iDROP: Robust Localization for Indoor Navigation of Drones With Optimized Beacon Placement

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Abstract—Drones in many applications need the ability to fly fully or partially autonomously to accomplish their mission. To allow these fully/partially autonomous flights, first, the drone needs to be able to locate itself constantly. Then, the navigation command signal would be generated and passed on to the controller unit of the drone. In this article, we propose a localization scheme for drones called robust localization for indoor navigation of drones with optimized beacon placement (iDROP) that is specifically devised for GPS-denied environments (e.g., indoor spaces). Instead of GPS signals, iDROP relies on speaker-generated ultrasonic acoustic signals to enable a drone to estimate its location. In general, localization error is caused by two factors: the ranging error and the error induced by relative geometry between the transmitters and the receiver. iDROP mitigates these two types of errors and provides a high-precision 3-D localization scheme for drones. iDROP employs a waveform that is robust against multipath fading. Moreover, placing beacons in optimal locations reduces the localization error induced by the relative geometry between the transmitters and the receiver.

Index Terms—Drones, indoor localization, indoor navigation, signal separation, ultrasound transceiver.

I. INTRODUCTION

O VER the past few decades, the global drone industry has expanded exponentially, and the number of applications in which drones play a significant part, both in indoor and outdoor environments, has subsequently increased. There is a wide range of indoor drone applications nowadays, ranging from recreational use to life-saving procedures. Examples include reconnaissance inside nuclear power plants, helping firefighters to locate people inside burning buildings, and security surveillance inside large warehouses.

Drones must have fully or partially autonomous flying capability in most of the aforementioned applications to perform their task successfully. To allow these autonomous flights, the drone first needs to localize itself constantly. Then, the navigation command signal is generated and passed on to the controller unit of the drone according to the current position and ultimate destination. In outdoor environments, drones can easily use GPS signals for self-localization; however, such an approach is not feasible in indoor spaces or GPS-denied areas.

In the absence of the GPS, vision-based methods are widely used for localization and navigation of drones (e.g., [1]). However, the accuracy of current vision-based approaches is usually limited by the drone's vibration during flight. In addition, the accuracy can degrade further in vision-impaired environments (e.g., low light environments). Moreover, vision-based methods are expensive both in terms of hardware price and computational complexity.

In addition to vision-based approaches, ranging-based methods are commonly deployed for indoor localization. In this category, the localization is based on the received signal information. Radio-frequency (RF)-based localization (e.g., [2] and [3]) and localization based on acoustic signals (e.g., [4]) are the examples for this group. Besides the characteristic of the received signal, the arrangement of the beacons plays an important role in the localization accuracy in this group.

In this article, we propose robust localization for indoor navigation of drones with optimized beacon placement (iDROP), a 3-D localization scheme for drones in GPS-denied environments. iDROP uses ultrasonic acoustically-based signals for localization. We claim that acoustic signals have some advantages over the localization schemes based on RF signals. Compared to RF signals, the significantly slower propagation speed of the acoustic signals allows for higher accuracy of localization. In addition, RF signals can penetrate through walls and ceilings, further degrading the accuracy of the localization. iDROP uses high-frequency acoustic signals, known as ultrasounds, to prevent any interference with human-generated sounds or the drone’s propeller noise. Moreover, iDROP develops an optimization framework to find the optimal placement for the ultrasound transmitter beacons. The following is a summary of our contributions.

1) We propose iDROP, a 3-D localization scheme for drones in GPS-denied environments that is robust against noise and multipath fading and provides location estimation with high accuracy.

2) iDROP uses the hybrid frequency hopping code-division multiple access (FH-CDMA) as the communication scheme to maximize robustness to noise and multipath fading and to facilitate signal separation at the receiver.

3) iDROP develops an optimization framework to reduce the height estimation error caused by the relative geometry between transmitters and receivers.

4) By leveraging the code-division multiple access (CDMA) techniques, iDROP reduces the communication...
link used for navigation commands by placing the receiver onboard the drone and transmitter beacons in the room.

5) Our simulation and experimental results indicate that iDROP’s localization error is less than 1.5 cm in 3-D space.

The remainder of this article is organized as follows. In Section II, we review some of the related works in this area. Then, in Section III, which is the first core of this article, we fully explain the first stage of our localization scheme for drones in no-GPS environments. In Section IV, we describe the preliminary simulation setup and present the results of localization with a random beacon placement similar to the procedure described by Famili and Park [4]. We evaluate the performance in this section and show that improving the localization accuracy by lessening the ranging error is insufficient for a high-accuracy localization scheme. Next, in Section V, which is the second core of this article, we thoroughly explain the methods we used to further enhance our localization scheme. Then, in Section VI, we describe our experimental testbed followed by the results and evaluation of our proposed scheme. Finally, we conclude our work in Section VII.

II. RELATED WORK

Our work is related to the following research studies: 1) indoor localization; 2) beacon placement optimization; and 3) autonomous navigation for drones in the absence (or lack) of GPS signals.

Localization a target in indoor environments without a GPS signal has been a topic of interest [5], [6], [7], [8], [9], [10]. Ranging-based methods are among the most well-known approaches for indoor localization. In this category, RF, acoustic, or ultrasound signals are deployed to find the distance between the beacons and the target. Then, by using the distance between the target and several beacons, the target’s position is estimated by leveraging techniques such as lateration or triangulation [4], [11], [12], [13].

Localization using wireless fidelity (Wi-Fi) technology [14], cellular positioning with either 4G long-term evolution (LTE) or 5G new radio (NR) signals [15], and geolocation via Bluetooth technology [16], among others, all fall into the category of ranging-based localization using RF signals. While RF-based ranging is more dominant in commercial systems, mainly due to its longer range compared to acoustics, it comes with a few major flaws that make it less suitable for applications where accuracy is more critical than working range; therefore, in the literature, researchers chose acoustic over RF (including Wi-Fi, cellular, RFID tags, and others) mainly due to the accuracy issue [11], [17], [18], [19], [20], [21], [22].

In our system, we chose acoustic; more specifically, ultrasound, for the following reasons. First and foremost, acoustic waves travel at the speed of sound (∼340 m/s) while RF waves travel at the speed of light (∼3 × 10^8 m/s) which is almost 10^6 time faster. For localization purpose, as an example, for a distance of 3 m, the travel time between the transmitter and the receiver is 9 ms if acoustic is being used, compared to 10 ns for RF which is almost six order of magnitude faster. This requires a much more precise clock with much higher sampling frequency to be able to continuously detect the time of arrival (TOA) accurately and perform localization. Consequently, the system becomes more costly and complex in design. Furthermore, even with these added complexities, the RF-based system cannot provide the subcentimeter level of accuracy achievable with acoustic waves.

One well-known category among RF-based ranging methods is using Wi-Fi [23] which works in crowded 2.4 and 5-GHz bands, where interference is high. However, our design based on ultrasonic acoustic waves work in the range of 20 to 50 kHz which do not have that inference and can achieve better performance. To achieve higher accuracy for localization using RF signals, a very large bandwidth is required. For example, with the available bandwidth in 4G LTE for localization (20 MHz), the accuracy is around 20 m which is thousand times worst than what we achieved using acoustic signal [15]. This is reduced to 5 m with the higher bandwidth available in 5G NR technology (100 MHz for sub-6-GHz band of 5G) [24], which is still far from achieving submeter accuracy. Similar limitations exist when using Wi-Fi technology. Recent advancements show promise in achieving submeter accuracy using mmWave 5G NR or 6G, and the 802.11az for Wi-Fi which is an ongoing project specifically designed for positioning using Wi-Fi technology. These new technologies can bring accuracy down to the centimeter level. However, all of these approaches require an extremely wide bandwidth. In comparison, acoustic localization achieves better accuracy without the need for such a large bandwidth.

There exist some commercial positioning systems that rely on RF signals and are capable of achieving high-accuracy localization with precision down to the centimeter level. However, these systems come with complicated designs, are power hungry, need large bandwidth, and most importantly, are extremely expensive. In comparison, we were able to achieve even better accuracy simply by using off-the-shelf ultrasonic sensors that are inexpensive, consume low amounts of power, and do not necessitate any large bandwidth or high sampling frequency.

