ROLATIN: **Ro**bust **L**ocalization **a**nd **T**racking for **I**ndoor **N**avigation of Drones

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***Abstract*—In many drone applications, drones need the ability to fly fully or partially autonomously to carry out their mission. To enable such fully/partially autonomous flights, the ground control station that is supporting the drone's operation needs to constantly localize and track the drone, and send this information to the drone's navigation controller to enable autonomous/semi-autonomous navigation. In outdoor environments, localization and tracking can be readily carried out using GPS and the drone's Inertial Measurement Units (IMUs). However, in indoor areas or GPS-denied environments, such an approach is not feasible. In this paper, we propose a localization and tracking scheme for drones called ROLATIN (Robust Localization and Tracking for Indoor Navigation of drones) that was specifically devised for GPS-denied environments. Instead of GPS signals, ROLATIN relies on speaker-generated ultrasonic acoustic signals to estimate the target drone's location and track its movement. Compared to vision and RF signal-based methods, our scheme offers a number of advantages in terms of performance and cost.**

***Index Terms*—indoor localization, drones, ultrasound transceiver, FHSS, Doppler shift, Kalman filter**

I. Introduction

The global drone industry has grown rapidly in the past few years and the number of applications in which drones play an important role, both in indoor and outdoor environments, has increased consequently. Today, there is a wide variety of indoor drone applications, spanning from recreational use cases to safety-of-life critical use cases. Examples include reconnaissance inside nuclear power plants, aiding firefighters to locate people inside burning buildings, security surveillance inside large warehouses, etc.

In all of the aforementioned applications, drones need to be able to fly fully or partially autonomously to carry out their mission. To enable such fully/partially autonomous flights, the ground control station or other infrastructure that is supporting the drone's operation needs to constantly localize and track the drone, and send this information to the drone's navigation controller to enable autonomous/semi-autonomous navigation. In outdoor environments, localization and tracking can be readily carried out using GPS and the drone's Inertial Measurement Units (IMUs). However, in indoor environments or GPS-denied environments, such an approach is not possible.

When GPS is not available, vision based methods are commonly used for drone localization and tracking (e.g., [1]). However, the accuracy of current vision-based methods is usually limited because of the vibration of a drone during flight. Moreover, the accuracy can deteriorate further in vision impaired environments (e.g., low light environments). Also, vision-based methods incur high computational complexity.

In addition to vision-based methods, there are other techniques, including RF-based localization (e.g., [2]), Doppler-shift-based tracking (e.g., [3]), and tracking using cellular networks (e.g., [4]). In indoor environments, where the cellular signal level is weak, cellular signal-based approaches are not feasible. Doppler-shift-based tracking also has limitations; by itself, it does not provide sufficient tracking accuracy.

In this paper, we propose a localization and tracking scheme for drones in GPS-denied environments that is referred to as *Robust Localization and Tracking for Indoor Navigation of Drones (ROLATIN)*. ROLATIN uses acoustic (or ultrasonic)-based localization and tracking. We claim that acoustic signal-based localization/tracking offers a number of advantages over RF signal-based approaches. The significantly slower propagation speed of acoustic signals, as compared to RF signals, enables higher tracking accuracy. Moreover, RF signals can penetrate walls and ceilings, which can further degrade localization/tracking accuracy. To avoid any interference with a drone's propeller noise or human-generated noise, ROLATIN uses high frequency acoustic signals, known as *ultrasounds*. Our contributions are summarized below.

- We propose ROLATIN, a three-dimensional localization and tracking scheme for drones in GPS-denied environments (such as indoor environments) which is highly robust against noise and multi-path effects and achieves high accuracy.
- To achieve high accuracy and robustness against noise, ROLATIN employs two stages. In the first stage, ROLATIN uses Frequency Hopping Spread Spectrum (FHSS) to localize a target drone continuously. In the second stage, the velocity of the drone is estimated by measuring the frequency shift of the received signal. ROLATIN uses a Kalman filter to combine the information obtained from the two stages to improve accuracy and to increase robustness against noise.
- We conducted comprehensive simulations to evaluate ROLATIN. According to our results, ROLATIN achieves much higher accuracy compared to prior works. Specifically, it incurs localization/tracking errors on the order of a few millimeters in the $X-Y$ plane, while prior works reported errors on the order of a few centimeters.

