mission requirements, and (3) process collected FTM measurements on the Companion Computer. In the implemented software, we create an SSH PIPE interface between the devices and access the IWLWIFI driver of the IoT device via the IW command in the Companion Computer. We then pass the command line arguments to trigger the search of the nearby FTM Responder, configure the FTM parameters (such as the desired bandwidth and the number of FTM samples) and access ToF measurements, eventually computing range values.

C. Target-to-drone Ranging Dataset

Once we realize on-drone FTM, we collect experimental data of FALCON drones ranging a target via onboard FTM. We then create a dataset that we later employ to emulate some missions.

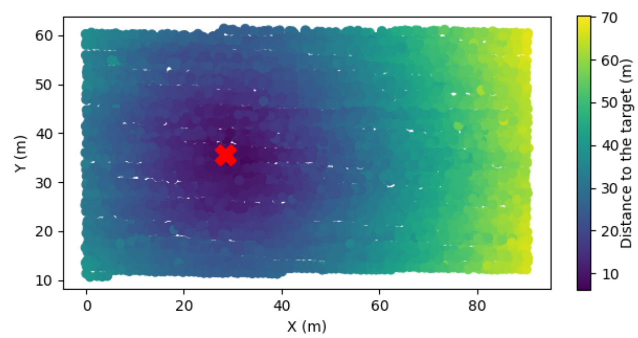


Fig. 5: Drone FTM dataset

To comply with urban Federal Aviation Administration (FAA) regulations [21] and to perform experiments in a controlled environment, we select a large football stadium [22] as a mission operation region. First, we configure an IoT device similar to the one in Fig. 4(a) as an FTM Responder and designate it as the target in this experiments. We put it on a 1.5m height tripod stand and position it in the stadium. Next, we fly a drone in a waypoint fashion, traversing the entire the stadium. While flying, the drone performs FTM measurements and computes range estimates to the target.

Fig. 5 is an example of one map out of a total of five in the database. The dataset has high spatial resolution because the drone collects data every 1m. It also has a multitude of samples at each location since the drone collects dozens of measurements at every point. Overall, 100s of drone batteries have been recharged in the effort to create this dataset.

IV. Experimental Evaluation

In this section, we perform an experimental evaluation of FALCON and baselines and study a broad set of performance factors from target-to-drone ranging error to an increasing number of drones in the network.

A. Target-to-drone Ranging

A FALCON drone incorporates the error of target ranging to compute its next waypoint to maximize localization accuracy. To range a target, it observes ToF of the RF signal from that target via on-board FTM device. Any ToF error such as

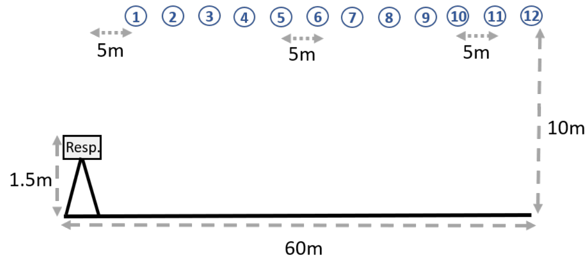


Fig. 6: Field setup of the drone's ranging locations

reflected signals creates ranging error. In addition, the drone's GPS error contributes to the ranging error because the drone estimates its distance to the target with respect to its GPS position. These two sources of error should be statistically independent and additive since they are unrelated. In this experiment, we evaluate the total ranging error by positioning a drone in 12 pre-determined locations from the target. The drone then hovers at an altitude, holding its position based on GPS measurements, and measures its distance to the target via on-board FTM.

Setup: We configure the CompuLab IoT device as the FTM responder and position it in an open field of the stadium on a 1.5m tall tripod to serve as a target. We then horizontally tape measure and mark 12 ranging locations from the target from 5m to 60m in steps of 5m. We position the drone over each of these marked locations and set it to hover at 10m altitude. The drone then uses dual GNSS GPS receivers to hold its position and range the target while hovering. Fig. 7 shows