Finally, it is worth mentioning that in certain use cases, such as high-security environments, the use of RF signals may be restricted due to the potential for easier attack scenarios. In contrast, acoustic signals are generally more widely allowed and may be preferred in such scenarios.

Beacon placement optimization is a well-known approach to optimize the location of beacons for indoor localization purposes [25], [26], [27], [28], [29], [30] or wireless network localization [31], [32]. There are two major categories here: first, optimizing the number of beacons and their location to have full coverage for the entire indoor venue, and second, optimizing the placement of beacons to minimize the localization error, which is caused by the relative geometry between the target and beacons. For the first issue, the type of sensors plays an important role because they both have different coverage. For example, if the system is based on low-power Bluetooth sensors, the transmission would be omnidirectional and the coverage is restricted only by the distance and obstacles;
However, if a system uses ultrasound-based sensors, then the beam angle of the sensors imposes an additional restriction on finding the number of beacons and their placement. After the required number of beacons is fixed, the second optimization platform needs to be deployed to find the placement for beacons to minimize the localization error caused by the relative geometry between the receiver and beacons.

There are some well-known techniques suitable for autonomous navigation of drones in the absence of GPS signals. Vision-based models use different visual techniques, such as visual odometry (VO), simultaneous localization and mapping (SLAM), and optical flow [33], [34], [35], [36]. The major drawback of using only visual techniques is poor image quality owing to the obstacles in a drone’s flying environment, which degrade the accuracy. A few researchers have tried to resolve this issue by leveraging certain auxiliary techniques, for example, some used deep neural networks in combination with visual techniques (e.g., [37] and [38]) or some gained benefits from the use of LiDAR (e.g., [39] and [40]) for autonomous flying.

Famili et al. [41] proposed a scheme for multipath-robust localization of drones in indoor environments. Their system worked based on measuring the time of flight (TOF) of acoustic ultrasonic waveform and conducting trilateration technique. Even though they tried to propose a multipath-robust system, they did not investigate the other error sources; in other words, their whole focus was on mitigation of ranging-based error and they did not analyze the trilateration-based localization error in general; therefore, they were not able to provide a solution for all the error sources. Unlike their system, in this work, we not only guarantee multipath robustness to ensure alleviation of the ranging-based errors, but we also formulate the localization error in general for trilateration techniques. Moreover, we propose a novel optimization framework to mitigate the geometric-induced localization error, and with that, to the best of our knowledge, our system is the first full scheme that considers all the localization error sources and provides techniques to mitigate them.

III. ROBUST LOCALIZATION WITH HYBRID FH-CDMA ULTRASOUND SIGNALS

iDROP is a novel and highly accurate 3-D localization scheme for drones in indoor environments that deploys two steps to reduce both sources of localization error, known as the ranging error, and the error cause by the relative geometry between the receiver and transmitter beacons.

In this section, we thoroughly investigate how iDROP reduces the ranging error and increases the localization accuracy by making the system robust against noise and the indoor multipath fading effect. Then, in Section V, we will elaborate how it minimizes the error caused by the relative geometry and increases the overall accuracy of localization by optimizing the placement of beacons in the room.

A. Measurement Method and Technique

As we have discussed in Section I, the ranging-based localization with ultrasonic signals has some advantages over the other techniques. Hence, iDROP uses ultrasound acoustic signals for distance estimation. Well-known measurement methods are the angle of arrival (AOA), TOA, time difference of arrival (TDOA), and received signal strength (RSS). Techniques for location estimation are angulation, lateration, and fingerprinting. AOA methods incur high expenses in terms of both the hardware cost and the processing power because they require special antenna arrays and complicated calculations. RSS and fingerprinting are too prone to changes in real time to be either reliable or highly accurate. All said, iDROP uses the trilateration technique and the TOA of the received ultrasound signals for localization. Multipath fading is one of the main challenges of relying on the TOA of the received signal. The presence of the copied version of the original signal in the receiver makes detecting the arrival time of the original signal hard or even impossible. iDROP overcomes the multipath fading effect by proposing a hybrid FH-CDMA communication scheme for its signal transmission.

B. Implementation Challenges

In terms of placement of the transmitter(s) and receiver(s) for a ranging-based localization, there are two general scenarios: have the receiver(s) onboard the drone and keep the transmitter(s) in the room, or vice versa. The localization calculation task takes place on the receiver side of the system; therefore, not having them onboard the drone requires another communication link for sending the final location estimation to the drone. This unnecessary communication link increases the cost, slows down the whole process, and may incur additional errors, which degrades the accuracy.

Therefore, it is better to have the receiver(s) mounting onboard the drone and the transmitter(s) in the room. In this case, having one transmitter in the room and multiple receivers onboard the drone [42] causes several problems. It adds extra weight to the drone, increases the power consumption, and most important, there is not enough space between the receivers, which incurs error owing to the relative geometry between the transmitter and receivers and significantly degrades the accuracy of the localization.

To overcome these challenges, iDROP mounts one receiver onboard the drone and keeps all the transmitters spatially distanced from each other in the room. However, this method raises a new challenge, the need for signal separation in the receiver. The receiver requires the capability of separately detecting the TOA of each signal transmitted from a different transmitter. To rectify this matter, iDROP deploys a code-division technique. It assigns a code to the transmitted signals of each of the ultrasound transmitters in the room, that is, ultrasound signals for distance estimation. Well-known measurement

\[
H_4 = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & -1 & 1 & -1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & -1 & 1 \end{bmatrix}. \tag{1}
\]
Data bits of each transmitter would be multiplied with one of the rows of this matrix. At the receiver side, received signals will be multiplied with all four codes, and signals from each transmitter get detected.

C. Hybrid FH-CDMA

iDROP deploys a hybrid FH-CDMA technique that, to the best of our knowledge, is the first time this technique has been applied for a localization purpose, and it is the most desirable scheme to address both problems of multipath and signal separation. The hybrid FH-CDMA is a communication scheme that combines two well-known techniques, the frequency hopping (FH) and the CDMA. iDROP uses this method to rectify the challenge of signal separation in the receiver with multiple access capability and, at the same time, brings robustness against noise and indoor multipath fading using the FH technology.

In our system, as long as we make sure that the hops happen fast enough that before the first multipath reflection has arrived at the receiver, we have already hopped to another carrier frequency, then we can promise a transmission that is robust against the multipath fading. We picked the hopping rate equal to the symbol rate, which is fast enough to avoid multipath according to the room channel characteristic.

First, at each ultrasound transmitter beacon in the room, the code assigned to that transmitter would be assigned to each data bit of that transmitter. Therefore, the symbols are no longer just a bit; they are coded bits that include four bits, that is, data symbols of different beacons are spread with their assigned code and generated the coded symbols. Then, because the hop rate equals the symbol rate, each coded symbol is transmitted in different FH channels. Here, the coded symbols enable signal separation of different transmitters in the receiver side, and the different frequency channels are for managing the multipath fading effect of the room.

Similar to the study by Gonzalez and Bleakley [13], in our scheme, the transmitting signal of the ith transmitter is modulated using binary phase shift keying (BPSK) modulation, then encoded with its dedicated code, and then the coded symbols are spread using a sinusoidal signal with a variable frequency depending on the pseudo-random code, which is known in both the transmitter and receiver sides

\[ s_i(t) = d_i(t) \cdot c_i(t) \cdot pT_B(t) \cdot \sin(2\pi f_m t + \phi) \]  

where \( T_B \) is the data symbol duration, \( d_i(t) \cdot c_i(t) \) is the transmitted symbol of the ith ultrasonic transmitter in the room where \( d_i(t) \) is the data bit and \( c_i(t) \) is the dedicated code to that transmitter, the rectangular pulse \( pT_B \) is equal to 1 for \( 0 \leq t < T_B \) and zero otherwise, and \( f_m \) is the set of frequencies over which the signal hops. Then, the received signal is in the form of

\[ r = \sum_{i=1}^{4} s_i(t - \tau_i) + M + N \]

where \( \tau_i \) is the propagation delay from the ith transmitter to the receiver onboard the drone that we are using for calculating the distance, \( N \) is the overall Gaussian noise, and \( M \) is the summation of all the multipath fading effects

\[ M = \sum_{i=1}^{4} \sum_{j=1}^{N} \alpha_{ij} \cdot s_i(t - \tau_{ij}) \]  

where \( \alpha_{ij} \) is the attenuation of path j for the ith transmitter, \( \tau_{ij} \) is the time delay of the path j for the ith transmitter, and \( N \) is the number of multipath signals. Multipath is a significant issue for indoor environments, and we are using the FH technique to help overcome this effect. As long as we make sure that at each transmitter, the speed of hopping is faster than the time delay of all the multipath signals corresponding to that transmitter (\( \tau_{ij} \)), then before the arrival of any of the reflected signals, we already have changed the frequency and different paths will not interfere with the original signal.

