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FALCON: Fine-Time-Measurement to Approach, Localize, and Track RF Targets via Drone Networks

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ABSTRACT

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We present FALCON, a novel mobile sensing system to approach, localize, and track RF targets via drone networks. We leverage existing Wi-Fi technology and its recent Fine Time Measurement (FTM) protocol to realize the first FTM sensing drones that can dynamically range targets in a mission. FALCON is also the first robotic system realizing FTM for autonomous navigation. In addition, we propose a new flight planning strategy to simultaneously approach and localize a target to enable higher resolution sensory measurements and to realize approaching-critical tasks in a mission in addition to localization and tracking. For that, we propose to jointly exploit drones’ diversity of observation and dynamics of approaching the target, and dynamically adjust the intensities of approaching and observation based on a mission requirement. Our implementation of the flight planning strategy on custom FTM-enabled drones shows that FALCON achieves up to $2\times$ localization accuracy gain compared to a baseline Bio-inspired approach, and in total spends 30% less time in localizing the target.
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Chapter 1

Introduction

In this thesis, we design, implement, and experimentally evaluate FALCON, Fine-Time-Measurement to Approach, Locate, and Track RF targets via drone networks. Prior work usually deploys antenna arrays on drones and computes the angle of arrival (AoA) to sense targets; however, the arrays have large physical size, e.g., nearly a meter scale [1] and require significant time to calculate AoA, e.g., 45 sec per single observation [2]. In contrast, we take advantage of existing Wi-Fi and its recent FTM protocol to realize, for the first time, drones that can sense range to targets by measuring round-trip-time (RTT) of Wi-Fi signals with nanosecond resolution. On the other hand, prior work also employs on-drone RSSI to observe and localize targets, e.g., [3] achieves localization accuracy of 10m. However, we show that FALCON obtains nearly a magnitude order better performance due to using time of flight (ToF) measurements versus RSSI.

Likewise, in this thesis we propose a novel flight planning strategy that navigates drones to simultaneously approach, localize, and track targets. By jointly achieving the objectives, drones in FALCON (i) improve their measurement resolution because drones are more likely to observe line-of-sight (LoS) signals as they approach targets, especially in the environment with obstacles such as trees and buildings and (ii) get an opportunity to realize many approaching-critical tasks in a mission, in addition to localizing and tracking targets. FALCON can be applied to outdoor IoT devices that need both accurate localization and fast approaching, for
instance for emergency close-in inspection, but lack GPS to share their position. It can also be used for “off-grid mobile sensors” that need to be positioned and tracked to continually exchange time-critical data as approaching targets enables faster data transmission. In FALCON, we make the following three contributions.

First, we realize on-drone FTM and integrate it on our multi-drone infrastructure. Standardized in 2016, IEEE 802.11mc FTM provides RTT between an initiator, usually STA, and a responder, usually AP. Prior work employs the protocol to self-position an STA in an indoor environment that has many stationary APs distributed in space, STA performing multilateration to localize itself, e.g., [4]. In contrast, drones in FALCON sense FTM measurements to dynamically decide their next reposition locations in a mission that are most favorable for accurate localization, fast approaching, and consistent tracking of potentially mobile targets. To enable on-drone FTM, we first integrate a device with Wi-Fi FTM compatible chipset on drone platforms and provide software to configure, initiate, and process FTM in a mission. We then upgrade our multi-drone infrastructure consisting of hardware, software, and networking components to support the new FTM feature. To the best of our knowledge, FALCON is not only the first multi-drone platform with FTM sensing capability but also the first robotic system to realize FTM for autonomous navigation.

Second, we propose a flight planning strategy to simultaneously approach, localize, and track targets. Prior work usually considers these problems independently, localization principles stemming from sensors placement literature, e.g., [5] explores sensors’ observation, while approaching and tracking are addressed from the perspective of robotics motion planning, e.g., [6] imitates flocking motion. In FALCON, we jointly exploit drones’ diversity of observation and dynamics of approaching to concurrently achieve these objectives. In the strategy, we provide tunable parameter $\lambda$
that can modify flight patterns of drones based on preferred 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 as mentioned previously. For instance, drones can
adjust their flights in a mission based on the quality of their sensory data. If the data
becomes too noisy, they can adjust $\lambda$ to focus on localization, actively spreading in a
mission to acquire diverse observation of the targets’ position. Similarly, drones can
dynamically tune the parameter to favor approaching if the sensory data is of high
quality and drones need to get to the targets quickly.