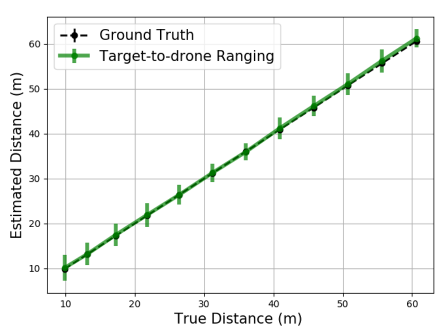
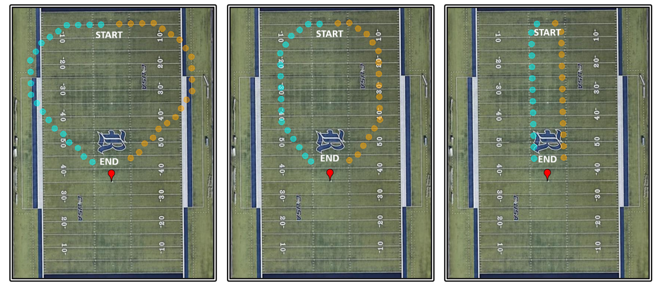


Fig. 7: On-drone target-to-drone ranging estimates

the mean and 2 standard deviations of the drone's FTM range estimation. The results indicate that 95% of the time the ranging error is around $\pm$2m and the error is consistent for over different distances. Two main features of the FTM-enabled drone contribute to the consistent measurements with distance: First, FTM operates based on the ToF. Unlike, for instance, received signal strength, ToF increases linearly with distance which, in principle, allows ranging error to be independent of distance. Second, the drone measures an air-to-ground channel. Contrary to terrestrial ground-to-ground channels, air-to-ground channels have dominant LoS and limited multi-path fading. It enables most of the signals to travel directly towards the target and produce consistent ToF measurements. In addition, we observed in the experiments that the dual-GPS accuracy is approximately $\pm$1m. Clear view of the sky and dual GPS receivers enable the drone to observe sufficient satellite signals to position itself in space. Moreover, the on-board gyroscope and low-level flight control logic enable the drone to stabilize at that position.



(a) (b) (c)

Fig. 8: Trajectories of two drones (cyan and orange) with λ value configured to (a) $\mathbf{0.5}$, (b) $\mathbf{2}$, and (c) $\mathbf{14}$

Finding: By exploiting the dominant LoS property of air-to-ground channels and the linear relationship between FTM signals and range estimates, an FTM-enabled drone can estimate distance toward the target with $\pm$2m error for different ranges.

B. How Much to Spread Out (λ)?

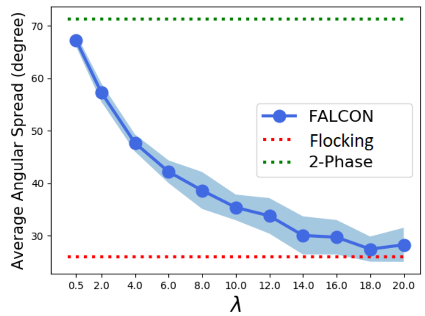
FALCON enables drones to balance their desired diversity of observation with dynamics of approaching via the parameter λ. Lower values of λ contribute to a more angular spread, whereas increasing it allows for more direct movement to the target. We experimentally characterize angular spread and travel distance via a simplified two-drone scenario. For that, we consider drones with a known target location to remove the impact of measurement error, and perform missions with different λ. In this way, we isolate the trade-off between angular spread and travel distance.

Evaluation Parameter	**Value**
Drone speed (v)	1m/s
Drone altitude	10m
Search space resolution	1m
Reposition update frequency (f)	0.25Hz
Collision threshold (c_{th})	8m
Approaching threshold (a_{th})	10m

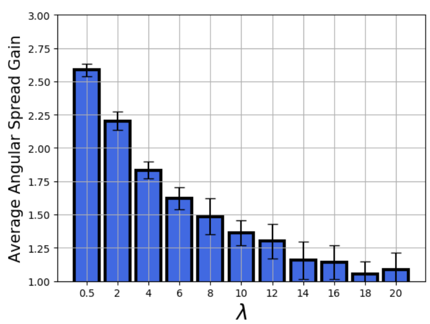
TABLE I: List of important evaluation parameters

Setup: In the experiment, we position drones in the Rice stadium in the region marked "START" as shown in Fig. 8. We position the target in the lower center of the stadium, marked with a red pin, to provide sufficient area for drones to spread out. Drones fly at 10m altitude and 1m/s speed, updating their reposition decision every 4s as listed in Table *I*. To avoid a collision, drones keep c_{th} distance between each other. At each reposition instances, drones log angular spread and travel distance. The mission proceeds until all drones approach the target, reaching a_{th}. In the experiment, we vary λ, with the smallest value being 0.5 due to the limited search area available for spreading as shown in Fig. 8(a). We increase λ to 20 in steps of 2.