For the hopping rate in our design, we considered the limitations of the maximum range of ultrasonic sensors. Furthermore, the system is designed to work in small medium size confined indoor environment rather than a large outdoor setup with no boundaries. Based on all these considerations, the hopping rate is \((r_{max}/c_{sound})^{-1}\), where \( r_{max} \) is derived based on the maximum range of the ultrasonic sensor and the dimensions of the given floor plan, and \( c_{sound} \) is the speed of sound. This ensures that the system waits for the first signal from the farthest transmitter before changing the frequency. Moreover, the distance of other multipaths to the system are still farther than this; therefore, the frequency has already shifted before their arrival.

Furthermore, it is noteworthy that the existence of four transmitters will not impact the system performance as we utilized the CDMA technique with orthogonal codes obtained from the Walsh–Hadamard matrix. As a result, signals and their corresponding multipaths from different transmitters will not interfere with each other.

By ensuring that multipath effects are eliminated using different FH-channels, the received signal would be only the delayed time of the transmitted signal plus noise

\[ r = \sum_{i=1}^{4} s_i(t - \tau_i) + N. \]  

By multiplying the received signal in each code related to each transmitter, the received signal from the ith transmitter in the receiver would be in the form of

\[ r^{(i)} = d^{(i)} \cdot pT_B(t - \tau_i) \cdot \sin(2\pi f_m (t - \tau_i) + \phi) + N. \]

Therefore, by implementing a cross-correlation between the received signal and the known transmitted signal (the one without the time delay) and detecting the sample at which the peak occurs, the distance is calculated as the following:

\[ d = \frac{n_{samples}}{f_s} \cdot c_{sound} \]
where $n_{\text{samples}}$ is the sample number of the maximum peak, $f_s$ is the sampling frequency, and $c_{\text{sound}}$ is the speed of sound.

### D. Three-Dimensional Localization

After having successfully measured the distance between an ultrasonic transmitter and the receiver, the next step is the 3-D localization of the receiver. To localize an object in two dimensions using trilateration, at least distances between the object and three sources are needed. Similarly, in 3-D localization, it is required to have the distance between the object and at least four sources to localize the object uniquely. Let us denote the distance between the receiver and the $i$th transmitter as $d_i$. Also, the position of the receiver is $[x \ y \ z]^T$ (which in fact is the position of the drone) and the position of the $i$th transmitter is denoted as $[x_i \ y_i \ z_i]^T$. Then, using the trilateration rules, we have

$$
\begin{align*}
(x_1 - x)^2 + (y_1 - y)^2 + (z_1 - z)^2 &= d_1^2 \\
(x_2 - x)^2 + (y_2 - y)^2 + (z_2 - z)^2 &= d_2^2 \\
&\vdots \\
(x_n - x)^2 + (y_n - y)^2 + (z_n - z)^2 &= d_n^2.
\end{align*}
$$

(7)

We can then simplify these quadratic equations and write them in the form of $\mathbf{Ax} = \mathbf{b}$, where $\mathbf{A}$ and $\mathbf{b}$ are equal to

$$
\mathbf{A} = \begin{bmatrix}
2(x_1 - x) & 2(y_1 - y) & 2(z_1 - z) \\
2(x_2 - x) & 2(y_2 - y) & 2(z_2 - z) \\
& \ldots & \\
2(x_n - x) & 2(y_n - y) & 2(z_n - z)
\end{bmatrix},
$$

and

$$
\mathbf{b} = \begin{bmatrix}
d_1^2 - x_1^2 - y_1^2 - z_1^2 + x^2 + y^2 + z^2 \\
d_2^2 - x_2^2 - y_2^2 - z_2^2 + x^2 + y^2 + z^2 \\
& \vdots \\
d_n^2 - x_n^2 - y_n^2 - z_n^2 + x^2 + y^2 + z^2
\end{bmatrix}.
$$

The vector $\mathbf{x} = [x \ y \ z]^T$, which includes the coordinate of the target drone, would be: $\mathbf{x} = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{b}$.

### E. Summary

In this section, we have elaborated how the FH-CDMA localization stage of the iDROP solves the challenge of signal separation in the receiver side in addition to providing robustness against the noise and the multipath fading effect of an indoor environment. By encoding the transmitting signals of each ultrasonic transmitter with a code generated using a Walsh–Hadamard matrix of size 4, iDROP guarantees the capability of signal separation at the receiver side. Then, for robust transmission against noise and multipath, iDROP uses different frequency hops to transmit encoded symbols of each transmitter. Therefore, every data symbol is spread with a complete orthogonal code while successive symbols are transmitted in different frequency-hopped channels. Fig. 1 illustrates this more extensively.

### IV. PRELIMINARY SIMULATION RESULTS

In this section, we evaluate the performance of the proposed FH-CDMA localization and show the localization error for $x$-, $y$-, and $z$-axis separately. First, in Section IV-A, we describe the test setup, and then we show the simulation result in Section IV-B.

#### A. Preliminary Simulation Setup

The performance of the localization scheme proposed in Section III is assessed by implementing simulation in MATLAB. Similar to the work done by Famili and Park [4], we locate the transmitters at the $(x, y, z)$ coordinates equal to $(2.5, 0, 1.5)$, $(5, 2.5, 2.5)$, $(2.5, 5, 2)$, and $(0, 5, 3)$ where all the numbers are in the meter unit. To better observe how we conduct the simulation, we break it down into three subsystems as follows.

1) **Transmitter:** The transmitter subsystem, which in fact is the ultrasonic transmitters at the known positions in the room, generates the desired FH-CDMA signals. We used signals in the frequency range of 20–50 kHz for two reasons. First, to avoid exciting excessive audible noise or facing interference from human-generated voice, we picked frequencies over 20 kHz to avoid overlapping with the human voice frequency range. Any overlaps may cause interference and result in degrading the performance. Meanwhile, according to the Nyquist theorem, the sampling rate needs to be at least twice the maximum frequency to avoid aliasing; hence, if the system works in the frequency range of 20–50 kHz, then the sampling frequency needs to be at least 100 kHz. To avoid the cost of processing and equipment, dealing with high frequency is not suitable; therefore, we do not transmit above 50 kHz, which means that the sampling rate simply could be 100 kHz or more. To generate the FH-CDMA waveform successfully, iDROP uses 6 different frequency hops with 5-kHz bandwidth dedicated to each hop. Also, it assigns a code to each transmitter, so every data bit of each transmitter would first be multiplied with the code and then transmitted via one of the six frequency hops centered at frequencies 22.5, 27.5, 32.5, 37.5, 42.5, and 47.5 kHz. The codes are orthogonal to each other and made by a Walsh–Hadamard matrix of size 4.

At each hop, one data symbol that has already been multiplied by its code would be transmitted, so the hop rate is equal to the data bit rate (actual data bit rate before multiplying by the code), which is fast enough to mitigate the multipath fading effect of the indoor environment. Although a sampling rate of 100 kHz would be enough for our simulation, we picked sampling frequency ($f_s$) equal to 340 kHz to make sure it would be large enough to avoid aliasing, and it also helped to simplify some of our calculations. Because the throughput is not essential in our case, we used BPSK modulation, which does not have a good transmission rate but is highly robust against noise.