The rest of this paper is organized as followings. In the next section, we are going through some of the related works in this area. Then, in section III and IV, which are the core sections of our paper, we fully explain our scheme for localizing and tracking a drone in an indoor environment. Next, in section V, we describe our test setup for simulations followed by section VI where we bring the simulation results for the proposed scheme. We conclude our work in section VII.

II. Related Work

Our work is related to the following research areas: (i) indoor drone localization and navigation, (ii) positioning and tracking of a moving object, and (iii) indoor localization techniques in general.

For indoor drone localization and navigation, there are several methods that research groups have been working on them including: vision based models using different visual techniques such as visual odometry (VO), simultaneous localization and mapping (SLAM), and optical flow technique [1], [5]– [7]. There are also a few research papers where they use deep neural network in combination by visual techniques (e.g., [8]) or use of LiDAR for autonomous flying (e.g., [9]). In [10], Mao et al. track a drone using acoustic signal. In this work, they devised a system where a drone can follow a user autonomously in an indoor environment. In their work, drone sends acoustic signal to the cell phone which the user used. Microphones in the cellphone received the signal and using the cellphone processor, the distance between the drone and user calculated. At the end, the cellphone sends a command signal to the drone and guide the drone to follow user. This work has robust indoor positioning and tracking for drones, just in terms of following the source in short distance and it does not have three-dimensional localization. Another research work presented the sound base direction sensing where simply by using the shift in the received signal's frequency (Doppler-shift effect), they found the direction of the drone, but again there is no exact localization here [3].

For positioning and tracking of a moving object in indoor scenarios for short ranges, there are quite a few research works where they use radio frequency (RF) or acoustic signals and simply by calculating the time of flight (TOF) of the signal between the system and the target object, they find the distance and therefore find the position of the target object [10]– [12].

In term of indoor localization, RF, acoustic, or ultrasonic signals are topics of interest [2], [13]– [16]. In [2], Chen et al. use a WiFi platform to achieve centimeter accuracy for indoor localization using Frequency Hopping Spread Spectrum (FHSS) technique. RF signals propagate in speed of light which makes the receiver processing harder and more expensive. As we mentioned earlier, in [10], Mao et al. use acoustic signal for tracking drones. Problem with acoustic signal is that human-generated noise or drone's propeller noise may interfere the signal, hence degrade the accuracy of localization.

III. Robust FHSS-based localization

As we have discussed previously, three-dimensional localization and tracking are the most important requirements in realizing fully or partially autonomous navigation of drones. In this section, we describe how ROLATIN carries out three-dimensional localization and in the next section we will elaborate on how it increases the robustness and accuracy when tracking drones. Well-known measurement methods for localization include angle of arrival (AOA), time of arrival (TOA), time difference of arrival (TDOA), and received signal strength (RSS) and techniques for location estimation are angulation, lateration, and fingerprinting. AOA requires the use of special antenna arrays and incurs high complexity calculations which make the approach expensive both in terms of cost and processing power. RSS and fingerprinting are too sensitive to real-time changes, and hence, they are not reliable.

ROLATIN uses trilateration techniques and the TOA of received ultrasound signals for localization. The main challenge of using TOA of received signals is multi-path fading. In [10], Mao et al. proposed an FMCW method to overcome the impact of interference and multi-path. In [13], Segers et al. compared the two spread spectrum methods, frequency hopping spread spectrum (FHSS) and direct sequence spread spectrum (DSSS). They showed that both FHSS and DSSS are effective in addressing multi-path effects to increase accuracy. According to their results, FHSS outperforms DSSS even in case of multi-users.

