RF Source Localization using Unmanned Aerial Vehicle with Particle Filter

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Abstract—**In this paper, we propose a solution for the localization problem of a radio frequency (RF) emitting source over a large scale environment with unmanned aerial vehicle (UAV). Target localization using received signal strength indicator(RSSI) is one of the most challenging problem because of noise characteristics. To evaluate the noise effect on RSSI, we perform a RSSI measurement test. This adds value for proper model and helps to implement a more realistic simulation system. For the localization process, the particle filter is utilized in this paper instead of tools such as Extended Kalman Filter with multi UAVs. Simulation environment and software-in-the-loop system are prepared to exhibit the conceptual proof with realistic models and autopilot system. Simulation results show that, mean search time for localization is 84.06 seconds and mean distance error is 13.96 meters.**

Keywords-RSSI; particle filter; RF; UAV; localization

I. Introduction

Due to the increasing popularity of unmanned aerial vehicles (UAV), increasing number of people and industries are trying to integrate these systems into their own applications. Technological developments because of increased demand have already made unmanned aerial vehicles more efficient, more autonomous and cheaper. One of the most common application for civil and military is localization of radio frequency (RF) emitting sources. A lot of research have been conducted out in order to develop methods for localization of RF source using a) the RF signal power [1], b) RF signal arrival direction [2] and c) time of arrival of the RF signal [3]. Even though lots of research papers address the localization problem, the localization in large-scale area brings additional problems such as the variation of noise character.

There are many different aspects for localization of RF sources, such as line-Of-Sight (LOS) or Non-Line-Of-Sight (NLOS) situations; tracking with only one sensor or many sensors; using different sensors like angle of arrival or signal strength and so on. To deal with all these challenges, an appropriate system structure should be suggested. Deghan et al. [4] addresses NLOS conditions for simultaneous localization of UAVs and RF sources. Bamberger et al. has developed an algorithm that uses RF direction and optimized flight trajectories for localization of the source [5]. In [6], stationary RF source localization system is presented with estimation and control algorithms for a team of robots in non-convex environments. Stachura et al. [[7] studied communication constraints in localization problems and developed algorithms for generating information gathering trajectories in order to ensure reliability of multihop communication networks. In [8], swarm UAV's control architecture is proposed for localization of a mobile RF emitting ground source. Scerri et al. [9] have examined large scale environment problems with localization of RF source with a crowded team of UAVs. In Scerri's work, Bayesian filter is exploited to compute the probability distribution over UAVs received signal strength (RSS). Delima [10] and Toussaint [11] addressed localization of RF sources with Kalman filtering where angle of arrival sensor is used. Isaacs et al. [12] studied RF source localization via particle filter where angle of arrival is used with directional antenna on quadcopter. They propose a control strategy to control yaw angle of quadcopter to receive angle of arrival without any gimbal mechanism.

In a recent work, Effati et al. [13] use estimation algorithm comparisons of Extended Kalman filter (EKF) and Unscented Kalman filter (UKF) for moving RF ground source. As a result of this study, UKF converges faster for localization of RF source. Jagadeesan et al. [14] propose a Bayesian optimization framework and show how to optimize the location estimation. Hevrdejs et al. [15] propose Zigbee devices' localization and mapping with bearing and RSS measurements. In Hevrdejs work, base RF device sends some signal to surrounding RF devices and gather all RSS values from them. After that, base RF device begins to turn around itself 360 degree to find bearing angle. Koohifar el al. [16] propose receding horizon path planning algorithm where unmanned aerial vehicle swarms cooperatively localize a moving radio frequency transmitter.

In our previous work [1], we propose an algorithm that uses received signal strength indicator (RSSI) to estimate the position of RF source. First, multiple UAVs begin to search for the RF source, actually for the first sensible signal strength sample in a large area. When one of the UAVs receive the signal, other UAVs also begin to head towards to it. At least one of the UAVs has to receive a valid RF signal sample to start gathering of all UAVs. When all the UAVs are able to receive RF signal, trilateration algorithm gives first initial estimation of this RF source. Then, EKF uses this estimation and begin to estimate position of RF source.