2) **Channel:** The channel subsystem adds white Gaussian noise (AWGN) and simulates the multipath fading of indoor environments. The drone’s movement is assumed to be restricted to a rectangular room with dimensions of $5 \times 5 \times 4$ m. We use a Rayleigh channel with several paths for simulating the multipath fading effect owing to the reflection of the signal from walls, floor, ceiling, and other objects and obstacles in the room. The Rayleigh channel
parameters that we set for our simulations are the sample rate, maximum Doppler-shift, number of different paths, delay of each path, and average path gain. We set all these parameters with respect to a typical indoor room environment. Any possible effects of noise and fading that may negatively affect the accurate detection of the TOA of the original signal are simulated using this Rayleigh channel and the AWGN added to the signal.

3) Receiver: The receiver subsystem, which is the ultrasound receiver onboard the drone, separates the signals from different transmitters by multiplying them into the transmitters’ codes and demodulating the frequency-hopped signals. Then, it cross-correlates the received signal with the original version and finds the bit that makes the peak in the cross-correlation, and using that, it estimates the distance from each transmitter to the drone using: 

\[ d = n_{\text{samples}} \times c_{\text{sound}} / f_s, \]

where \( n_{\text{samples}} \) is the sample number at which the maximum cross-correlation occurs and \( f_s \) is the sampling frequency.

B. Results and Motivation

Here, we present the results of our preliminary simulations using the simulation setup we described. We assessed the performance of the FH-CDMA localization by calculating the error between the actual position of the drone and our estimated position. We used a Monte Carlo method with an adequately large number of iterations for each simulation.

In Fig. 2, we show a drone’s actual trajectory as well as the estimated trajectory using only FH-CDMA localization (the first stage of the iDROP). The locations of the ultrasound speaker transmitters are also indicated in this figure. The actual and estimated trajectories seem to overlap perfectly because the localization estimation error is significantly small relative to the room’s dimensions. All the other obstacles and objects in the room, including a table, several chairs, and glass windows, are not shown in the figure to clearly show the drone’s flight trajectory.

Fig. 3 shows the relationship between FH-CDMA localization performance and the signal-to-noise ratio (SNR) of the signal received by the ultrasound receiver. The localization error is inversely proportional to the SNR value of the signal, as expected. In the figure, note that the z-axis localization error is much greater than that of the x- or y-axis at any given SNR.

By conducting more simulations with different drone trajectories, we observed that the error of z-axis localization is always drastically more than the x–y plane localization error. This is despite the fact that all the x-, y-, and z-axes should have almost similar errors because they face a similar channel. This observation motivated us to further investigate the localization error factors and propose a scheme to improve the z-axis localization error.

V. ENHANCING THE ACCURACY OF LOCALIZATION

As we saw in the previous section, the localization error for the z-axis is much greater than that of the x- or y-axis. This is owing to the relative geometry between the transmitter beacons and the target receiver. In general, localization error for ranging-based localization is originated from two sources, first the error in estimating the distance between the target and each of the beacons, known as ranging error, and the other resulted from the relative geometry between the target and beacons.

In Section III, we showed how iDROP lessens the ranging error by deploying the hybrid FH-CDMA communication scheme for distance estimation and making the scheme robust against the noise and the indoor multipath fading effect. This section shows how iDROP copes with the error induced by the relative geometry between the drone and ultrasound transmitter beacons. To the best of our knowledge, iDROP is the first scheme that provides solutions to mitigate both the ranging- and the geometry-related errors and proposes highly accurate localization for drones in indoor environments.

A. Dilution of Precision

A useful metric for measuring the localization accuracy is the Cramer–Rao bound (CRB), which is the lower bound on the location variance that can be achieved using an unbiased location estimator [25]. Rajagopal [25] showed that for a 2-D trilateration system with an unbiased estimator, under the assumption that the range measurements are independent and have zero-mean additive Gaussian noise with constant variance \( \sigma^2 \), the CRB variance of the positional error \( \sigma^2(r) \) at
position \( r \), as defined by \( \sigma^2(r) = \sigma_x^2(r) + \sigma_y^2(r) \) is given by

\[
\sigma(r) = \sigma_r \times \sqrt{\frac{N_b}{\sum_{i=1}^{Nb} \sum_{j=i+1}^{Nb} A_{ij}}}
\]

where \( N_b \) is the number of beacons, \( A_{ij} = |\sin(\theta_i - \theta_j)| \), \( \theta_i \) is the angle between \( b_i \) and \( r \), and \( b_i \) is the \( i \)th beacon.

This shows that the localization error is a multiplication of the ranging measurement error with another term, which is the function of the number of beacons and the angle between beacons and the target object. In satellite calculations, this function is called the geometric dilution of precision (GDOP), therefore: \( \sigma(r) = \sigma_r \times \text{GDOP} \). Because CRB is directly proportional to GDOP, we can consider GDOP as a reasonable guideline to measure the localization accuracy [25], [31], [43], [44].

In general, for 3-D localization of an object at \((x, y, z)\) using ultrasound beacons, we have

\[
\text{GDOP} \cdot \sigma_r = \sqrt{\text{Var}(x) + \text{Var}(y) + \text{Var}(z) + \text{Var}(ct)}
\]

where \( c \) is the speed of sound and \( \tau \) is the receiver’s clock offset. In our simulations, we assume that the transmitter and receiver use the same clock and, hence, we set the timing offset to zero. Therefore, we have

\[
\text{GDOP} = \sqrt{\frac{\sigma_x^2 + \sigma_y^2 + \sigma_z^2}{\sigma_r^2}}.
\]  \( \tag{8} \)

Let \((x, y, z)\) denote the drone’s position and \((x_i, y_i, z_i)\) denote the position for each of the ultrasound transmitter beacons in the room. Then, the drone range to each beacon is calculated from the following:

\[
\begin{aligned}

r_i = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2}. & \quad \tag{9}

\end{aligned}
\]

Because of the ranging measurement error, the exact \( r_i \) is not known, which causes errors in the solution of (9) for \((x, y, z)\). To find a relationship between the solution errors and the ranging errors between the drone and each of the ultrasound transmitter beacons in the room, similar to the work of Massatt and Rudnick [45], we take the differential of (9) and ignore terms beyond first order

\[
\Delta r_i = \frac{\Delta x(x - x_i) + \Delta y(y - y_i) + \Delta z(z - z_i)}{\sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2}}
= \Delta x \cos \alpha_i + \Delta y \cos \beta_i + \Delta z \cos \gamma_i
\]

where \([\cos \alpha_i \ \cos \beta_i \ \cos \gamma_i]^T\) is the unit vector pointing from the drone to the \( i \)th beacon.

Let \( \Delta \mathbf{X} = [\Delta x \ \Delta y \ \Delta z]^T \) be the position error vector and \( \Delta \mathbf{R} = [\Delta r_1 \cdots \Delta r_n]^T \) be the target range error vector. Then, we can define matrix \( \mathbf{U} \) as

\[
\mathbf{U} = \begin{bmatrix}
  u_1^1 & u_1^2 & u_1^3 \\
  \vdots & \vdots & \vdots \\
  u_n^1 & u_n^2 & u_n^3
\end{bmatrix}
\]

where \([u_1^1 \ u_1^2 \ u_1^3] = [\cos \alpha_i \ \cos \beta_i \ \cos \gamma_i] \). Now, we can write \( \Delta \mathbf{R} = \mathbf{U} \Delta \mathbf{X} \), and then we have \( \Delta \mathbf{X} = (\mathbf{U}^T \mathbf{U})^{-1} \mathbf{U}^T \Delta \mathbf{R} \). We know that

\[
\text{Cov}(\Delta \mathbf{X}) = \mathbf{E}(\Delta \mathbf{X} \Delta \mathbf{X}^T) = \begin{bmatrix}
  \sigma_x^2 & \sigma_{xy} & \sigma_{xz} \\
  \sigma_{yx} & \sigma_y^2 & \sigma_{yz} \\
  \sigma_{zx} & \sigma_{zy} & \sigma_z^2
\end{bmatrix}.
\]  \( \tag{10} \)