Third, we perform an extensive experimental evaluation of FALCON. We be-
gin with a controlled experiment where we analyze drone FTM ranging error by
performing on-drone distance estimation from predefined locations. The results indi-
cate that the error is around $\pm 2 m$, and it is consistent for varying ranges due to
the dominant LoS property of air-to-ground channel and the linear relationship of
ToF measurements and distances. To understand the impact of $\lambda$ on the trade-offs
between angular spread gains and extra travel distance, we perform missions with a
known target position and with different $\lambda$. As a baseline, we consider a Bio-inspired
scheme that encourages drones to move directly towards the latest estimated target
location. We find that, with two drones in the network and $\lambda = 2$, FALCON can re-
alize $2.2 \times$ average angular spread gain at the expense of only 27% additional average
travel distance compared to Bio-inspired scheme. Then, we perform missions where
drones actively sense and continually reposition to localize and approach an unknown
target. Findings reveal that, compared to the Bio-inspired scheme, FALCON consis-
tently and rapidly acquires information about the target position due to its diverse
observation feature, and localizes a target $2 \times$ more accurately and in 30% less time.
Chapter 2

FALCON Framework

2.1 Design Overview

2.1.1 On-drone Sensing

In the design of FALCON, we first realize a new on-drone target sensing mechanism. Unlike existing sensing systems that either require drones to carry bulky antenna arrays and compute time-consuming AoA or rely on readily available and yet generally noisy RSSI, drones in FALCON accurately and quickly range targets by sensing RTT of Wi-Fi signals. We describe on-drone FTM implementation in details in Chapter 3.

2.1.2 Flight Planning

Next, we design a flight planning strategy that navigates drones to approach, localize, and track targets. In the literature, these problems are usually considered independently, whereas we achieve them concurrently so that drones can improve measurement resolution and realize approaching-critical tasks in addition to localization and tracking. For that, we jointly exploit diverse observation of drones and their dynamics of approaching targets.

Fig. 2.1 demonstrates FALCON in the context of prior work. To begin with, note that drones perform a mission as a team, cooperating and coordinating throughout the process. Also, drones launch from a nearly collocated position, in this example from the bottom-left side of the search area. They could have been transported to
the area as a group, on a first responder vehicle for instance, or already been waiting in there, possibly on a charging station. Next, notice that the sensors’ placement strategy encourages drones to spread out around the target, to different sides of the area in Fig. 2.1(a). This enables drones to view the target from diverse locations and collect statistically independent samples. The problem with this approach is the extra travel distance that already battery constrained drones have to travel. Even worse, that additional distance scales up with increasing search area, drones risking to run out the battery and failing a mission, and drones are not close to the target anyway. Similarly, Fig. 2.1(b) shows that the Bio-inspired scheme motivates drones to form a flock and fly directly to the latest estimated target position. In the best-case scenario, when drones sense the target precisely throughout a mission, the scheme helps to quickly get to the target. However, most of the time, drones navigate to the wrong direction due to imperfect sensory measurements and similar information resulting from fixed and close formation flight. In FALCON, we encourage drones to dynamically spread out and approach the target while they are actively sensing it as
Figure 2.2: Two drones ranging a target with (a) poor observation and (b) diverse observation shown in Fig. 2.1(c). The spreading component ensures accurate localization while approaching component enables fast advancement to the target. Also, we provide drones flexibility to configure the intensity of spreading and approaching, creating a possibility to dynamically adjust to different mission requirements. In the discussion of the strategy, we first provide analysis of one-shot positioning of sensors for a known source. Building on that, we then describe our proposed strategy.

2.2 One-shot Positioning of Sensors for a Known Source

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

To demonstrate the significance of diverse observation, consider Fig. 2.2 in which two drones range a target and then fuse their measurements to gain information about the target location. The mean of the measurements is illustrated as dotted lines while variances are shown as blue and brown segment areas. Once measurements are fused,
the red area indicates the potential location of the target. We designate it as the “confusion area”. Notice that as drones get close to each other, as in Fig. 2.2(a), the confusion area expands, indicating poor observation and hence limited information about target location. On the other hand, spreading out and observing the target from a different view, as in Fig. 2.2(b), provides much more details of the target location. It is demonstrated as a shrinking confusion area.

Before characterizing the confusion area, we first introduce some notations. For the ease of demonstrating the concept, 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 known source are 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 $\epsilon$ is a standard Gaussian noise with zero mean and $\sigma_i^2$ variance. Then, sensors can share their data, forming vectors of ranges $d = [d_1, ..., d_N]$ and $r = [r_1, ..., r_N]$ as well as $\Sigma$ covariance matrix.

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

$$L_d = \frac{1}{(2\pi)^{N/2} \left| \Sigma \right|^{1/2}} e^{-\frac{1}{2} (d - r)^T \Sigma^{-1} (d - r)}, \quad (2.1)$$

where $|\Sigma|$ is the determinant of $\Sigma$. $L_d$ in Eq. (2.1) can vary between sharp and flat distributions. Intuitively, flat distribution indicates less information about the source location while sharply peaked distribution is a sign of abundance of information.