Similar to the approach used in [14], in our scheme, transmitting signal of the k-th drone is modulated using Binary Phase Shift Keying (BPSK) modulation and then it is spread using a sinusoidal signal with variable frequency depending on the pseudo-random code:

$$s^{(k)}(t) = d^{(k)} \cdot pT_B(t) \cdot \sin(2\pi f_m t + \phi), \tag{1}$$

where T_B is the data symbol duration, d^k is the transmitted data symbol of ultrasonic speaker on k-th drone, 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:

$$\begin{aligned} r^{(k)} = d^{(k)} \cdot pT_B(t-\tau) \cdot \sin(2\pi f_m(t-\tau) + \phi) + \\ M(t) + N(t), \end{aligned}$$

where τ is the propagation delay that we are using for calculating the distance, $N(t)$ is the Gaussian noise, and $M(t)$ is the multi-path effect, which can be expressed as the following summation:

$$M(t) = \sum_{i=1}^{N} \alpha_i \cdot s^{(k)}(t-\tau_i), \tag{2}$$

where α_i is the attenuation of path i and τ_i is the time delay of path i. Multi-path is an inevitable effect in indoor environments due to the reflection of the original signal from walls, ceiling, floor, and other objects inside the room. For calculating the precise TOA, multi-path fading could be a big issue because multiple copies of the original signal with different arrival times make it impossible to detect the exact TOA of the original signal. We are using FHSS to mitigate the multi-path effect and be able to detect the exact TOA of the original signal. As long as we make sure that the speed of hopping is faster than the time delay of each path (τ_i), then before arrival of any of the reflected signals we already have changed the frequency and different paths don't interfere with the original signal.

By ensuring the elimination of multi-path effect using FHSS technology, the received signal would be just the time delayed of transmitted signal plus noise:

$$r^{(k)} = d^{(k)} \cdot pT_B(t-\tau) \cdot \sin(2\pi f_m(t-\tau)+\phi) + N(t). \quad (3)$$

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

$$d = \frac{n_{samples}}{f_s} \cdot c_{sound}, \quad (4)$$

where $n_{samples}$ is the sample number of the maximum peak and f_s is the sampling frequency.

Using the method described above, the distance between an ultrasonic transmitter (speaker) and receiver (microphone) can be calculated. The next step is three-dimensional localization of the transmitter. For localizing an object in two dimensions using trilateration, at least distances between the object and three sources are needed. In three-dimensional localization, we need to compute the distances between the target object and at least four different sources in order to uniquely localize the target object. Let's denote the distance between a transmitter and i-th receiver as d_i. Also, the position of the transmitter is denoted as $[x\ y\ z]^T$ and the position of the i-th receiver is denoted as $[x_i\ y_i\ z_i]^T$. Then using trilateration rules we have:

$$\begin{gathered}(x_1-x)^2+(y_1-y)^2+(z_1-z)^2 = d_1^2\\ (x_2-x)^2+(y_2-y)^2+(z_2-z)^2 = d_2^2\\ \vdots\\ (x_n-x)^2+(y_n-y)^2+(z_n-z)^2 = d_n^2 \end{gathered} \quad (5)$$

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

$$\mathbf{A} = \begin{bmatrix} 2(x_n-x_1) & 2(y_n-y_1) & 2(z_n-z_1)\\ 2(x_n-x_2) & 2(y_n-y_2) & 2(z_n-z_2)\\ \vdots & \vdots & \vdots\\ 2(x_n-x_{n-1}) & 2(y_n-y_{n-1}) & 2(z_n-z_{n-1}) \end{bmatrix},$$

$$\mathbf{b} = \begin{bmatrix} d_1^2-d_n^2-x_1^2-y_1^2-z_1^2+x_n^2+y_n^2+z_n^2\\ d_2^2-d_n^2-x_2^2-y_2^2-z_2^2+x_n^2+y_n^2+z_n^2\\ \vdots\\ d_{n-1}^2-d_n^2-x_{n-1}^2-y_{n-1}^2-z_{n-1}^2+x_n^2+y_n^2+z_n^2 \end{bmatrix}.$$

The vector $\mathbf{x} = [x\ y\ z]^T$ which includes the coordinate of the object that need to be localized would be: $\mathbf{x} = (\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T\mathbf{b}$. Further, we can multiply a constant in each row of $\mathbf{A}$ and $\mathbf{b}$ to assign weights according to the channel quality of each receiver, i.e., assign weights according to the SNR of the received data.