If we assume that \( \text{Var}(r_i) = \sigma_r^2 \) and that the errors \( \Delta r_i \) are uncorrelated, then

\[
\begin{aligned}

\mathbf{E}(\Delta \mathbf{X} \Delta \mathbf{X}^T) &= \begin{bmatrix}
  (\mathbf{U}^T \mathbf{U})^{-1} \mathbf{U}^T \Delta \mathbf{R} \mathbf{U} (\mathbf{U}^T \mathbf{U})^{-1} \mathbf{U}^T \Delta \mathbf{R}^T
\end{bmatrix} \\
&= (\mathbf{U}^T \mathbf{U})^{-1} \mathbf{U}^T \mathbf{E}(\Delta \mathbf{R} \Delta \mathbf{R}^T) (\mathbf{U}^T \mathbf{U})^{-1} \mathbf{U}^T \\
&= (\mathbf{U}^T \mathbf{U})^{-1} \mathbf{U}^T \mathbf{U} (\mathbf{U}^T \mathbf{U})^{-1} \mathbf{U}^T = (\mathbf{U}^T \mathbf{U})^{-1} \sigma_r^2.
\end{aligned}
\]

Equations (8) and (10), and the aforementioned result show that the diagonal elements of \((\mathbf{U}^T \mathbf{U})^{-1}\) can be used to calculate the GDOP. GDOP consists of vertical dilution of precision (VDOP) and horizontal dilution of precision (HDOP), that is, \( \text{GDOP} = \sqrt{\text{HDOP}^2 + \text{VDOP}^2} \), where HDOP represents the effect of the relative geometry between transmitters and the receiver on the \(x-y\) plane estimation accuracy and VDOP, meanwhile, shows the impact of geometry on the \(z\)-axis estimation. This explains why we saw different accuracy for the \(z\)-axis estimation and \(x-y\) plane estimation in our preliminary tests. Table I shows the evaluation of the GDOP values.

| GDOP Values | Evaluation of the Geometry of the Beacons |
|-------------|-----------------------------------------|
| < 1         | Ideal                                   |
| 1           | Very Good                               |
| 2 – 5       | Good                                    |
| 5 – 10      | Medium                                  |
| 10 – 20     | Sufficient                              |
| > 20        | Bad                                     |

| TABLE I |

\section*{B. Optimized Beacon Placement}

Here, we propose an optimization algorithm to minimize the \(z\)-axis estimation error induced by the relative geometry between transmitter beacons and the receiver, while keeping the horizontal error related to geometry in an acceptable range.

Even though the optimal beacon placement for localization of a single static target in 2-D scenarios is well understood, the optimal placement for a mobile target in a 3-D space is still an open problem [27]. Finding an optimal beacon placement configuration for indoor localization to minimize the localization error owing to the relative geometry between the transmitter beacons and the target receiver at any given position is a well-established NP-Hard problem [26], [27], [28], [29].

Most of the earlier localization techniques have been assayed to localize the unknown object only in 2-D scenarios, which does not consider the real-world geometrical arrangement between the target and beacons in three dimensions. In the following, we will describe our systematic approach to find the optimized beacon placement in the room to improve the \(z\)-axis estimation accuracy and mitigate the overall estimation error by developing a greedy algorithm.
1) Problem Formulation: Find the optimal placement for a set of four ultrasound transmitter beacons with the goal of minimizing the VDOP$_{avg}$ and keeping the HDOP$_{avg}$ below a required threshold, where VDOP$_{avg}$ and HDOP$_{avg}$ are the average of calculated VDOP and HDOP for a set of four beacons on all the given positions in the drone domain. Owing to the constant mobility of the drone, it is not sufficient to compute the VDOP and the HDOP just for one position. Therefore, we considered all the possible locations the drone may pass by during its flight (i.e., all the points in the drone domain) and computed the average of the VDOP and the HDOP over all those possible locations and used them in our calculations. Moreover, if we simply constructed the optimization framework to minimize the average GDOP, then there would be no guarantee that it would improve the $z$-axis estimation accuracy; hence we used the average of the VDOP and the HDOP values. The optimization problem can be formulated as follows:

$$\min_{\text{DroneDomain}} \sum \text{VDOP}$$

s.t.  \(\text{HDOP}_{avg} < h\).

The minimization of the average VDOP is because the goal here is to find the optimized beacon placement to improve the drone’s height estimation accuracy. The consideration for keeping the average HDOP below a threshold is to have a reasonable overall 3-D localization error owing to the relative geometry, that is, this constraint ensures that improving the $z$-axis estimation is not with the cost of sacrificing the $x-y$ plane estimation accuracy.

The acquired inputs are as follows. The drone domain, set $D$, is a subspace of the room where the drone is allowed to fly. Optimization calculations are based on the average of VDOP and HDOP over all the points in this domain. The beacon domain, set $B$, is acceptable locations for beacons in the room. The entire ceiling and top half of all walls are acceptable candidates for the beacon locations. HDOP$_{avg}$ tolerance ($h$) is a constraint that dictates HDOP$_{avg}$ be smaller than $h$, and VDOP$_{avg}$ tolerance ($v$) is a constraint that dictates VDOP$_{avg}$ be smaller than $v$.

As we discussed earlier, if each measurement has the same uncertainty with zero mean and unit variance and they are uncorrelated from each other, then the aforementioned HDOP and VDOP in the preceding steps can be derived from the diagonal elements of the matrix $Q$ as follows:

$$Q = (U^TU)^{-1} = \begin{bmatrix} \sigma_x^2 & \sigma_{xy} & \sigma_{xz} \\ \sigma_{xy} & \sigma_y^2 & \sigma_{yz} \\ \sigma_{xz} & \sigma_{yz} & \sigma_z^2 \end{bmatrix}$$

where $VDOP = \sqrt{\sigma_z^2}$, $HDOP = \sqrt{\sigma_x^2 + \sigma_y^2}$, and

$$U = \begin{bmatrix} x_1 & y_1 & z_1 \\ x_2 & y_2 & z_2 \\ \vdots & \vdots & \vdots \\ x_n & y_n & z_n \end{bmatrix}$$

where $(x, y, z)$ is the drone’s position, $(x_i, y_i, z_i)$ is the location coordinate of the $i$th ultrasound transmitter beacon, and $r_i$ represents the distance between the drone and the $i$th ultrasound transmitter beacon.

2) Algorithm Design: To find a solution with manageable computational time and effort, we develop a greedy algorithm that is based on the class of evolutionary algorithms (EAs) to find the beacon placement.

In the algorithm, first, an initial set of $P = 50$ randomly generated individuals is created. Each individual here is a set of four transmitter beacons selected randomly from the beacon domain. To avoid being trapped in a local minimal, we distributed the initial individuals in different groups: all the beacons on the ceiling, all of them on the walls, or some on the ceiling and some on the walls. We generated some random individuals for each of these groups. We chose 50 randomly generated individuals, because if there were fewer than 50, we would not have been able to include all the different groups, and if there were more than 50, it would have made the solving time unnecessarily long.

Then individuals are sorted according to the fitness (cost) function, and those with better fitness are chosen for reproduction. The fitness function is the average of VDOP over the entire drone domain that is achieved using that specific arrangement of four beacons. Then, the algorithm picks the first 40 individuals in the line as a parents group that will be used to reproduce new individuals. Each two adjacent pair of them makes a new set of four beacons using a crossover technique; therefore, it would be 20 offsprings in total. Next, the algorithm checks every new-generation individual according to the fitness function. Out of 70 total populations, including both the parents and offsprings, the last 20 in the line will be eliminated, so the population remains 50.

For generating a new offspring, each set of parents includes eight beacons total (4 beacons per parent). The crossover technique switches some of the coordinate parameters of the first four beacons with the ones from the second set of four beacons.