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

$$F = E\{(\nabla_U \log L_d)(\nabla_U \log L_d)^T\}, \quad (2.2)$$
where \( \nabla_U \log l_d \) is the gradient of the log likelihood function with respect to the source location. \( F \) in Eq. (2.2) can be interpreted as the curvature of the log-likelihood function and indicates how well \( U \) can be estimated from \( d \). \( F \) can also be expanded [7] as

\[
F = \sum_{i=1}^{N} \begin{bmatrix}
\frac{(x_u-x_i)^2}{\sigma_i^2 r_i^4} & \frac{(x_u-x_i)(y_u-y_i)}{\sigma_i^2 r_i^4} \\
\frac{(x_u-x_i)(y_u-y_i)}{\sigma_i^2 r_i^4} & \frac{(y_u-y_i)^2}{\sigma_i^2 r_i^4}
\end{bmatrix}.
\] (2.3)

Applying trigonometric substitution, it can then be simplified to

\[
F = \sum_{i=1}^{N} \begin{bmatrix}
\frac{\sin^2(\phi(S_i))}{\sigma_i^2} & \frac{\sin(2\phi(S_i))}{\sigma_i^2} \\
\frac{\sin(2\phi(S_i))}{\sigma_i^2} & \frac{\cos^2(\phi(S_i))}{\sigma_i^2}
\end{bmatrix},
\] (2.4)

where \( \phi(S_i) = \arctan\left(\frac{y_i-y_u}{x_i-x_u}\right) \) and denotes the angle between \( S_i \) and \( U \) with a reference to global \( X \) coordinate. Observe that in Eq. (2.3) the confusion area is described by measurement locations of the sensors, and it is further expressed by the angular placement of the sensors in Eq. (2.4). To find the numeric value of the information, determinant of \( F \) can be computed as

\[
D = \sum_{i=1}^{N} \sum_{j>i}^{N} \frac{\sin^2(\phi(S_i) - \phi(S_j))}{\sigma_i^2 \sigma_j^2}.
\] (2.5)

\( D \) is an amount of source location information contained in the confusion area, smaller confusion area implying larger total information.

First, notice that when \( N = 1 \), \( D \) in Eq. (2.5) equals zero for any source location, therefore \( N \geq 2 \) is required for the sensor placement technique. Next, observe that the total information is described by angular spread between neighboring sensors, \( \sin^2(\phi(S_i) - \phi(S_j)) \). For a 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. 2.2 with range measurements of equal mean and the same variances, positioning drones 90 degrees with
respect to the target results in the maximum total information. When more than two sensors are involved in the positioning of a target, the technique takes into account the angular spread of all two-pair combinations of the sensors.

### 2.3 Flight Planning

In FALCON, drones initially have no knowledge of a target location, they instead actively sense and autonomously navigate to localize, approach, and track a target in a mission. To do so, each drone first ranges a target via on-board FTM to understand how far a target is from that drone. Next, they share their recent sensory information and current GPS locations with each other to have a different perspective of a target and then estimates it based on the fused data. Finally, drones compute the next best waypoints that are most favorable for the mission objective, repositioning to the optimized waypoints accordingly. To consistently improve their knowledge of the target location and get closer to it at the same time, drones frequently execute those steps in a mission.

We extend notations from Section 2.2 to include a time component 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 $t$. To better demonstrate the concept, we consider that $P$ has a rectangular shape with some $(x_{\text{min}}, y_{\text{min}})$ and $(x_{\text{max}}, y_{\text{max}})$ waypoints while drones travel at uniform speed $v$ and update their next reposition waypoint at an interval $f$. When making a flight decision, drones keep minimum $c_{th}$ distance between each other to avoid collision. Also, $a_{th}$ denotes how close mobile sensors would like to approach the target. In a mission, each drone optimizes its next waypoint and reposition accordingly. Then, the problem becomes computing objective favoring waypoints $S_{k,t+1}$ for $\forall k \in N$ in
the network for as long as drones have sufficient energy to operate in a mission.

**Challenges:** The main challenge in this problem is a reciprocal effect in which flight planning defines target estimation results while target estimation influences flight planning decisions in a mission. Specifically, drones consider their current location at $t$ to estimate the target location $\hat{U}_t$ while $\hat{U}_t$, on its turn, defines drones’ next reposition waypoint. It implies that drones should consistently reposition to informative waypoints to enable accurate estimation and approaching. In addition, drones have constrained initial position due to nearly collocated starting location in a mission. This condition is highly unfavorable for target localization as it results in an extremely inaccurate target estimation. It indicates that drones should start exploiting diverse observation as soon as a mission begins, and also algorithms relying on the assumption of spatially distributed swarms, e.g., [8, 9, 10], are not really applicable for our problem.

**Optimization:** We propose a distributed and real-time flight planning strategy where each drone $k$ for $\forall k \in N$ computes its next reposition waypoint $S_{k,t+1}$ by
performing following optimization:

\[
S_{k,t+1} = \arg\max_{\{S_{i,t+1}\}_{i=1}^N} \sum_{i=1}^N \sum_{j>i}^N \sin^2(\hat{\phi}_t(S_{i,t+1}) - \hat{\phi}_t(S_{j,t+1})) \frac{\sigma_i^2 \sigma_j^2 \hat{d}_t(S_{i,t+1}) \lambda \hat{d}_t(S_{j,t+1})}{\lambda}
\] (2.6a)

subject to

if \( k = i \) (or \( k = j \)), then

\[
S_{k,t+1} = (x_{k,t+1}, y_{k,t+1})
\] (2.6b)

\[
x_{\min} \leq x_{k,t+1} \leq x_{\max}
\] (2.6c)

\[
y_{\min} \leq y_{k,t+1} \leq y_{\max}
\] (2.6d)

\[
||S_{k,t+1} - S_{k,t}|| \leq v \times \frac{1}{f}
\] (2.6e)

otherwise

\[
S_{i,t+1} = S_{i,t}
\] (2.6f)

We describe the optimization function and discuss the key ideas of the strategy by focusing on each issue at a time.