In this paper, we present an algorithm that uses received signal strength indicator (RSSI) in particle filtering to estimate and refine the source's position using only one UAV

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in large scale environments. We use ArduPlane autopilot to demonstrate software-in-the-loop (SITL) simulation setup with integrated UAV planner where localization algorithms are included. Based on the previous paper, this paper presents following improvements. In previous work, multi UAVs are required to run EKF algorithm for localization. This paper proposes particle filter algorithm to solve localization problem and only single UAV is required. This yields cost efficiency. In previous work, whenever one of the UAVs receives the first RF sample, others should arrive at around the first one to be able to receive signal from the same source. As a result of this method, whenever a UAV receives the first RF sample, the localization process begins immediately without any wait or delay, therefore it provides time efficiency. We demonstrate this improved method by simulations using a software-in-the-loop system architecture. It locates the RF source in a simulated 5×5 km^2 area. The appropriate usage of this method is employing it after the first RF sample reception by one of the UAVs till all UAVs' arrival into the signal propagation volume. Thus, this paper implicitly deals with the trajectory planning of UAVs in period beginning with the first RF signal reception and terminating with arrival of all UAVs at the RF signal. The filter simulation results show that the localization lasted in 84.06 seconds after the first signal reception with 13.96 m mean error distance using only one UAV.

The rest of the paper is organized as follows. Section II introduces the proposed architecture and the problem overview, Section III explains the RF signal modeling with the real measurement tests, Section IV provides localization algorithm for estimation and refinement. Section V presents the SITL system and simulation results. Finally, Section VI concludes the paper with projected future work.

II. Problem Overview and Proposed Architecture

A. Problem Setup and Assumptions

This paper which is a progression of our previous paper [1] studies the problem of RF emitting source localization using only one UAV with particle filter algorithm, with the following assumptions:

- There is no prior information about the location of the RF source.
- The signal source is assumed to be on a flat terrain.
- The transmitting power of RF source is constant and known. The unknown transmitting power problem is answered in previous work [1].
- Localization algorithm only uses signal strength and UAV's location acquired by GPS. There is no other sensor or further information source to be used for the solution.
- The RF source and the seeker UAV is always on LOS of each other.
- RF source does not emit continuously, but rather emitter periodically keeps silent.
- The UAV and the source have omni-directional monopole antennas.
- UAV flies in altitude hold mode, where UAV's altitude may change ± 5 m.

Comparing the performance of UAVs with different speeds is out of the scope of this paper.

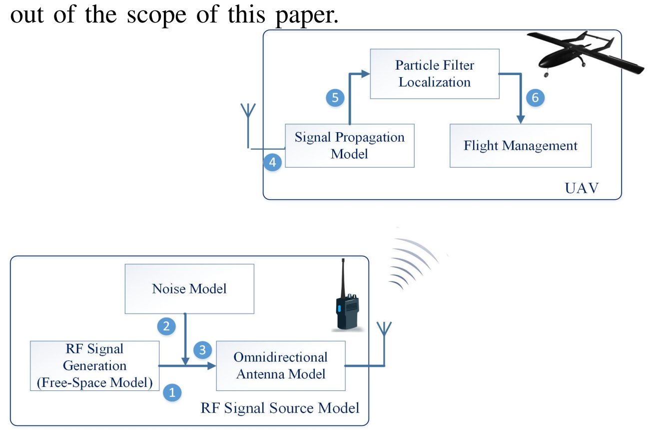

Figure1. Simulator diagram and flow: 1) generated RSSI value by using Free-Space Propagation Model for distance between the UAV and the source, 2) generated additive Gaussian noise whose parameters determined by real outdoor flight tests, 3) noisy (realistic) RSSI value, 4) measured RSSI value that has the antenna model characteristics, 5) calculated distance between the source and the UAV using measured RSSI, 6) estimated location of the source generated by the particle filter.