After the initialization, the described procedure would repeat for 100 iterations. We checked the algorithm for different iteration numbers and saw that larger ones (e.g., 1000) merely make the process slower without bringing any significant improvement to the final result. Moreover, iterations less than 100 still did not provide a minimal answer, so we picked 100 as the number of iterations. After that, the first individual
C. Additional Sensor for Height Estimation

We have improved the accuracy of the z-axis estimation by optimizing the beacon placement. However, as is seen in Fig. 4(a), the z-axis estimation accuracy is still slightly worse than the location estimation accuracy of the x−y plane. To further improve the height estimation, we use a separate ultrasonic transceiver mounted onboard the drone to continuously estimate the height. Then, using a filter, we incorporate this measurement with the z-axis estimation that has been already available from the first step of iDROP. This significantly improves the z-axis estimation accuracy.

We mount the ultrasonic transceiver facing upward onboard the drone and find the distance between the drone and the ceiling by calculating the TOF of the ultrasonic signal transmitted from the sensor onboard the drone, after it is reflected from the ceiling. Then, simply by subtracting this result from the room height, we find the drone’s height at each moment. The channel between the drone and the ceiling is usually more reliable than the one between the drone and the floor because usually there are no objects between the drone and the ceiling that induce errors. The height estimation using this extra ultrasonic transceiver is then: \( h_{\text{drone}} = H - d \) and \( d = c_{\text{sound}} \cdot t/2 \); where \( d \) is the distance between the drone and the ceiling; \( t \) is the total time it takes the signal to travel from the ultrasonic transceiver onboard the drone and hit the ceiling, reflect, and be received in the ultrasonic transceiver onboard the drone; \( H \) is the room height; and \( h_{\text{drone}} \) is the estimation for the drone’s height. The final revised height estimation is then: \( z_{\text{revised}} = w_1 \cdot z + w_2 \cdot h_{\text{drone}} \), where \( w_1 \) and \( w_2 \) are the weights assigned for the z-axis estimation from the first stage of iDROP and this stage, and \( z \) is the estimated height from the first stage of the iDROP.

The weights, \( w_1 \) and \( w_2 \), represent the degree to which we rely on information about the z-axis estimation from the first stages of the iDROP procedure and the auxiliary height measurement sensor, respectively. While it is possible to simply average these values with no weights \( (w_1 = w_2 = 1/2) \), we discovered through various experiments that even though the optimization algorithm improves the z-axis estimation, it is still not as accurate as the x−y plane estimation. Conversely, in our testing environment, the drone had an unobstructed view of the ceiling throughout the entire flight, resulting in excellent performance for the auxiliary height estimator. As a result, we assigned a higher value to \( w_2 \) and a lower value to \( w_1 \). After testing various values for \( w_1 \) and \( w_2 \) empirically, we discovered that \( w_1 = 0.2 \) and \( w_2 = 0.8 \) resulted in optimal performance. As a caveat, these values were obtained from tests conducted in our indoor environment, so it is recommended to conduct preliminary experiments in another environment to determine the optimal values. If that is not possible, assigning equal values to \( w_1 \) and \( w_2 \) (a simple nonweighted average) is preferable.

VI. EXPERIMENTAL RESULTS AND EVALUATIONS

A. Experimental Setup

To assess the performance of iDROP, we conducted some experimental tests coupled with MATLAB simulations. As seen in Fig. 5, the experimental test setup consists of two stations: first, the drone and the system onboard it, and second, the ground control station that helps to input the transmitted data into the MATLAB program running on a Dell XPS 15 laptop. The drone that we used for the experiment is a Parrot Mambo Drone. It is a cheap, off-the-shelf, and ultralight drone
suitable for indoor experiments. Also, it has the capability of carrying some light loads. The designed system mounted onboard the drone consists of an Arduino Uno microcontroller connected to an HC-SR04 sensor for ultrasonic distance measurement purposes and a XBee S1 module for wireless communication with the ground controller. In the ground control unit, another Arduino Uno microcontroller connected to an XBee S1 receives the data and further transfers them into the MATLAB program running on the laptop. All the experiments were conducted in a hallway inside a building with dimensions 5 m × 5 m × 4 m. This hallway contains several objects and obstacles, including tables, chairs, and glass windows.

In the MATLAB program, we know the true path (ground truth) and compare the estimated results acquired from the iDROP scheme with that ground truth. The overall 3-D error is derived based on

\[ e_{xyz}(x, y, z) = \sqrt{(x_{est} - x_{gth})^2 + (y_{est} - y_{gth})^2 + (z_{est} - z_{gth})^2} \]  

where \([x_{est} \ y_{est} \ z_{est}]^T\) is the vector of the estimated position of the drone in the Cartesian coordinates obtained using iDROP and \([x_{gth} \ y_{gth} \ z_{gth}]^T\) is the ground truth (the exact location) vector. To eliminate randomness and testing errors, we repeat the same test 1000 times for each point and average the results to obtain the final error representation for every location in the room. In real-world experiments, the ideal ground truth is achieved by conducting tests in an optic reference lab equipped with high-performance lasers, which is commonly used for ground-truth testing of commercial localization systems. However, to avoid the complexity and high cost of testing using such lasers, we designed predefined courses and measured the exact locations of different points in that course to obtain a ground truth for our experiments. We then flew the drone in that predefined course and compared the reported values from the iDROP scheme with these predefined points to measure the error, using (11). We conducted the test for each course several times and averaged the results to obtain a more accurate representation of the error, though we could not repeat the course 1000 times (as in simulation step) due to practical constraints. Additionally, we considered the location of the drone to be the center of the ultrasonic sensor mounted on top of it, and that was the reference point used to measure and compare the error of the system.

B. Final Results

In Fig. 4(a), a comparison of the localization error for both the z-axis and the x – y plane, in different SNRs, before and after using the proposed EA optimization framework is seen. The new (x, y, z) coordination of the ultrasound transmitters in the room that is obtained from the EA optimization framework is (4.5, 0, 2.5), (5, 4, 3.5), (1.5, 2), and (1.5, 2, 4) where all the numbers are in meters. As seen in this figure, using the optimized placement for transmitters improves the z-axis localization accuracy significantly. Moreover, it does not drastically degrade the x – y plane localization accuracy. The reason for developing the EA optimization framework is to find the optimal placement of transmitters in the room to mitigate the localization error caused by the relative geometry between the transmitters and the target drone. More specifically, it is designed to mitigate the z-axis localization error without significantly degrading the x – y plane localization accuracy. This plot shows that the proposed EA optimization framework performs as expected.

In Fig. 4(b), the z-axis localization error for seven different random drone trajectories, in cases where the hybrid FH-CDMA technique is used for localization in comparison with the cases that leverage the hybrid FH-CDMA technique for localization in combination with using the new optimal coordination for transmitters, is seen. Moreover, this figure shows a similar comparison for the overall 3-D localization error. As depicted in this figure, for all of these random trajectories for the drone in the room, both the z-axis and the overall localization error improve when the optimized beacon placement is used.

In Fig. 6(a), the localization error of the z-axis with the x – y plane is compared. This figure justifies the necessity of having the auxiliary sensor for height estimation. As seen in this figure, even though the optimized placement for transmitters improved the z-axis localization accuracy significantly, the z-axis error may not be as low as the x – y plane localization error. This figure shows how the last step of iDROP

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**Fig. 6.** (a) Evaluating the performance of iDROP: comparison between the x – y plane average estimation error and the z-axis. (b) Evaluating the performance of iDROP: overall 3-D localization accuracy.
further improves the $z$-axis estimation by constantly transferring the measured data from the ultrasound sensor onboard the drone (HC-SR04) to the receiver module connected to the Dell XPS 15 laptop. Therefore, iDROP successfully improves the $z$-axis estimation without sacrificing the $x-y$ plane localization accuracy.