### 2.3.1 Unknown Target Location

Despite unknown target location, drones actively sense a target, share their data, and then fuse it to estimate \( \hat{U}_t \). As an on-drone target estimator, we implement Extended Kalman Filter (EKF), a well-known approach for many analogous problems, e.g., [11, 12, 13]. EKF updates drones’ belief about target position as they sense the target, and helps to determine the best location that reflects that belief.

Unlike sensors positioning with known target location, drone \( k \) computes the angle between its candidate waypoints and the estimated target \( \hat{U}_t \), indicated as

\[
\hat{\phi}_t(S_{i,t+1}) = \arctan\left(\frac{y_{i,t+1} - y_{\hat{u},t}}{x_{i,t+1} - x_{\hat{u},t}}\right)
\] (2.7)

Notice that compensating for an unknown target location with estimation \( \hat{U}_t \) could result in a mismatch in the confusion area due to different reference points. However,
we alleviate it by leveraging mobility of the drones, and navigate them to informative locations in a mission. In reciprocal, drones accurately estimate the target by taking advantage of the rich information from new locations.

\subsection{Flight Planning over Time}

Drones in FALCON continually plan their next waypoints and frequently reposition accordingly as the mission progresses over time. To compute its next reposition waypoint $S_{k,t+1}$, drone $k$ takes into account its speed $v$, update frequency $f$ and current position $S_{k,t}$ to consider all and yet only physically reachable candidate waypoints in $P$ as indicated in Eq. (2.6b-2.6e). To have a diverse perspective of the target, the drone also considers other drones in the network and their recently shared current locations as indicated in Eq. (2.6f). One might suggest to also account for future reposition waypoints of all $N$ drones to mimic centralized decision making. However, doing so will increase the computational complexity of the objective function from linear to exponential in the number of drones, making real-time flight planning infeasible for constrained drone platforms.

When focusing only on the diversity of observation feature of the strategy, then notice that

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

component of Eq. (2.6a) encourages spreading out over time. It is especially important in flight navigation as it allows to improve localization accuracy as the mission continues. In particular, the estimated target location $\hat{U}_t$ is most probably far away from the true target location at the beginning of the mission due to similar observations from nearly collocated drones. However, as drones spread out in a mission and update their estimation results based on diverse observation, their belief about the
target location more accurately reflects true target location. As a result, it enables to accurately localization of a target.

2.3.3 Dynamics of Approaching

In FALCON, drones move toward a target while localizing and tracking it at the same time. For that, we integrate the inverse of $\hat{d}_t(S_{i,t+1})$ in the objective function to stimulate approaching, where $\hat{d}_t(S_{i,t+1}) = ||\hat{U}_t - S_{i,t+1}||$. Since the objective function also considers neighboring drones to make waypoint decision, $\hat{d}_t(S_{j,t+1})$ with index $j$ is integrated in the function. In addition, we provide drones flexibility to control the rate of approaching a target by introducing a parameter $\lambda$. Serving a critical role in the objective function, $\lambda$ determines the intensity of approaching and magnitude of diverse observation. In return, diversity of observation impacts localization accuracy while the dynamics of approaching impacts total travel distance in a mission.

In one extreme, when the value $\lambda$ is large, the strategy encourages drones to fly directly towards the estimated target with almost no spreading. The associated advantage, in that case, is minimal total travel distance while possible disadvantage might be lower accuracy due to lack of diverse observation. On the other extreme, when the $\lambda$ is zero, drones focus solely on diverse observation and try to localize a target accurately as possible. However, the distance traveled increases since drones fly to spread out in the search area, plus they are not motivated to approaching the target. In FALCON, $\lambda$ provides drones flexibility to choose between those trade-offs based on mission requirements.

Potentially, drones can dynamically adjust $\lambda$ during a mission based, for instance, on the quality of the sensory data. If measurements become too noisy, and a mission requires more observation, then drones can tune $\lambda$ to a lower value to focus more
on spreading. Conversely, if measurements are of high quality and drones need to get to a target quickly, then $\lambda$ can be adjusted to a higher value to concentrate on approaching. In that way, the flight strategy can always be informal of sensory measurements and dynamically adjust flight pattern to consistently favor the mission objective.
Chapter 3

FTM-enabled Multi-Drone System

FALCON leverages the ubiquity of Wi-Fi technology and recent Wi-Fi FTM ranging standard to localize, approach, and track IoT devices. For that, we realize the first on-drone FTM and integrate it with our existing drone network infrastructure. Moreover, we create an FTM dataset by ranging a target via FTM-enabled drone in outdoor environment. With that experimental dataset, we can then emulate different missions in addition to field missions to analyze impact of various factors on FALCON and other baseline flight planning strategies.