B. Proposed Architecture

Using distance between the RF source and the UAV, RSSI value is generated for specific frequency and transmitter power value. In order to obtained more realistic simulation results based on RSSI values, additive Gaussian white noise (AGWN) is added on generated RSSI based on the outdoor RF measurement experiments. At the final step of signal strength value generation, the gain values for both transmitter and receiver sides are determined using azimuth angle of UAV-antenna gain approach. At the other side of the system, after UAV measures the RSSI, using Friis Free Space Equation, RSSI is converted to distance and this value is measurement parameter of particle filter algorithm. Finally, as long as particle filter algorithm estimates location of the RF source, the trajectory of the UAV is updated. Proposed simulation flow is depicted in Fig. 1.

III. RF Signal Analysis

A. Signal Propagation

The obtained signal strength values have to be converted into the distance values. Initially, since the LOS between UAV and RF source is always clear, Friis Free Space Equation [17] based on free-space signal propagation is used for calculating the distances between the source and the seeker UAV as given by

$$d = \sqrt{\frac{P_t G_t G_r \lambda^2}{4\pi^2 P_r}}, \qquad (1)$$

where d is the distance between the receiver and the transmitter, P_t is the transmitted power, P_r is the received power, λ is wavelength, G_t is the transmitter antenna gain and G_r is the receiver antenna gain. Since the free-space propagation model does not include RF effects such as reflection and RSSI uncertainty [18], these effects added on Friis model in Eq. 1

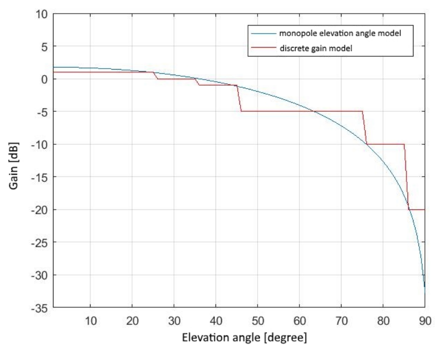

Figure2. Relation between elevation angle and antenna gain. Motion of the UAV changes the angles between RF source antenna and UAV receiving antenna which will have an additional effect on received RSSI

as additive white Gaussian noise (AWGN) with covariance R. Noisy RSSI value is calculated by

$$RSSI_n = RSSI_{Friis} + \mathcal{N}(0, R). \quad (2)$$

In addition to the RF signal noise, antenna gain is also modeled. Since both the source and the UAV have omnidirectional monopole antennas, it is also assumed that antenna mounted on UAV is oriented towards the direction of the gravity and the antenna of the RF source is oriented towards perpendicular to ground. In reality, as UAV does pitch and roll motion, the orientation of the antenna changes. However, it is assumed that the orientations of both antennas are constant and independent from the motion of the UAV.

In the modeling stage of antennas, MATLAB Antenna Toolbox is used. Based on the physical characteristics of the antennas used on real measurements, the gain of the monopole antenna is calculated as a function of azimuth and elevation angle of the UAV according to the source. Since the antenna is omni-directional, the gain is not effected by azimuth angle. However, there is a non-linear relation between elevation angle and antenna gain. In simulation stage, these relation is discretized and simplified as a look-up-table function. Both the modeled non-linear function and discretized approximation are shown in Fig. 2