In Fig. 6(b), the performance of iDROP with that of the benchmark scheme (which relies only on FH-CDMA distance estimation to localize a target drone) in terms of the overall 3-D localization error is compared. The average value of 3-D localization error for iDROP is 1.2 cm. As is seen in the figure, the benchmark scheme’s localization error is more than twice that of iDROP. This is because the benchmark scheme merely focuses on mitigating ranging-based error by deploying the FH-CDMA communication scheme for localization. Other drone localization schemes proposed in the literature do the same and try to improve the localization accuracy by proposing their technique to mitigate the ranging-based error. However, iDROP proposes a scheme that deals with both ranging-based error and geometry-related error, and in this way, it further improves the accuracy.

iDROP achieves significant improvement in comparison with other drone localization schemes in [4], [13], [42], [46], and [47]. For instance, O’Keefe and Etele [42] proposed a scheme that incurs an average error of 5.2 cm for the 3-D localization for drones. The scheme proposed by Segers et al. [46] incurred an error of 2 cm or greater in terms of localization error just for the $x-y$ plane (2-D localization). Table II compares iDROP with other comparable schemes introduced in the literature.

| System | Measurement | Multipath Solution | 3D Localization | Claimed Accuracy | Optimized Beacon Placement | Improved $Z$-axis Estimation |
|--------|-------------|--------------------|-----------------|-----------------|--------------------------|--------------------------|
| [46] (2014) | Ultrasound, TOA | None | No | 2 cm for 2D | No | No |
| [11] (2017) | Acoustic, TOA | FM-CW | No | 2.6 cm for 1D | No | No |
| [42] (2019) | Ultrasound, TOA | None | Yes | 5.2 cm for 3D | No | Yes |
| [4] (2020) | Ultrasound, TOA | FH-CSS | Yes | 1.4 cm for 3D | No | No |
| [41] (2021) | Ultrasound, TOA | FH-CDMA | Yes | 1.5 cm for 3D | No | No |
| iDROP | Ultrasound, TOA | FH-CDMA | Yes | 1.2 cm for 3D | Yes | Yes |

As seen in Table II, iDROP proposes a novel solution for each of the existing challenges, and that is why it has a better overall performance in comparison with the works in the literature. For instance, Mao et al. [11] proposed an FM-CW technique to overcome the multipath fading effect; however, their scheme was designed only for tracking a drone on a line, and they did not consider 3-D localization and its challenges. Famili and Park [4] proposed a multipath robust scheme for 3-D localization of drones; however, their scheme had significantly low accuracy for $z$-axis estimation. Moreover, their claimed accuracy is merely based on MATLAB simulations, and they did not provide any real-life experiments with an actual drone to assess their proposed scheme. O’Keefe and Etele [42] failed to propose an optimal solution for beacons because of their choice of system design and lack of signal separation capability. They also did not consider a multipath-robust communication technique. Therefore, their proposed scheme had high localization errors. In another work, Famili et al. [41] proposed a multipath robust system for drones’ 3-D localization in indoor environments. Even though their proposed scheme fixed the signal separation challenge and eliminated the unnecessary communication link between the actual drone to assess their proposed scheme.
the drone and the transmitter beacons in the room, they failed to explain the reason behind having a bad z-axis estimation and their system lacked the optimal beacon placement analysis. iDROP has robustness against multipath fading and noise and provides signal separation capability. Moreover, it proposes an optimized placement for beacons in the room and improves the z-axis estimation accuracy. Overall, iDROP provides a highly accurate 3-D localization in real-time scenarios for drones.

VII. CONCLUSION

In this article, we presented a multipath-robust localization system with optimized beacon placement that can be used for autonomous navigation of drones in indoor environments. First, the drone can locate itself in 3-D space using the TOA of the received FH-CDMA ultrasound waveform. Then, to improve the z-axis estimation accuracy, a EA optimization framework finds an optimized location for the transmitter beacons in the room. Moreover, an additional ultrasound transceiver provides a separate measurement of the drone’s height for improving the z-axis estimation accuracy. Finally, we evaluate the performance of our proposed system by conducting experiments coupled with simulations.

REFERENCES

[1] R. Depaola, C. Chimento, M. L. Anderson, K. Brink, and A. Willis, “UAV navigation with computer vision—Flight testing a novel visual odometry technique,” in Proc. AAA Guid. Navig. Control Conf., 2018, pp. 1–12.
[2] G. Chi et al., “Wi-drone: Wi-Fi-based 6-DoF tracking for indoor drone flight control,” in Proc. 20th Annul. Int. Conf. Mobile Syst. Appl. Serv., 2022, pp. 56–68. [Online]. Available: https://doi.org/10.1145/3498361.3538936
[3] C. Chen, Y. Chen, Y. Han, H.-Q. Lai, and K. J. R. Liu, “Achieving centimeter-accuracy indoor localization on WiFi platforms: A frequency hopping approach,” IEEE Internet Things J., vol. 4, no. 1, pp. 111–121, Feb. 2017.
[4] A. Famili and J.-M. J. Park, “ROLATIN: Robust localization and tracking for indoor navigation of drones,” in Proc. IEEE Wireless Commun. Netw. Conf. (WCNC) (IEEE WCNC), Seoul, South Korea, Apr. 2020, pp. 1–6.
[5] J.-V.-V. Gerwen, K. Ghebelen, J. Wan, W. Joseph, J. Hoebeke, and E. De Poorter, “Indoor drone positioning: Accuracy and cost trade-off for sensor fusion,” IEEE Trans. Veh. Technol., vol. 71, no. 1, pp. 961–974, Jan. 2022.
[6] I. Bisio, C. Garibotto, H. Halaem, F. Lavagetto, and A. Sciarro, “On the localization of wireless targets: A drone surveillance perspective,” IEEE Netw., vol. 35, no. 5, pp. 249–255, Sep./Oct. 2021.
[7] F. J. González-Castaño, F. Gil-Castilheira, D. Rodríguez-Pereira, J. Á. Regueiro-Janeiro, S. García-Méndez, and D. Candal-venturera, “Self-corrective sensor fusion for drone positioning in indoor facilities,” IEEE Access, vol. 9, pp. 2415–2427, 2021.
[8] R. Sharma and V. Badarla, “Analysis of a novel beacon placement strategy for range-based indoor localization systems,” Ph.D. Dissertation, Dept. Electr. Comput. Eng., Carnegie Mellon Univ., Pittsburgh, PA, USA, Aug. 2019.
[9] W. Mao, A. Stavrou, H. Wang, and J.-M. J. Park, “Pilot: High-precision indoor localization for autonomous drones,” IEEE Trans. Veh. Technol., vol. 70, no. 5, pp. 4984–4992, May 2021.
[10] A. Yusefi, A. Durdu, M. F. Aslan, and C. Sungur, “LSTM and filter based comparison analysis for indoor global localization in UAVs,” IEEE Access, vol. 9, pp. 10054–10069, 2021.
[11] G. Himona, A. Famili, A. Stavrou, V. Kovani, and Y. Kominis, “Isochrons in tunable photonic oscillators and applications in precise positioning,” in Proc. Phys. Stat. Optoelectron. Devices XXXI, 2023, Art. no. 124150E. [Online]. Available: https://doi.org/10.1117/12.2649877
[12] J. Xiong, K. Sundaresan, and K. Jamieson, “ToneTrack: Leveraging frequency-agile radios for time-based indoor wireless localization,” in Proc. 21st Annu. Int. Conf. Mobile Comput. Netw., 2015, pp. 537–549. [Online]. Available: http://doi.acm.org/10.1145/2789168.2790125
[13] J. R. Gonzalez and C. J. Bleakley, “High-performance robust broadband ultrasonic location and orientation estimation,” IEEE J. Sel. Topics Signal Process., vol. 3, no. 5, pp. 832–844, Oct. 2009.
[14] M. Kotaru, K. Joshi, D. Bhuradia, and S. Katti, “SpotFi: Decimeter level localization using WiFi,” in Proc. ACM Conf. Spec. Interest Group Data Commun., 2015, pp. 269–282. [Online]. Available: https://doi.org/10.1145/2785956.2787487
[15] W. Xu, A. Dammann, and T. Laas, “Where are the things of the Internet? Precise time of arrival estimation for IoT positioning,” in The Fifth Generation (5G) of Wireless Communication, A. Kishk, Ed. Rijeka, Croatia: IntechOpen, 2019, Ch. 5. [Online]. Available: https://doi.org/10.5772/intechopen.78063
[16] S. Shiraki and S. Shioida, “Contact information-based indoor pedestrian localization using Bluetooth low energy beacons,” IEEE Access, vol. 10, pp. 119863–119874, 2022.
[17] W. Wang, A. X. Liu, and K. Sun, “Device-free gesture tracking using acoustic signals,” in Proc. 22nd Annul. Int. Conf. Mobile Comput. Netw., 2016, pp. 82–94. [Online]. Available: http://doi.acm.org/10.1145/2973750.2973764
[18] X. R. I, D. Liu, M. Hou, Y. Li, and Ji. Li, “Using acoustic signal and image to achieve accurate indoor localization,” Sensors, vol. 18, no. 8, p. 2566, 2018. [Online]. Available: http://www.mdpi.com/1424-8220/18/8/2566
[19] S. Yun, Y.-C. Chen, and L. Qiu, “Turning a mobile device into a mouse in the air,” in Proc. 13th Annu. Int. Conf. Mobile Syst. Appl. Serv., 2015, pp. 15–29. [Online]. Available: http://doi.org/10.1145/2742647.2742662
[20] W. Mao, J. He, and L. Qiu, “CAT: High-precision acoustic motion tracking,” in Proc. Mobicom, 2016, pp. 69–81.
[21] Z. Zhang, D. Chu, X. Chen, and T. Moscibroda, “SwordFight: Enabling a new class of phone-to-phone action games on commodity phones,” in Proc. 10th Int. Conf. Mobile Syst. Appl. Serv., 2012, pp. 1–14. [Online]. Available: http://doi.acm.org/10.1145/2307636.2307638
[22] R. Nandakumar, V. Iyer, D. Tan, and S. Gollakota, “FingerIO: Using active sonar for fine-grained finger tracking,” in Proc. CHI Conf. Human Factors Comput. Syst., 2016, pp. 1515–1525. [Online]. Available: http://doi.org/10.1145/2880360.2835850
[23] L. Sun, S. Sen, D. Koutsoukoras, and K.-H. Kim, “WiDraw: Enabling hands-free drawing in the air on commodity WiFi devices,” in Proc. Mobicom, 2015, pp. 77–89.
[24] A. Famili, M. Foruharhdeh, T. Atalay, A. Stavrou, and H. Wang, “GPS spoofing detection by leveraging 5G positioning capabilities,” in Proc. IEEE Latin Amer. Conf. Comput. (LATINCOM), 2022, pp. 1–6.
[25] N. Rajagopal, “Localization, beacon placement and mapping for range-based indoor localization systems,” Ph.D. Dissertation, Dept. Electr. Comput. Eng., Carnegie Mellon Univ., Pittsburgh, PA, USA, Aug. 2019.
[26] H. Wang, N. Rajagopal, A. Rowe, B. Sinopoli, and J. Gao, “Efficient beacon placement algorithms for time-of-flight indoor localization,” in Proc. 27th ACM SIGSPATIAL Int. Conf. Adv. Geograph. Inf. Syst., 2019, pp. 119–128. [Online]. Available: https://doi.org/10.1145/3347146.3359344
[27] N. Rajagopal, S. Chayapaty, B. Sinopoli, and A. Rowe, “Beacon placement for range-based indoor localization,” in Proc. Int. Conf. Indoor Position. IndoorNavig. (IPIN), Oct. 2016, pp. 1–8.
[28] A. Famili, A. Stavrou, H. Wang, and J.-M. J. Park, “Pilot: High-precision indoor localization for autonomous drones,” IEEE Trans. Veh. Technol., vol. 70, no. 5, pp. 6445–6459, May 2023.
[29] N. Patwari, A. O. Hero, M. Perkins, N. S. Correal, and R. J. O’Dea, “Relative location estimation in wireless sensor networks,” IEEE Trans. Signal Process., vol. 52, no. 8, pp. 2137–2148, Aug. 2003.
[30] T. Wang, Y. Shen, A. Conti, and M. Z. Win, “Network navigation with scheduling: Error evolution,” IEEE Trans. Inf. Theory, vol. 63, no. 11, pp. 7509–7534, Nov. 2017.
and tracking, 5G positioning, and wireless communications/networking.