Figure 3.1: Drone Platform
3.1 Multi-Drone Infrastructure

In the design of FALCON, we take advantage of our multi-drone infrastructure [3] that we upgrade and modify as necessary. As a result, FALCON consists of 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. 3.1. Each drone has two main control blocks, Flight Controller and Companion Computer, that assist it in navigation. Flight Controller is resource-constrained embedded hardware that mainly focuses on communicating with on-board sensors and managing dynamics of the flight as directed by a mission. Companion Computer, on the other hand, is a more powerful embedded computer that executes a mission logic. We integrate UP-Board with the Intel Atom x5 Z8350 quad-core processor as our Companion Computer. It runs on Linux OS and performs flight planning in a mission.

**Software:** FALCON also 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, the API helps to analyze each building block of FALCON separately and to build an emulator that can run a mission on an 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 and maintain continuous communication with each other throughout a mission. To communicate, drones support both USB Wi-Fi dongles and SDRs.
3.2 FTM on Drone Platform

To enable on-drone FTM, we first considered different network devices that support IEEE 802.11mc FTM RTT 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 are able to carry and perform missions with it. Unfortunately, no such device currently exists in the market. In addition, there are only limited FTM compatible chipsets, for instance, Intel AC8260, and most of them are dedicated to large systems like desktop computers and laptops. The only available miniature device with IEEE 802.11mc FTM support is an IoT device provided by Compulab. By slightly modifying the device and leaving only integral components, we integrate it on a FALCON drone. At the end, the device only adds extra 200g weight and takes only 11cm × 8.5cm × 3.5cm space on drone platform, meeting all our requirements.

Next, we establish a connection between the IoT device and the Companion Computer to enable data exchange between the IoT device that houses FTM specific hardware and firmware and the Companion Computer that runs a mission logic. For that, we first connect those two devices via Ethernet cable as shown in Fig. 3.2(b). Then, we provide a piece of software that can (1) initiate FTM Responder scan, (2) configure FTM parameters based on mission requirements, and (3) process received FTM measurements within Companion Computer. In the software, we create an SSH PIPE interface between the devices and access IWLWIFI driver of the IoT device via IW command in Companion Computer. We then pass on appropriate command line arguments to trigger the search of the nearby FTM Responder, to configure FTM parameters (such as desired bandwidth and number of FTM samples) and to access ToF measurements, eventually computing range values.
Figure 3.2 : (a) IEEE 802.11mc FTM compatible IoT device and (b) FALCON drone with on-board FTM.

3.3 Drone FTM Dataset

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

We perform our experiments at Rice Stadium because is one of the most spacious areas on the campus. First, we configure an IoT device similar to one in Fig. 3.2(a) as an FTM Responder and designate as a target in this experiment. We put it on a 1.5m height tripod stand and position it in the stadium. Next, we fly the drone in a waypoint fashion, traversing the whole stadium. While flying, the drone performs FTM measurements and computes range estimates to the target.

Fig. 3.3 is an example of one map out of a total 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 around 100 FTM
measurements at every point. Overall, 100s of drone batteries have been recharged in the effort to create this dataset.

**Figure 3.3**: Drone FTM Dataset
Chapter 4

Experimental Evaluation

4.1 Drone FTM Ranging

A drone in FALCON leverages the error of target ranging to compute its next way-point that maximizes localization accuracy. To range a target, it observes ToF of the RF signal from that target via an on-board FTM device. Any error in ToF measurement, such as reflected signals, propagates into a ranging error. In addition to that, 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. Statistically, these two sources of error should be independent and additive since one does not imply the other. In this experiment, we evaluate the total ranging error that an FTM-enabled drone observes in a mission. For that, we position the 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 an IoT device by CompuLab as an FTM responder and position it in an open field of Rice 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 its dual GNSS GPS receivers to hold its position and ranges the target while hovering.
Fig. 4.2 shows the mean and 2 standard deviations of drone FTM range estimation. The results indicate that 95% of the time the ranging error is around ±2m and the error is consistent for varying true distances. Two main features of the FTM-enabled drone contribute to consistent measurements. First, FTM operates based on the ToF. Unlike, for instance, received signal strength (RSS), ToF linearly dependents on the range which, in principle, allows a ranging error independent of distance. Second, the drone observes the air-to-ground channel. Contrary to the terrestrial ground-to-ground channel, the air-to-ground channel has dominant LoS and limited multi-path fading. It enables most of the signals to travel directly towards the target and to produce consistent ToF measurements. In addition, we have observed in the experiment that the GPS accuracy is around ±1m. A clear view of the sky and the dual GPS receivers enable the drone to observe sufficient satellite signals to position itself in space while on-board gyroscope enables it to stabilize in that position.

**Finding:** By exploiting dominant LoS property of air-to-ground channel and linear relationship between FTM signals and range estimates, an FTM-enabled drone can...
sense distance toward the target with ±2m error for varying ranges.

4.2 How far to spread out (λ)

In a mission, FALCON enables drones to choose desired diversity of observation and dynamics of approaching via adjustable λ parameter. While lower values of λ contribute to a more angular spread, increasing it allows for more direct movement to the target. We experimentally characterize the angular spread and the travel distance via a simplified two-drone scenario. For that, we assume drones with a known target location and perform missions with different λ. This enabled us to study trade-offs between angular spread gains and additional travel distances.