In the evaluation, as a baseline, we consider a flocking strategy that navigates drones directly towards the target as a flock, focusing on minimal travel distance. To compare FALCON with an extreme spreading case, we also consider a 2-Phase strategy that directs drones to maximally spread out first and then approach the target at the cost of the extra travel distance. Because neither flocking strategy nor 2-Phase strategy is dependent on λ, we report their results over all values of λ.



(a) Angular spread as a function of λ



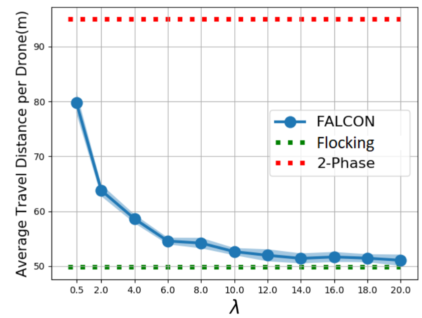
(b) Angular spread gain as a function of λ

Fig. 9: Average angular spread and average angular gain relative to the baseline flocking scheme

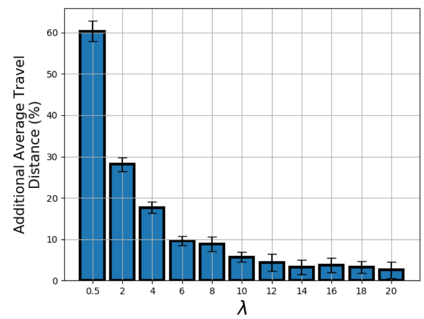
Angular Spread: Fig. 9(a) depicts the drones' average angular spread throughout a mission vs. λ. The flocking strategy obtains approximately $26°$ average angular spread by directly navigating drones to the target in a flocking formation. In contrast, the 2-Phase strategy attains $2.7\times$ more average angular spread than the flocking strategy by first traveling with greater angular spread and then approaching the target at a $90°$ angle. Unlike both of these schemes, FALCON allows drones to choose angular spread by adjusting λ.

As shown in Fig. 9(a), the standard deviation of the average angular spread increases with increasing λ. This is due to GPS error that has increased impact on the deviation of the angular spread when drones fly close to each other, whereas this impact is minor when drones fly in a spread-out fashion. Thus, larger values of λ are more sensitive to GPS error. Moreover, there is a step effect when $\lambda \geq 10$. This arises due to the joint effect of discretization of the search space and the fact that at larger values of λ, drones tend to reposition over similar waypoints that lie in the direction of the straight path to the target.

Fig. 9(b) shows the average angular spread gain of FALCON in with respect to the flocking scheme vs. λ. The figure suggests that FALCON enables $2.2\times$ average angular spread gain with λ set to 2 and even more when $\lambda < 2$. However, as λ increases, the diversity of observations decreases rapidly and the approaching feature dominates the flight decision. For instance, less than $1.5\times$ gain can be attained when λ is 8. Also, as $\lambda \geq 14$, drones fly with minimal spreading, reaching diminishing returns on average angular spread gains.



(a) Travel distance as a function of λ



(b) Additional travel distance as a function of λ

Fig. 10: Average travel distance per drone and additional average travel distance relative to the flocking scheme

Travel Distance: Since λ trades angular spread for travel distance, we now explore travel distance: Fig. 10(a) depicts average distance traveled per drone throughout a mission as a function of λ. First, notice that drones travel only 50m by following the flocking scheme and moving straight towards the target. The 2-Phase strategy, on the other hand, requires drones to fly approximately twice that distance to complete both spreading and approaching phases. In FALCON, the travel distance can be adjusted based on the λ value, which in turn can be chosen, for instance, based on the quality of the sensory data or remaining energy level in a mission.

Fig. 10(b) shows the additional average travel distance of FALCON relative to the flocking scheme. The results indicate that with λ set to 2, the extra distance is less than 30% while average angular spread gain is more than $2\times$ compared to the flocking scheme. The figure also suggests that as λ increases, the additional distance decreases and becomes even negligible for $\lambda \geq 14$ due to a rapidly diminishing observation. In that case, the approaching feature dominates the flight decision, allowing for less travel distance. In the experiment, the maximum extra travel distance is approximately 60% which corresponding to $\lambda = 0.5$. It also enables more than $2.5\times$ angular spread gain as shown in Fig. 9(b).