B. Experimental RF Measurement Tests

In preliminary stage of analysis, RF signal is modeled using Friis Equation. To determine proper covariance R value of RSSI noise in Eq. 2, RF measurement test performed in real environment. In measurement stage, a UHF band walkie-talkie is used as RF source. To measure RF signals, the UAV is equipped with a software defined radio (SDR), which is called RTL-SDR RTL2832U, and a UHF band omni-directional whip antenna. This model of the RTL-SDR device includes Rafael Micro R820T chip and can work at a frequency range from 24 MHz to 1766 MHz. When RF source begins emitting RF signal, SDR device provides in-phase and quadrature signals (I/Q) after quadrature demodulation. These raw I/Q data is transformed to frequency domain by Fast-Fourier Transform (FFT). At the final stage of RF measurement, DC offset

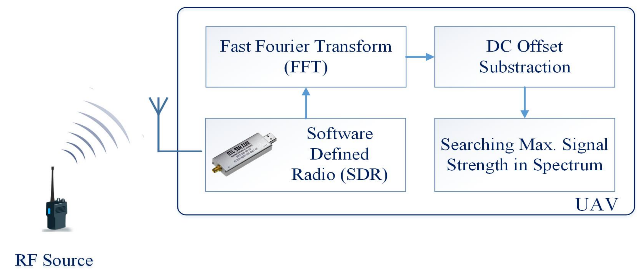

Figure3. RSSI calculation flow: RF signal is received by SDR and transformed to frequency domain via FFT. After DC offset subtraction, RSSI is obtained by finding the maximum signal strength of signal spectrum.

of signal is subtracted and the maximum magnitude value in frequency spectrum is obtained as measured RSSI value. Components and RF measurement test structure are shown in Fig. 3.

Experimental tests are accomplished by using Seagull Decathlon 46 model UAV platform shown in Fig. 4B. The trajectory followed by the UAV during one of the tests includes the take off stage, then a loop around three waypoints shown as white squares in Fig. 4A, and finally the landing stage. Fig. 4 shows ground station screen and the Seagull Decathlon 46 UAV platform at the landing stage. During the depicted test, UAV has flown away 1261 m at most from the RF source and at each time step the UAV location information and accompanying RSSI measurement are logged. Using the exact distance values between the source and the UAV, theoretical RSSI-distance curve is obtained by means of Friis equation in Eq. 1. Then the measured RSSI values are compared with the theoretical results. The comparison is illustrated in Fig. 5.

Experimental results show that the mean value of RSSI value is similar to Friis curve. However, the RSSI samples are agilely scattered by the noise. Based on the noise level acquired by these outdoor experiments, RF propagation model in simulator is enhanced by calculated mean values and standard deviations from discrete distances.

IV. Localization and Tracking Algorithm

When the seeker UAV enters into the source radiation range, it begins to provide RSSI samples which include large magnitude of noise. Deterministic methods are not able to work properly to localize the RF source due to this noise characteristics. Therefore, it is crucial to use filtering techniques to eliminate this noise and use meaningful data for localization. In this paper particle filter algorithm [19], [20] is utilized. Its procedure is explained below.

1) Initially, a set of particle x_t is prepared and all these particles are distributed uniformly and they are independent from each other. Also all particles have the same initial weight.