Setup: We place two drones in the position marked “START” in Fig. 4.3 and place the target in the center of the stadium as illustrated by the red pin in Fig. 4.3. Drones then fly following FALCON flight planning strategy with a predefined λ value, capturing angular spread and travel distance at each reposition instance. The mission proceeds until all drones approach the target. Throughout the mission, drones fly at a
<table>
<thead>
<tr>
<th>Evaluation Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drone speed ((v))</td>
<td>1m/s</td>
</tr>
<tr>
<td>Search space resolution</td>
<td>1m</td>
</tr>
<tr>
<td>Reposition frequency ((f))</td>
<td>0.25Hz</td>
</tr>
<tr>
<td>Collision threshold ((c_{th}))</td>
<td>8m</td>
</tr>
<tr>
<td>Approaching threshold ((a_{th}))</td>
<td>10m</td>
</tr>
<tr>
<td>Drone altitude</td>
<td>10m</td>
</tr>
</tbody>
</table>

Table 4.1: List of important evaluation parameters

10m altitude and at 1m/s speed, updating their reposition decision every 4s as shown in Table 4.1. Given the sub-meter accuracy of the GPS, we consider the search space with 1m resolution. We also configure \(a_{th}\) and \(c_{th}\) to avoid a collision. We repeat the experiment varying the \(\lambda\) and the smallest value we consider is 0.5 because of space constraints, as illustrated in Fig. 4.3(a). We then increase \(\lambda\) incrementally from 2 to 20 in steps of 2, repeating the experiment approximately 10 times for each \(\lambda\).

In the evaluation, as a baseline, we consider a *Bio-inspired* strategy that navigates drones directly towards the target, focusing on less travel distance. To compare our strategy with extreme spreading case, we also consider 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 the Bio-inspired strategy nor 2-Phase strategy is dependent on \(\lambda\), we plot their results over all values of \(\lambda\).

**Angular Spread:** For varying \(\lambda\) values, Fig. 4.4(a) depicts the average angular spread observed by drones in a mission. It indicates that drones with a Bio-inspired
strategy obtain 26 degree average angular spread by directly moving towards the target at close proximity in a mission. By first traveling in a greater orthogonal spread and then approaching the target at 90 degree angle, 2-Phase strategy attains $2.7 \times$ more average angular spread compared to Bio-inspired strategy in a mission. Unlike these baseline schemes, FALCON enables drones to choose angular spread, for instance, based on a mission requirement. It exploits the diversity of observation and dynamics of approaching provides via adjustable $\lambda$.

Moreover, Fig. 4.4(a) suggests that the standard deviation of the average angular spread increases as $\lambda$ rises. This is because GPS error amplifies as angular spread decreases, thus the error having a stronger impact when drones travel close to each other. This impact is minor in relation to drones that fly at greater angles, which
suggests that rising $\lambda$ increases the sensitivity of angular spread to the GPS inaccuracies. Also, there is a step effect manifested in $\lambda \geq 10$. This is attributed to the effect of discretization of the search space and the fact that at higher values of $\lambda$ the strategy favors similar and more direct paths towards the target.

Fig. 4.4(b) shows the average angular spread gain of the proposed strategy in comparison to the Bio-inspired scheme for different $\lambda$ values. The figure suggests that FALCON can enable $2.2\times$ average angular spread gain with $\lambda = 2$ and even more with $\lambda < 2$. As illustrated in Fig. 4.3(b), the strategy encourages drones to spread out in the field and to move towards the target simultaneously. Both observation and approaching features are able to contribute equally to the path decision via sine and range squared impact in the objective function. However, as $\lambda$ increases, diversity of observations decrease rapidly and the approaching feature dominates the path decision. For instance, less than $1.5\times$ gain can be attained with $\lambda = 8$. Also, shrinking...
observation results in a steep to flat decreasing slope pattern in Fig. 4.4(a) and suggests that drones rush towards the target rather than spreading, thus observing diminishing returns on average angular spread gains as $\lambda \geq 14$.

**Travel Distance:** Fig. 4.5(a) depicts average distance traveled per drone in a mission vs. $\lambda$. First, notice that drones travel only 50m by following the Bio-inspired scheme and moving straight towards the target. 2-Phase strategy, on the other hand, requires drones to fly approximately twice that distance to complete both spreading and approaching phases. In FALCON, drones can choose travel distance by adjusting $\lambda$ parameter based, for instance, on energy-constraints and/or sensory data quality.

Fig. 4.5(b) shows an additional average travel distance of FALCON relative to the Bio-inspired scheme. The results indicate that with $\lambda = 2$, less than 30% extra distance needs to be traveled to provide $2.2 \times$ average angular spread gain. The figure suggests that as $\lambda$ increases, the additional distance decreases and becomes even
negligible for $\lambda \geq 14$ due to an exponentially diminishing observation feature. The approaching feature dominates the path decision and allows for less travel distance. The maximum extra travel distance in the experiment is approximately 60% that corresponds to $\lambda = 0.5$, which also enables more than $2.5 \times$ angular spread gain as shown in Fig. 4.4(b).