G. Balamurugan, J. Valarmathi, and V. P. S. Naidu, “Survey on UAV navigation in GPS denied environments,” in Proc. Int. Conf. Signal Process. Commun. Power Embedded Syst. (SCOPES), Oct. 2016, pp. 198–204.

S. Bastiaens et al., “Experimental benchmarking of next-gen indoor positioning technologies (unmodulated) visible light positioning and ultra-wideband,” IEEE Internet Things J., vol. 9, no. 18, pp. 17858–17870, Sep. 2022.

R. P. Padhy, S. Verma, S. Ahmad, S. K. Choudhury, and P. K. Sa, “Deep neural network for autonomous UAV navigation in indoor corridor environments,” Procedia Comput. Sci., vol. 133, pp. 643–650, Jul. 2018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1877050918310524

P. Chhikara, R. Tekchandani, N. Kumar, V. Chamola, and M. Guizani, “DCNN-GA: A deep neural net architecture for navigation of UAV in indoor environment,” IEEE Internet Things J., vol. 8, no. 6, pp. 4448–4460, Mar. 2021.

N. Jeong, H. Hwang, and E. T. Matson, “Evaluation of low-cost LiDar sensor for application in indoor UAV navigation,” in Proc. IEEE Sensors Appl. Symp. (SAS), Mar. 2018, pp. 1–5.

M. Rausch and G. Feher, “Stationary LIDAR sensors for indoor quadcopter localization,” in Proc. IEEE SENSORS, 2020, pp. 1–4.

A. Famili, A. Stavrou, H. Wang, and J-M. J. Park, “RAIL: Robust acoustic indoor localization for drones,” in Proc. IEEE 95th Veh. Technol. Conf. (VTC-Spring), 2022, pp. 1–6.

J. O’Keefe and J. Etete, “Ultrasonic localization of a quadrotor using a portable beacon,” in Proc. AIAA Scitech Forum, Jan. 2019, p. 16.

M. A. Spirito, “On the accuracy of cellular mobile station location estimation,” IEEE Trans. Veh. Technol., vol. 50, no. 3, pp. 674–685, May 2001.

N. Patwari, J. N. Ash, S. Kyperountas, A. O. Hero, R. L. Moses, and N. S. Correal, “Locating the nodes: Cooperative localization in wireless sensor networks,” IEEE Signal Process. Mag., vol. 22, no. 4, pp. 54–69, Jul. 2005.

P. Massatt and K. Rudnick, “Geometric formulas for dilution of precision calculations,” J. Inst. Navig., vol. 37, no. 4, pp. 379–392, 1991.

L. Segers, J. Tiete, A. Bruken, and A. Touhai, “Ultrasonic multiplex-access ranging system using spread spectrum and MEMS technology for indoor localization,” Sensors, vol. 14, pp. 3172–3187, Feb. 2014.

A. Paredes, F. J. Álvarez, T. Aguiler, and J. M. Villadangos, “3D indoor positioning of UAVs with spread spectrum ultrasound and time-of-flight cameras,” Sensors, vol. 18, p. 89, Dec. 2017.

M. A. Pizarro, J. P. Beltrán, M. Cominelli, F. Gringoli, and J. Widmer, “Accurate ubiquitous localization with off-the-shelf IEEE 802.11ac devices,” in Proc. 19th Annu. Int. Conf. Mobile Syst. Appl. Serv., 2021, pp. 241–254. [Online]. Available: https://doi.org/10.1145/3458664.3468850

M. Rea, T. E. Abrudan, D. Giustinianno, H. Claussen, and V-M. Kolmonen, “Smartphone positioning with radio measurements from a single WiFi access point,” in Proc. 15th Int. Conf. Emerg. Netw. Exp. Technol., 2019, pp. 200–206. [Online]. Available: https://doi.org/10.1145/3359989.3365427

K. Jiokeng, G. Jakllari, A. Tchana, and A-L. Beylot, “When FTM discovered MUSIC: Accurate WiFi-based ranging in the presence of multipath,” in Proc. IEEE INFOCOM Comput. Commun., 2020, pp. 1857–1866. [Online]. Available: https://doi.org/10.1109/INFOCOM41043.2020.9155464

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