IV. Enhancing the Robustness of FHSS Localization and Tracking

In the last section, we proposed a method for localizing and tracking drones using TOA of FHSS ultrasonic signals and estimated the distance. Another method for tracking is by estimating the relative velocity of the drone with respect to each of the receivers. This can be done by measuring the received signals' frequency shift (i.e., Doppler-shift effect) and then estimating the distance. The major problem with merely using this method is that the error would increase over time, and therefore, this method by itself cannot provide reliable and accurate tracking over an extended period of time.

However, by leveraging a Kalman filter to combine the data from both methods (i.e., TOA-based distance estimation and velocity estimation based on frequency shift measurements), we can prevent the errors from the velocity estimation to increase over time. In this approach, obtained data from each of the methods play an important role for maintaining the system's high accuracy over time. Velocity estimation based on frequency shift measurements cancels out the measurement error of TOA-based distance estimation and improve the accuracy of system. On the other hand, at each time instant, the data obtained from TOA-based distance estimation is the main source of initial data for calculating the final distance and the system is not merely depending on the velocity estimation which makes it not reliable over time. Therefore, combination of the data from both methods keeps system's estimation of distance highly accurate for all the time. This approach achieves greater robustness to noise and enables more accurate localization and tracking. In this section, we first describe how ROLATIN estimates the velocity, and then explain how it combines distance and velocity estimations using a Kalman filter.

A. Velocity Estimation by Measuring Doppler Shift

Doppler shift can be expressed using the following equation:

$$F_s = \frac{\mathbf{v}}{c} \cdot F, \quad (6)$$

where F_s is the amount of the frequency shift, $\mathbf{v}$ is the relative velocity between transmitter and receiver, c is the speed at which the signal propagates (if the signal is an RF signal, c would denote the speed of light, and if the signal is an acoustic signal, c would denote the speed of sound), and F is the actual frequency in which the signal is transmitted. Using 6, it is possible to determine whether the receiver and transmitter are moving toward each other or moving away from each other by treating $\mathbf{v}$ as a vector in the equation.

A number of prior studies have used Doppler shift measurements to estimate the speed and direction of an Unmanned Aerial Vehicle (UAV). In [3], Shin et al. use Doppler-shift to estimate the speed and direction of a flying UAV. However, relying exclusively on Doppler shift has limitations. For instance, the initial position of the target drone has to be known and high accuracy cannot be achieved. To address these limitations, some approaches use Doppler shift measurements as an auxiliary localization method to increase the performance of the primary localization method [10]– [11], [17]. ROLATIN adopts this strategy as well.

ROLATIN uses the following procedure to estimate the relative velocity between the target drone and each of the microphones in the room (where the drone is located):

- A speaker mounted on board the drone continuously transmits sine waves at frequency F.
- After receiving the signal in each of the microphones, first, ROLATIN applies FFT techniques to obtain the frequency content of the received signal and find the pick in the frequency domain and then estimates the frequency shift of the signal, F_s, by calculating the difference between the peak frequency of the received signal and F.
- An estimate of the drone's velocity is calculated using Equation 6.

B. Combining Distance and Velocity Estimation Using a Kalman Filter

ROLATIN combines the estimates from the FHSS-based distance estimation method and the estimates from Doppler shift-based velocity estimation method. The motivation for this approach is to improve the performance of distance estimation in terms of accuracy and robustness against noise. There are two approaches for combining these two types of estimates—using a Kalman filter [10] or through an optimization framework [17]. We concluded that the second approach is not appropriate because of its significantly higher computational complexity, which would put an excessive amount of burden on the processing elements of ROLATIN. Hence, ROLATIN employs the first approach. One of our main aims is to ensure that ROLATIN's computing complexity and communication overhead are low compared to the state of the art. In the following paragraphs, we will provide a brief description of how ROLATIN combines distance and velocity estimates using a Kalman filter.