**Finding:** i) With two drones in the network and $\lambda = 2$, FALCON can realize $2.2 \times$ average angular spread gain at the expense of only 27% additional average travel distance compared to the baseline Bio-inspired scheme. ii) Moreover, approaching feature of FALCON ensures that the extra travel distance does not exceed 10% for $\lambda > 6$ while diverse observation feature provides average angular spread gain between $1.6 \times -2.6 \times$ for $\lambda < 6$. iii) As $\lambda \geq 14$, approaching feature dominates the path decision and drones rush towards the target mimicking Bio-inspired strategy. iv) FALCON is sensitive to GPS errors at larger values of $\lambda$ because of the relative high angular fluctuations caused by the errors in a smaller angular spread.

### 4.3 Target Localization

Thus far, we have studied FALCON in the context of the known target position. In this experiment, we consider drones that do not have that knowledge but can estimate the range to the target by sensing RF ToF measurements. We set drones on a mission to localize and approach the target. Here, we explore how two cooperative drones following the FALCON flight planning strategy can improve localization accuracy and localization time in a mission.

**Setup:** First, we place the target in the middle of the Rice Stadium and place drones randomly near the location marked “RICE”. To emulate approximate collocation, we provide 5m -10m separation between drones. We then set $\lambda$ value to 2
and configure the remaining flight parameters based on Table 4.1. In a mission, each drone periodically computes its own next waypoint to reposition. For that, it first self-positions via GPS and ranges the target via on-board FTM. Then it shares its position and range estimates with the other drone, performing target estimation afterward. Finally, it computes its next waypoint following a specified flight planning strategy. A mission is completed when the target estimation converges and drones come at least $a_{th}$ close to the target.

In addition to the baseline Bio-inspired scheme, we consider Random-Fast and Diverse-Start strategies in the experiment. Random-Fast assumes infinitely fast drones that can fly randomly in the stadium. The number of waypoints observed via Random-Fast is similar to the total number of waypoints a typical drone would have repositioned in a mission following FALCON. Despite the infeasibility of infinitely fast drones, this method provides a reference for achievable localization accuracy when a target is viewed from many uniformly random locations in the field. Diverse-Start, on the other hand, considers drones that start a mission from diverse positions, from different corners of the stadium, and otherwise follow FALCON. It helps to analyze the impact of initial diverse observation on the localization time.

As discussed in Section 2.3.1, the diversity of observation is the key factor for accurate target localization. We quantify observation via Fisher Information (FI) following Eq. (2.5) and normalize it over maximum achievable information with two drones [5].

**Information Gain:** Fig. 4.6(a) shows normalized FI with a 95% confidence interval vs. time. It suggests that although FALCON and Bio-inspired scheme start with similar low information due to an initial approximate collocated position, FALCON gains information at a much higher rate compared to Bio-inspired strategy during a
mission. For instance, in the first 20 sec of a mission FALCON attains $10\times$ more information compared to the Bio-inspired scheme. Because of the diverse observation feature of FALCON, drones are motivated to spread out as soon as a mission starts. As they spread out from their initial positions, drones are able to 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 a Bio-inspired scheme which navigates drones to stay close to each other as a flock throughout a mission and to 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 variations in the information corresponding to continuous estimation and repositioning processes. Unlike FALCON, Bio-inspired scheme is only able to gradually increase its information in the first 40 sec, achieving less than 20% of information. Initially, drones in

**Figure 4.6**: (a) Normalized Fisher Information vs. time and (b) localization accuracy vs. time.
the Bio-inspired scheme are both far away from the target and flying at close proximity; they severely lack observation and therefore experience an extreme scarcity of information. They spend some time flying around as a flock, mostly in the wrong direction due to the insufficiency of observation, and trying to figure out the location of the target. As they eventually have a better idea of the target position later in a mission and come closer to it, 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, the lack of diverse observation in the process of approaching the target results in the inconsistency of acquired information. It is demonstrated as FI standard deviation of ±0.1 in Fig. 4.6(a). FALCON, in contrast, consistently acquires almost all information about the target location in a short period and retains as a mission progresses.

Random-Fast strategy instantaneously achieves several orders magnitude more information compared to FALCON or Bio-inspired schemes. 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.

**Localization Accuracy:** For different strategies, Fig. 4.6(b) shows localization accuracy with a 95% confidence interval vs. time. Notice how information gain pattern reflects localization error. First, both FALCON and Bio-inspired strategy initially localize the target with a mean error of around 11m and a standard deviation of ±2m, both of which are high, because a mission just has started and drones are nearly collocated to each other. Then, a Bio-inspired scheme helps by gradually improving the localization accuracy, the average error converging to 3m with standard deviation always fluctuating around ±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 Bio-inspired strategy and brings down the standard deviation of the error to a negligible value. Unlike FALCON or Bio-inspired, Random-Fast instantly achieves localization accuracy of around 0.6m via imaginary fast drones that can sample randomly in the search space and collect an abundance of information. It serves as an absolute lower bound on the localization accuracy in this experiment, and FALCON is definitely closer to that bound than the Bio-inspired scheme.