Finding: i) With two drones and $\lambda = 2$, FALCON can realize $2.2\times$ average angular spread gain at the expense of 27% additional average travel distance compared to the baseline *flocking scheme. ii) As λ increases beyond 6, the approaching feature of FALCON reduces the extra travel distance to less than 10%. iii) Drones heavily focus on approaching when $\lambda \geq 14$, mimicking the flocking strategy in the flight decision. iv) The diversity of observation feature of FALCON enables average angular spread gains up to $2.6\times$ compared to the flocking strategy.*

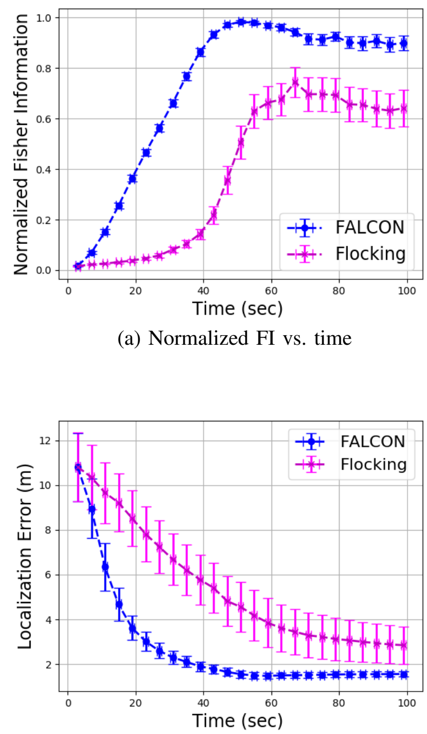
C. Target Localization

Thus far, we have studied FALCON in the context of a known target. Here, drones must also localize the target such that spreading out can now impact localization accuracy alongside sensor measurement errors from FTM and GPS.

Setup: We randomly position drones in the upper region of the stadium and provide 5m -10m separation between drones to imitate a nearly co-located starting location. Similar to Section IV-B, we place the target in the lower center of the stadium. We set λ to 2 and configure the remaining parameters of the experiment based on Table I. In a mission, each drone periodically computes its next waypoint to reposition. For that, the drones first self-position via GPS and perform on-drone target-to-drone ranging estimation via FTM. Then, they share their individual GPS positions and range estimates, and subsequently perform target estimation. Finally, depending on the specified flight planning strategy, the drones compute their next reposition waypoints. A mission is considered completed when the target estimation converges and drones are within distance a_{th} of the target.

In addition to the baseline flocking scheme, we consider a Random-Fast strategy and a Diverse-Start strategy in the experiment. The Random-Fast strategy assumes infinitely fast drones that fly to random waypoints in the stadium. For comparison, we set the number of waypoints visited by the Random-Fast strategy equal to the average number of waypoints for FALCON. Despite the infeasibility of infinitely fast drones, this method provides a reference for achievable localization accuracy when the target is viewed from uniformly random locations in the field. The Diverse-Start strategy, on the other hand, considers drones that start a mission from diverse positions, from different corners of the stadium, and otherwise follow FALCON's flight planning strategy. This benchmark reveals the impact of initial diverse observation on localization time. 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 [6].

Information Gain: Fig. 11(a) shows normalized FI with a 95% confidence interval vs. time. 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 target location 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.



(a) Normalized FI vs. time

(b) Localization error vs. time

Fig. 11: Two networked drones localizing and approaching a target in a mission

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 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. 11(a). FALCON, in contrast, consistently acquires almost all information about the target location in a short period and retains it as a mission progresses.

The Random-Fast strategy instantaneously achieves several orders magnitude more information compared to FALCON or the flocking scheme. While infinitely fast speed allows drones to sample many locations at once, the randomness property of the strategy provides drones with a different view of the target. Hence, the Random-Fast strategy instantly obtains $89\times$ more FI compared to the maximum achievable information with FALCON.

Localization Accuracy: We now explore how the information gain impacts localization accuracy: Fig. 11(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, that are nearly co-located, 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.