Let D_k denote the actual distance between the speaker and a microphone in the k-th window, t denote the duration, v_k denote the measured Doppler velocity, n_k capture the error in Doppler measurements, d_k denote the measured distance, and w_k denote the distance measurement error. These variables have the following relationship:

$$\begin{aligned} D_k &= D_{k-1} + v_k \cdot t + n_k \\ d_k &= D_k + w_k \end{aligned} \tag{7}$$

As we mentioned before, d_k and v_k are from distance and velocity measurements, respectively. By using a Kalman filter, we can exploit the redundancy between these two measurements to reduce the impact of noise and further improve the accuracy of distance estimation. According to [10], the optimal distance estimation $\hat{D}_k$ is given by

$$\hat{D}_k = \hat{D}_{k-1} + v_k \cdot t + \frac{\hat{p}_{k-1}+q_k}{\hat{p}_{k-1}+q_k+r_k}(d_k - \hat{D}_{k-1} - v_k \cdot t), \tag{8}$$

where $\hat{p}_k = \frac{r_k(\hat{p}_{k-1}+q_k)}{\hat{p}_{k-1}+q_k+r_k}$, and the variables, q_k and r_k, denote the standard deviation for n_k and w_k, respectively.

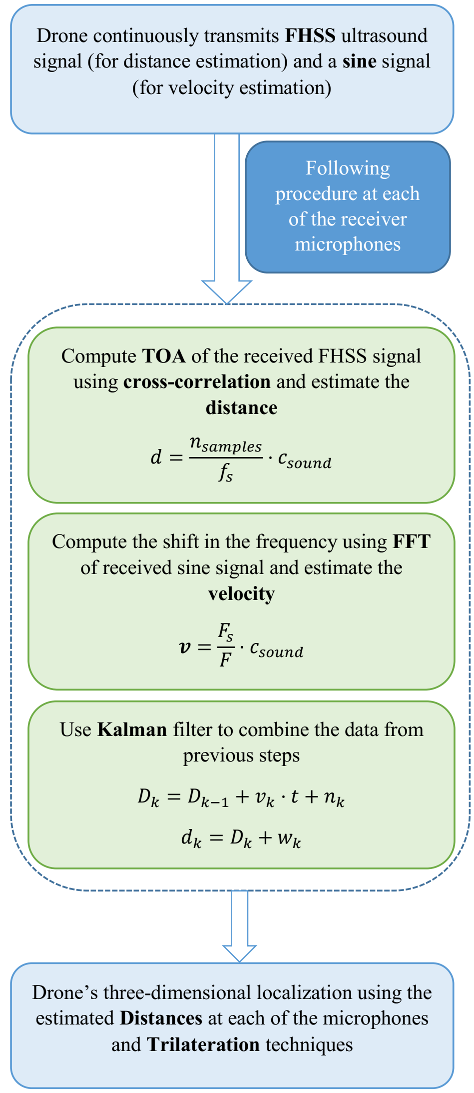

Fig. 1. ROLATIN's procedure for three-dimensional localization.

The procedure that ROLATIN employs to localize and track a drone in a GPS-denied environment is illustrated in Figure 1.

V. Simulation Setup

The performance of ROLATIN was comprehensively assessed using simulations in MATLAB. We provide details of the simulations in the following subsections.