![Localization Time](image1)

**Figure 4.7**: (a) Localization convergence time vs. approach and (b) normalized Fisher Information vs. approach.

**Localization Time**: Fig. 4.7(a) depicts localization convergence time for different approaches while Fig. 4.7(b) shows normalized FI of those approaches when a mission starts and when the target localization converges. First, observe that Diverse-Start is the fastest one to localize a target among other approaches, on average spending less than 30 sec. This is attributed to the fact that drones in Diverse-Start are already spread out at the beginning of a mission (viewing the target from different
corners of the stadium) and already have around one-third of the total information when a mission just begins as indicated in Fig. 4.7(b); only the remaining information needs to be acquired during a mission to quickly localize a target. However, drones in FALCON and Bio-inspired scheme start a mission from nearly collocated positions and their initial information is on the scale of one-fiftieth. To localize a target, the Bio-inspired scheme on average spends around 1 min, navigating drones to move as a flock. FALCON, in contrast, needs 30% less time compared to the Bio-inspired scheme to localize a target by jointly spreading and approaching a target in a mission.

Finding: i) The diverse observation feature of FALCON enables a higher rate of information gain compared to the Bio-inspired scheme and provides more than 90% of FI in a short period, unlike the Bio-inspired scheme that only achieves around 65% FI later in a mission. ii) Through consistent and rapid information gain, FALCON localizes a target both $2 \times$ more accurately and in 30% less time compared to Bio-inspired scheme. iii) Due to significant information available initially from spread out drones, Diverse-Start strategy can localize a target on average in less than 30 sec, performing better than than the FALCON and Bio-inspired schemes. iv) Random-Fast strategy instantly attains several orders of magnitude more information compared to any other strategy and localizes a target with sub-meter level accuracy, serving as a lower bound on achievable accuracy in this experiment.
Chapter 5

Related Work

5.1 Bio-inspired Approach

Cooperative behavior of animals has inspired numerous path planning strategies, e.g., [14, 15, 10, 6] One of the most well-known and well-understood Bio-Inspired approach [6] has been motivated by flocking behaviors of birds and has been employed by many multi-robot systems for target tracking, e.g., [16, 17, 18]. Robots in that approach 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 Bio-Inspired approach also adheres to the leader-follower hierarchy [19, 20]; a more experienced bird (or more advanced robot) takes the lead while other members join as followers. Unlike the Bio-inspired approach, FALCON navigates drones to simultaneously to localize, approach, and track a target by jointly optimizing for diverse of observation and dynamic approaching. Simple rules and the leader-follower hierarchy of the Bio-inspired approach enables the better scale to a swarm of 100’s, while FALCON allows for more advanced on-board processing with drones of equal standing.

5.2 Fine Time Measurement (FTM)

FTM protocol provides an estimate of round-trip time between an FTM initiator, generally STA, and an FTM responder, generally AP, with nanosecond resolution [21].
Considering transmission frequency and the speed of light, FTM enables meter-level ranging accuracy between an STA and an AP [22]. The existing implementation of the protocol focuses on self-positioning an STA in an indoor environment, e.g., self-localize a person with a smartphone inside a building [4]. For that, STA usually performs multilateration in an environment that has multiple distributed AP infrastructure deployed. Unlike any prior work, FALCON is the first system to realize on-drone FTM and to propose a path planning strategy to autonomously navigate a network of drones via FTM range measurements.

5.3 Experimental Multi-Drone Systems

While there are many algorithmic works in prior literature, few of them design a multi-drone system and perform field experiments, e.g., [3, 23, 24, 25]. Moreover, most of the existing systems are designed with different goals than FALCON. For instance, [25] proposes a multi-quadrotor framework that navigates quadrotors to defend an object from a known attacker. Similarly, [24] presents a multi-drone system and a communication scheme for scanning the maritime area and transmitting telemetry images and data. The most relevant work [23] 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 [23], FALCON takes advantage of ubiquitous Wi-Fi for ranging a target and dynamically navigates drones in a mission. Leveraging [3] infrastructure, FALCON integrates the Wi-Fi FTM feature on the multi-drone platform, implements a novel path planning strategy, and proposes an end-to-end system to approach, localize, and track RF targets.
Chapter 6

Conclusion

In this thesis, we propose FALCON, an end-to-end system to approach, localize, and track RF targets via drone networks. In FALCON we realize the first FTM sensing drones that leverage existing Wi-Fi technology and its recent protocol to dynamically range a target. It is also the first robotic system to realize on-drone FTM for autonomous navigation. Moreover, we propose a novel flight planning strategy that enables drones to simultaneously localize and approach the target in a mission. For that, we formulate a strategy that jointly optimizes drones’ diversity of observation and dynamics of approaching the target. We implement FALCON on a multi-drone platform and perform an extensive experimental evaluation. The results suggest that FALCON achieves up to twice the localization accuracy compared to the baseline Bio-inspired scheme. It also spends 30% less time localizing the target in comparison to the baseline.
Bibliography


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