$$w_0^{[n]} = 1/N_p, n = 1, 2, ..., N_p \tag{3}$$

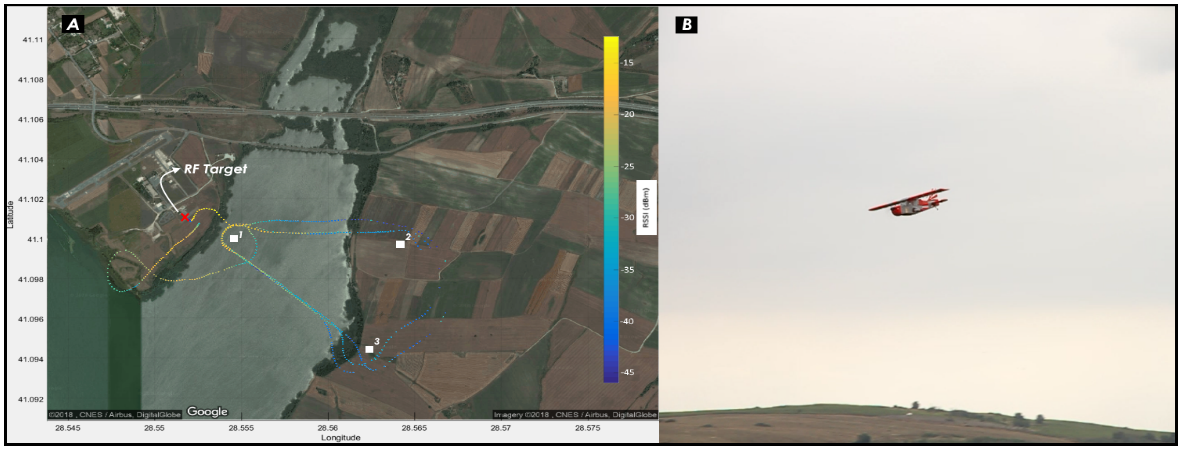

Figure4. Experimental RF measurement tests: A Seagull Decathlon 46 UAV platform (right) follows waypoints (white squares) which defined in order to cover whole RF range area. All sample measurements taken during the flight are plotted on the map and the RSSI values are colored on the plotted samples (left).

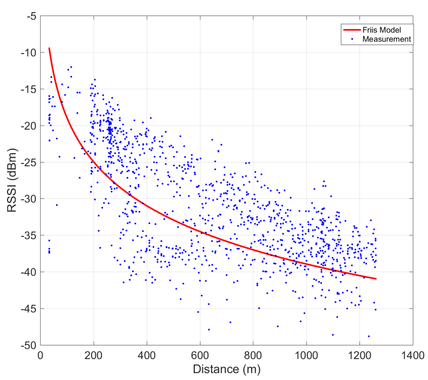

Figure5. Comparison of RSSI values from experimental results shown in the Fig. 4 and theoretical free-space model with distances between UAV and RF source.

where n-th particle at time instance t is shown by $x_t^{[n]}$, and its weight is shown by $w_t^{[n]}$. N_p is the total number of the particles. 2500 particles are used in the simulations.

2) Iterations for $0 < t < T_{\text{simulation}}, t \in \mathbb{Z}$:

a) Sample the particles $x_t^{[n]}$ from the proposal distribution $q(x_t^{[n]}|x_{t-1}^{[n]}, u_t)$, where u_t is the input control. Since RF source is stationary, $u_t = 0$.

b) Update weights $w_t^{[n]}$,

$$w_t^n \propto w_{t-1}^{[n]} \frac{p(z_t|x_t^{[n]})p(x_t^{[n]}|x_{t-1}^{[n]})}{q(x_t^{[n]}|x_{t-1}^{[n]}, z_t)} \tag{4}$$

where z_t is the measurement at time t. There is a trick to make appropriate weighting. As it is mentioned before, RSSI to distance conversion is a non-linear function, the standard deviation of noise (σ_{rss}) on RSSI sensor should be converted properly to the standard deviation of distance (σ_d). The conversion is simply done by again using the Friis equation.

c) Normalize the weights:

$$w_t^{[n]} = w_t^{[n]} / \sum_{n=1}^{N_p} w_t^{[n]} \tag{5}$$

d) Resample uniformly all particles according to the weights and replace the $w_t^{[n]} = 0$ particles with the new particles.

e) Result of the particle filter is:

$$x_t = \sum^{N_p} w_t^{[n]} x_t \tag{6}$$

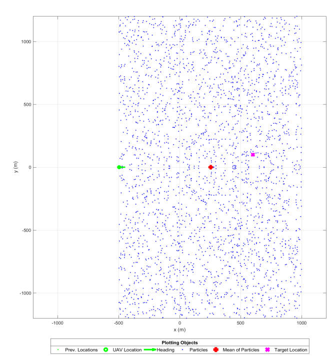

Figure6. Initial uniform distribution of particles over the area in front of UAV. Since the RF signal is not received from the route passed by UAV until the first RF measurement, the particles are distributed only front-side of the UAV at initial stage.