A. Transmitter

The transmitter subsystem, which in is the ultrasonic speaker on board the drone, generates the desired FHSS signals. We used signals in the frequency range between 25 KHz and 55 KHz because of two reasons. First, frequencies at 20 KHz or below need to be avoided because that range would overlap with a human voice's frequency range. Any overlap would result in degraded performance. Moreover, according to the Nyquist theorem, the sampling rate needs to be at least twice the

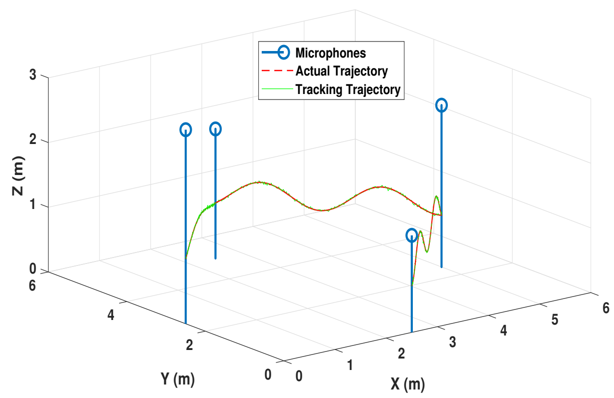

Fig. 2. Comparison between ROLATIN's estimated trajectory of a drone and its actual trajectory.

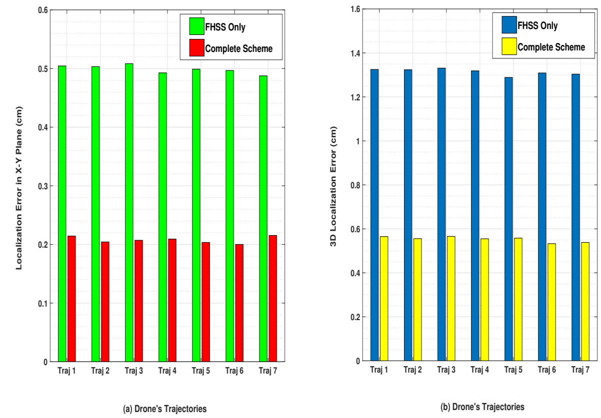

Fig. 3. Localization error for the seven trajectories.

maximum frequency to avoid aliasing, i.e., if the system works in the frequency range of 25 KHz to 55 KHz, then the sampling rate should be at least 110 KHz. Since we don't intend to deal with high frequencies to avoid both processing and equipment cost, we don't transmit above 55 KHz which means that sampling rate simply needs to be 110 KHz or more. ROLATIN uses FHSS waveforms. In this waveform, the frequency range is from 25 KHz to 55 KHz with 6 sub-frequency carriers located at 27.5 KHz, 32.5 KHz, 37.5 KHz, 42.5 KHz, 47.5 KHz, and 52.5 KHz and the bandwidth dedicated for each of these sub-carriers is 5 KHz. A single hop occurs within the transmission time of each data bit, and this hopping rate is fast enough to mitigate the effects of multi-path interference. We set the sampling frequency (f_s) to 340 KHz. In terms of modulation, ROLATIN uses BPSK (Binary Phased Shift Keying) to take advantage of BPSK's high robustness to noise.

B. Channel

In the simulations, we used a Rayleigh channel model that considers the impact of additive white Gaussian noise (AWGN) and multi-path interference on the transmitted signals. Moreover, we assumed that the target drone's movement is restricted to a rectangle room whose dimensions are 5 m $\times$ 5 m $\times$ 3 m.

C. Receiver

The receiver sub-system cross-correlates the received signal with a reference signal, and then finds the sample bit which makes the peak in the cross-correlation. Then, it estimates the distance from the drone to the microphone using the following relation: $d = n_{samples} \times c_{sound}/f_s$, where $n_{samples}$ is the sample number that the maximum cross-correlation occurs and f_s is the sampling frequency. There are four microphones in the room, and the same procedure is used by each of them.

We placed the four microphones at specific locations with the aim of achieving the best receiving coverage for every possible location of drone in the room, i.e., we placed microphones in the positions that ensure at any drone's location in the room, there is at least one microphone in a very close distance to the drone that can receive the ultrasound signal with high signal to noise ratio (SNR). Specifically, the (x, y, z) coordination of the microphones in the room is $(2.5, 0, 1.5)$, $(5, 2.5, 2.5)$, $(2.5, 5, 2)$, and $(0, 5, 3)$ where all the numbers are in meter.