Unlike FALCON or the flocking strategy, the Random-Fast strategy instantly achieves localization accuracy of approximately 0.8m via hypothetical infinitely fast drones that can sample randomly in the search space and collect an abundance of information. It serves as a lower bound on localization accuracy in this experiment, and FALCON is much closer to that bound than the flocking scheme.

Note that the obtained results are based on an idealized experimental scenario as more complex experimental conditions will result in higher FTM ranging errors, and therefore require more drones to achieve accurate localization.

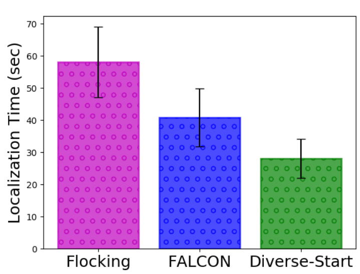


Fig. 12: Localization convergence time vs. flight planning strategy with two networked drones

Localization Time: For the different methods, Fig. 12 depicts localization convergence time whereas Fig. 13 shows normalized FI when a mission starts and when the target localization converges. 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. 13; 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 nearly co-located 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.

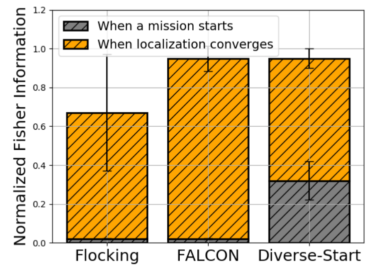


Fig. 13: Target location information vs. flight planning strategy with two networked drones

Finding: i) Exploiting diverse observation as soon as the mission begins, FALCON gains information about the target at a much higher rate compared to the flocking scheme, achieving more than 90% of FI in a short period. ii) FALCON also maintains the acquired information by continually observing the target from the diverse position over time. iii) Flying close to each other like a flock, drones in the flocking are slow and inconsistent in regards to information gain, FI fluctuating in the range of $0.55 - 0.75$

Finding: ii) Consistent and rapid information gain pattern enables FALCON localize the target both $2\times$ more accurately and in 30% less time compared to the flocking scheme. v) The initial diverse position of the Diverse-Start strategy provides the drones with significant starting information so that it outperforms FALCON and the flocking schemes in terms of localization time. vi) Instantly attaining several orders of magnitude, the Random-Fast strategy localizes a target with sub-meter level accuracy, serving as a lower bound on achievable accuracy in this experiment.

D. 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. Moreover, avoiding collisions among drones becomes more pressing and increasingly impacts their flight dynamics. In this experiment, we explore how FALCON realizes localization and tracking with a single drone, and, as the number of drones increases, we analyze the impact of collision avoidance on the flight pattern. We also study the contribution of additional drones to localization accuracy and localization time.

The setup of this experiment is similar to the one in Section IV-C except for the varying number of drones in the network.

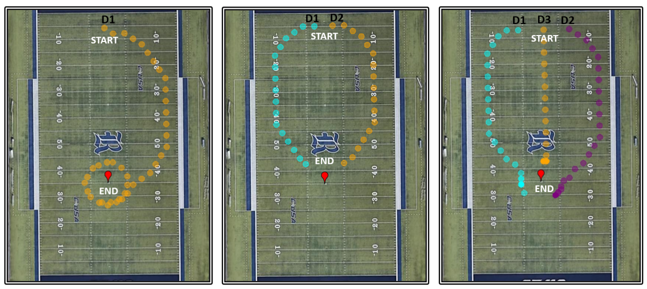


Fig. 14: Trajectory of FALCON with (a) one, (b) two and (c) three drones in a mission.

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. 14(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 [23] 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} 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. 14(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).

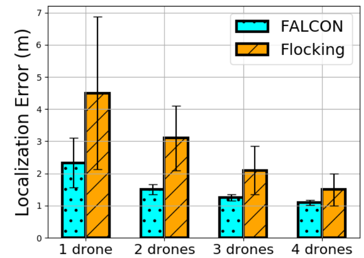


Fig. 15: Localization accuracy as the number of drones increase in the network

When there are more drones in a mission, for instance, three as shown in Fig. 14(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, for instance $c_{th} = 8m$ in Fig. 14(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. 15 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. 16 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