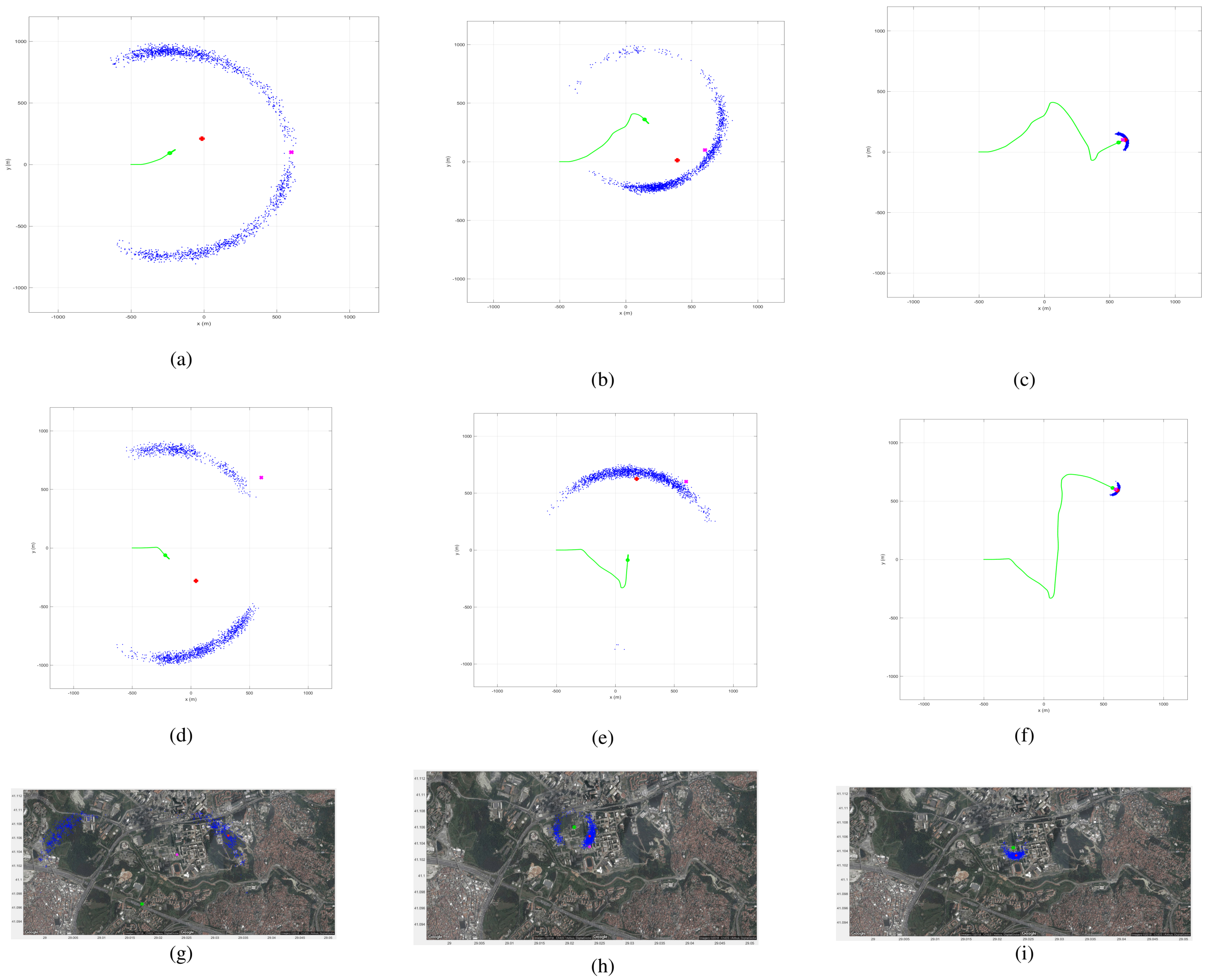

Figure7. Localization results for both simulation and SITL tests. UAV (green) always tries to track the mean value of the particles (red) until the last received RSSI values satisfy the localization. It can be seen in the following localization phase that the particles (blue) and their mean values concentrate on the RF source (magenta) shown in simulation results (from (a) to (f)) and SITL results (from (g) to (i))