VI. Results & Evaluations

In this section, we show the results of our simulations and evaluate the accuracy of ROLATIN by calculating the error between the actual position of the target drone and the estimated position. We assess the scheme's performance by benchmarking it with respect to a simple reference scheme that employs *only* the FHSS-based distance estimation to localize a target drone. We evaluated ROLATIN using seven different simulation experiments, each with different drone trajectories. The placement of the microphones remained the same for all of the trajectories.

In Figure 2, we show a drone's actual trajectory as well as ROLATIN's estimated trajectory in one of the simulation experiments. The locations of the microphones are also indicated in the figure. The two lines representing the actual and estimated trajectories seem to perfectly overlap because the tracking error is very small relative to the dimensions of the room.

In Figure 3(a), we compare the performance of ROLATIN with that of the benchmark scheme (which relies only on FHSS-based distance estimation to localize a target drone) in terms of the localization error in the $X-Y$ plane. The average value of the localization error for ROLATIN is 0.22 cm. As can be seen in the figure, the benchmark scheme's localization error is more than twice that of ROLATIN. Other drone localization/tracking schemes proposed in the literature incur a localization error that is significantly greater than that of ROLATIN. For instance, the scheme proposed by Segers et al. [13] incur an error of 2 cm or greater in terms of localization error.

In Figure 3(b), we compare the performance of ROLATIN with that of the benchmark scheme in terms of the localization error in three-dimensional space. The average localization error for ROLATIN is 0.55 cm. As we can see, this error is greater than the error of localization in $X-Y$ plane and that is because

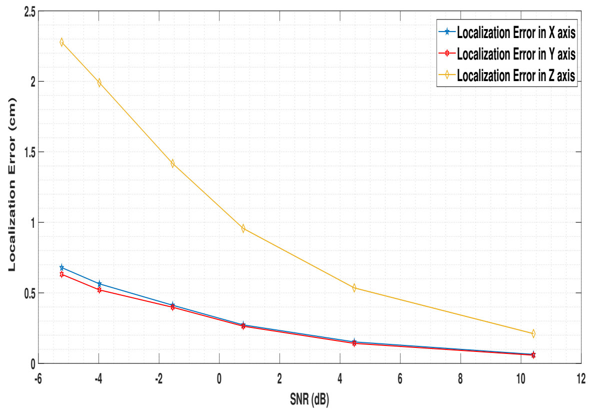

Fig. 4. Localization error vs. SNR (dB).

the error in height estimation is greater than error in the $X-Y$ plane.

In Figure 4, we show the relationship between ROLATIN's performance and the signal-to-noise ratio (SNR) of the signal received by the microphones. As expected, the localization error was inversely proportional to the SNR value of the signal. In the figure, note that the Z axis' localization error is much greater than that of the X or Y axis. This is due to the geometric dilution of precision (GODP), which describes error caused by the relative position of the receiver microphones [18]. Correct placement of the receiver microphones is important and has a big effect on the accuracy of the three-dimensional localization, specially for the Z axis' localization. As an example, if we put all the microphones at the same height, error of localization in Z-axis increases significantly. The reason is that matrix singularity occurs in the trilateration algorithm and for avoiding that, it is necessary to have at least one of the microphones located at the different height than the rest of them.

In most practical applications, the localization accuracy in the $X-Y$ plane is more important than that of the Z-axis. This is because precise navigation of a drone in the $X-Y$ plane is more important than precisely controlling its vertical position in most applications.

VII. Conclusions

In this paper, we have proposed a localization and tracking scheme for drones in GPS-denied environments that we refer to as ROLATIN. ROLATIN takes advantage of the beneficial features of ultrasonic acoustic signals to estimate a drone's location and track its movement. It uses a Kalman filter to combine estimates from FHSS-based distance estimation and estimates from Doppler shift-based velocity estimation. Our results indicate that ROLATIN achieves much higher localization accuracy compared to the schemes proposed in the literature.

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