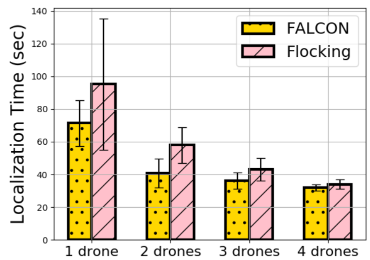


Fig. 16: Localization time as the number of drones increase in the network

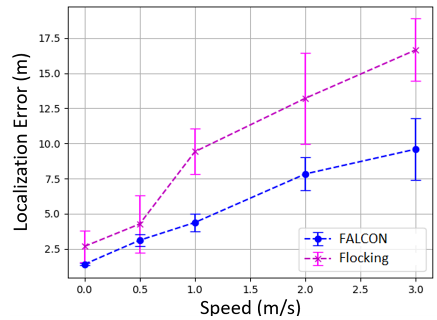


Fig. 17: Impact of target mobility on FALCON's localization error

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. 14(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. 16.

Finding: i) FALCON exploits mobility of drones and diverse measurements observed throughput in a mission to accurately ($2.3m$) localize and track a target even with a single drone. ii) As the number of drones increases in FALCON, collision avoidance serves as a supplementary form of diversity to distribute the spread among all drones in a mission. iii) The flocking scheme relies on the number of drones to improve localization accuracy and localization time while FALCON exploits informative locations to achieve similar and even better results with fewer drones.

E. Mobile Target

The FALCON system can be used to localize and approach not only static but also mobile targets. In this experiment, we consider two cooperative drones that are instructed to localize and approach a moving target. For that, we employ the combination of both experimental missions and emulation-based missions with the experimental dataset. We vary the speed of the targets from 0.5 m/s to 3.0 m/s, essentially capturing the different dynamics of movements starting from walking speed to running speed. The target begins from the center of the stadium and moves linearly to its other end, in the opposite direction from the region marked "START". In this experiment, we explore the impact of the target mobility on the localization accuracy considering FALCON as well as the baseline flocking scheme.

In Fig. 17 we show the localization error of the baseline flocking scheme and the FALCON strategy for different target speeds reaching up to 3 m/s. The λ parameter of the proposed drone flight strategy is configured to a value of 0.5 throughout this experiment. Observe that, due to the lack of spreading and the insufficiency of observation diversity, drones in the flocking scheme experience difficulty localizing the moving target. In particular, as the speed of the target reaches 1 m/s (i.e. exceeding the speed of the drones) the error almost doubles. Moreover, the fluctuations in the standard deviations become large and deviate between large intervals reaching up to 5m due to similar limited observation reasoning. In contrast, FALCON always achieves a much smaller localization error compared to the flocking scheme even when the speed of the target exceeds the speed of the drones. In fact, the diversity of observations in FALCON allows drones to gain a sufficient amount of information to be able to keep the mean as well as the standard deviation of the error low (below 10m even for the target's highest speed).

Finding: The diversity of observation component of FALCON enables drones to accurately localize both static as well as mobile targets even when the targets move faster than the drones.

F. Computational Complexity

In FALCON, 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 perform $W \times (N-1)$ 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.

Notice that, to make a flight decision, each drone considers only its own set of W candidate reposition waypoints and a single waypoint location of neighboring drones, avoiding exponential dependence of the strategy on the number of drones. While 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 resolution of 1m, in the experiments, it takes just few milliseconds for two drones flying at 1m/s with $f = 0.25$Hz to compute their next best reposition waypoints on our UP-Board companion computer.

Finding: FALCON's computation complexity increases only linearly with the number of drones. In the experiments, the drones need only few milliseconds to compute the next reposition waypoints.

V. Related Work

Flocking Approach: Cooperative behavior of animals has inspired numerous navigation strategies, e.g., [5], [24]–[26]. One of the most well-known and well-understood flocking approaches, [5], was motivated by flocking behaviors of birds; this approach has been employed by many multi-robot systems for target tracking, e.g., [27]–[29]. In such work, robots follow three simple 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. The flocking approach also adheres to leader-follower hierarchy [30], [31]; a more experienced bird (or 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): Existing implementations of the protocol mainly focus on self-positioning the client in an indoor environment, e.g., self-localizing a person with a smartphone inside a building [12]. For that, the client usually performs multilateration in an environment that has multiple distributed APs deployed. Recently, [32] proposed to complement existing GPS and odometry systems by jointly fusing Wi-Fi 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 on-drone target-to-drone range sensing mechanism via FTM and to propose a flight planning strategy to autonomously navigate a network of drones via FTM range measurements to localize targets.