Then, the result of the particle filter is assigned as the temporary target of the UAV. However, update process is not live. A certain delay has been added between route updates. The reason is that when the filter is running, fluctuating situations may be encountered. The temporary target generated by the particle filter should pass the transient high frequency oscillation. The delayed update provides both the low pass temporary target location filter and reasonable target changes that is suitable for smooth trajectories. This delay usually extends the localization duration. However, insistent measurements towards a wrong temporary target while flying a smooth trajectory makes the particle filter to eliminate the particles causing that wrong estimation. Smooth trajectories meet the long sampling time requirement which eliminates the effect of noise.

V. Simulation Results

Localization of a RF source in a 5×5 km^2 search area is prepared for simulation studies. A simulator with SITL autopilot is designed considering the maximum range of RF signal which is gathered by outdoor experiments. Searching stage is already expressed in the previous work [1]. 3 degrees of freedom (DOF) UAV model is used and tracking of the localization result is done by changing heading angle. Dynamics are modeled simply to show the proof of concept of this particle filter localization. RF signal is modeled with field tests in order to increase its fidelity.

At first, UAV flight starts from its initial point and the position of the RF source is placed randomly. The seeker UAV flies a predetermined trajectory to sweep the entire area until it receives a valid RF signal strength sample. After the first signal reception, particles are uniformly distributed into the forward field of the UAV. Particle distribution area is determined while considering the position of the UAV and the maximum range according to the RF signal sensitivity of the receiver. An initial distribution is presented in Fig. 6. The output of particle filter determines the temporary target of the UAV. Thus, trajectory of the UAV is adaptively changed. When the last 10 measured RF signal strength samples are greater than a certain magnitude which also can be changed as a parameter, it is assumed that the RF source is detected. Thus, the detection decision is related to an acceptable level and period of continuous RF signal strength reception. For instance, at 900 MHz, -35 dBm RSSI value is set for the decision threshold. These values have been simulated 100 times as Monte Carlo Simulations where RF source location is randomly placed in each simulation and mean error value is found as 13.96 m. Results of the simulation can be seen at Figs. 7a to 7f.

After all simulation results, software-in-the-loop (SITL) system is designed to see results close to the field tests. In planned field tests, Pixhawk with ArduPlane autopilot is decided to use. Therefore, SITL system is designed based on ArduPlane autopilot and X-Plane simulation program are used to use advanced UAV models and visualize it. In X-plane simulation, cruise speed of UAVs is observed approximately $16m/s$ which is the same speed as the Seagull Decathlon 46 UAV platform used in the experimental RF measurement test flights. We designed a software communicating with ArduPlane autopilot to send desired heading values for UAV to track the RF source. Since the SITL system tries to simulate the field tests as much as possible, the prepared planner software can be used for field tests the same as SITL system. Results of the SITL system and localization can be seen in Figs. 7g, 7h and 7i.

VI. Conclusion and Future Work

In this paper, we developed an architecture to present RF signal characteristics and build simulation platform and Software-in-the-loop system to show the results of the localization algorithm in large scale environments. Field tests are presented to simulate exact RF signal characteristics and particle filter performance for localization is shown in large scale environment with UAV.

For future work, based on the assumptions, moving RF source will be considered for localization. NLOS and ground reflection situations will be examined. Also with designed SITL system, outdoor flight tests are considered to validate the algorithms.

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