Recently, the usage of Wi-Fi FTM has been increasing in different applications as many works adapt it in their design [33]–[40]. For instance, [33] integrates FTM for mmWave network beam search strategy and adapts it for handover procedure while Google provides an example application [34] for Wi-Fi Aware services. Moreover, recent work has investigated the security features of the protocol [41], [42]. In particular, [41] analyzes security guarantees of the protocol across the logical and physical layer meanwhile [42] employs FTM as a metric to discriminate a neighbor from an attacker in IoT devices. To further improve the achievable accuracy of the FTM measurements, machine learning approaches have also been proposed in the prior work [43]–[45].

Experimental Multi-Drone Systems: While there are many algorithmic prior works, relatively few design a multi-drone system and perform field experiments, e.g., [4], [46]–[49]. Moreover, most existing systems are designed with different goals than FALCON. For instance, [48] proposes a multi-quadrotor framework that navigates quadrotors to defend an object from an attacker. Similarly, [47] presents a multi-drone system and a communication scheme for scanning the maritime area and transmitting telemetry images and data. Recently, [49] proposed a software-defined control framework and presented a prototype of fully reconfigurable drone network. The most relevant work to FALCON [46] aims to localize VHF radio collared animals via multiple drones equipped with yagi antennas, capturing bearing information about the target. For that, drones divide the search space into disks of equal radius and travel to pre-defined sample locations that are based on vertices of an equilateral triangle inscribed in the disk. In contrast to [46], FALCON takes advantage of ubiquitous Wi-Fi for ranging a target and dynamically navigates drones in a mission. Leveraging the infrastructure of [4], FALCON integrates Wi-Fi 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. Discussion

In this paper, we demonstrate the principles of FALCON, presenting its design, implementation, and experimental evaluation. Yet, there are opportunities for extending the system, and in this section, we discuss potential future research directions.

In addition to a single target scenario, FALCON can be extended to missions with *multiple targets*. For that, the proposed target-to-drone range sensing mechanism can be modified to associate different targets based on their unique MAC address accessible via FTM. The challenge is to dynamically reposition N drones to service M targets. The flight strategy could be adapted in 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 in a mission. Then, there are potential issues of unreachable targets due to $N < M$ and communication among networked drones and multiple targets, thereby generating new research questions.

For ease of demonstrating the key contributions, we presented FALCON in the context of $2D$, and also evaluated with drones flying at a fixed altitude. The flight planning strategy can be extended to incorporate an additional dimension, formulating Eq. (4) as a 3×3 matrix and adjusting Eq. (6a-6h) to accommodate $3D$ navigation. This will provide the networked drones an additional degree of freedom to exploit diverse observations and spread out in $3D$. On the other hand, as drones decrease their altitude and fly closer to the ground, a multipath effect from the ground will have an impact on the sensing measurements as signals reach the receiver antenna in multiple paths. Thus, there will be trade-offs between the additional spreading gain due to the elevation and potential sensory measurement degradation due to multipath. Also, modifying the flight planning for $3D$ navigation will increase the number of reposition candidate waypoints W at each epoch; however, it will still have a linear impact on the computational complexity of the system.

Moreover, we remark that, in complex environments such as urban areas that have many obstacles (tall building) and limited/degraded GPS coverage, drones might need to build a map of the environment to be able to accurately self-position and perform a mission in that environment. In such cases, FALCON can be implemented along with Simultaneous Localization and Mapping (SLAM) methods in robotics [50]. In that case, SLAM can focus on building the map of the environment and self-positioning the drones while FALCON can focus on the mission objective, with the two systems complementing each other.

Lastly, note that Falcon assumes that the target drones have Wi-Fi communication, and a result its usage may be limited to certain types of drones (such as entertaining small-sized or medium-sized drones as opposed to some industrial drones that may fly out of the Wi-Fi range).

VII. 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 first range sensing drones that leverage Wi-Fi's recent FTM technology to dynamically range targets. Moreover, we propose a novel flight planning strategy that enables drones to simultaneously localize and approach the targets by jointly optimizing the drones' diversity of observation and the dynamics of approaching. We implement FALCON on a multi-drone platform and perform an extensive set of missions for experimental evaluation. We show that, compared to a baseline bio-inspired scheme, FALCON achieves up to twice localization accuracy and requires 30% less flight 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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