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Localization and Tracking of RF Emitting Targets with Multiple Unmanned Aerial Vehicles in Large Scale Environments with Uncertain Transmitter Power

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***Abstract*—In this paper we study the localization and tracking of a radio frequency (RF) emitting target using multiple unmanned aerial vehicles (UAVs) over a large scale environment. Although localization of RF emitting targets using multiple measurements is a well studied problem, the standard approaches become inefficient when the signal power is uncertain and there is significant noise in the received signal strength (RSS) when the search environment is large scale. We present a localization and tracking architecture, where a data driven neural network model is used for estimating the unknown signal strength and extended Kalman filters are utilized for eliminating the RSS noise and increase the precision of target tracking performance. We present simulation results in a 10×10 km^2 search area, where 3 fixed wing UAVs localize and track a target with up to 28.3 m average error distance.**

I. Introduction

With the increasing autonomy, range and cost efficiency of Unmanned Aerial Vehicles (UAVs) over the years, utilization of UAVs in search and rescue operations have been gaining significant popularity in both civil [1], [2] and military [8] applications. One of the most common scenarios is where the target is emitting a radio frequency (RF) signal, and UAVs measure and process this signal to localize the target [3]. Although this problem was addressed up to some degree by the previous research, there are still scenarios where the current algorithmic capabilities and hardware constraints prevent an efficient solution. One of such problems is the case where the target's transmitter power is unknown or uncertain, which makes the target localization much more difficult. In addition, the hardware setup for estimating the direction of the signal might not be available in some situations, hence the UAVs might need to rely only on the signal strength for localizing the target. Also, localization of RF sources in large scale environments poses additional challenges due to the variation of noise characteristics of the received signal strength (RSS) with large distances.

In this paper, we present an algorithm that uses a data driven model to estimate the target transmitter power and then applies trilateration and extended Kalman Filtering to estimate and track the target's position using multiple UAVs in large scale environments. We show via simulations that the average distance error can be reduced significantly with this method, even though the algorithm lacks the knowledge of the exact transmitter power and the considered search environment has a significantly large area.

A. Previous Work

Localization of RF Targets poses many challenges, such as location estimation, path planning, addressing Non-Line-of-Sight (NLOS) problems and utilization of appropriate sensing architecture. Deghan et al. [4] developed a novel observation model that can address NLOS conditions for simultaneous localization of UAVs and RF emitting sources. Bamberger et al. developed a RF direction finder called pseudo-Doppler [5], with emergent autonomous control concepts to control sensor platforms and optimize flight trajectories for effective geolocation of the target. In [6], estimation and control algorithms were proposed for a team of robots for localization of stationary RF targets in non-convex environments. Stachura et al. studied localization problems with communication constraints [7] and developed algorithms for generating information-gathering trajectories for ensuring reliability of multihop communication networks. In [8], a control architecture that allows multiple UAVs to cooperatively detect mobile RF emitting ground targets is presented. The UAVs are equipped with low-precision RF direction finding sensors and it is assumed that the targets may emit signals randomly with variable duration. Scerri et al. [9] examined an RF emitting target localization problem that involves a large team of UAVs over a large scale environment. In Scerri's work, signal characteristics received from different UAVs are fed into a Bayesian filter to compute probability distribution over emitter locations. Delima and Toussaint [10], [12] presented a cooperative control method to detect RF targets with angle of arrival sensors on UAVs.

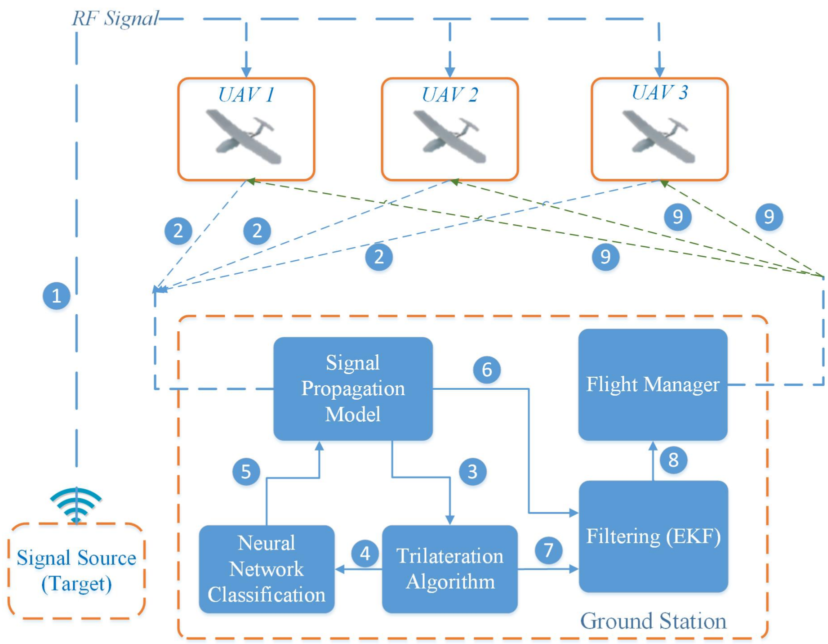


Fig. 1. *Overview of the system architecture for the specific case of* 3 *UAVs. 1) RF signal emitted by the RF target, 2) RSS for each UAV, 3) distance vector generated from signal propagation model by using RSS values for all possible transmitter powers, 4) distance differences between estimated positions of the target for all possible transmitter powers by using Trilateration algorithm, 5) classified transmitter power, which is output of the neural network classification block, 6) distance vector between the target and the UAVs, computed according to classified transmitter power, 7) estimated position of the target, which is used as the initial value for Filtering (EKF), 8) final estimated position of the target, 9) the desired route for UAVs from flight manager.*

Kalman filtering was used in order to minimize target location error and target localization time. In [11], different configurations of multiple UAVs and onboard sensors were analyzed for localizing an RF emitting target by using a Kalman filter to fuse information collected from UAVs.

In all of the previous work mentioned above, the power of the RF signal is assumed to be known beforehand, which enables direct utilization localization and tracking algorithms. In this paper, we develop a multiple UAV target localization architecture that enables efficient localization and tracking of the target without knowing the RF signal power a priori. We analyze the signal data to model the mismatch between the assumed transmitter power and the actual transmitter power, and train a neural network for online classification of the transmitter power of RF emitting target. Afterwards, the transmitter power estimation and trilateration, extended Kalman filter (EKF) is used for eliminating the noise on RSS and enable precise tracking of the target in the large-scale environment. We present via simulations that the developed architecture can localize and track a target randomly located in an 10×10 km^2 area up to 28.3 m average error distance, using 3 fixed wing UAVs.

The rest of the paper is organized as follows: section II introduces the system architecture and the problem setup, section III gives details on localization algorithm, section IV provides the implementation of estimation and tracking algorithms. Finally, section V presents the simulation results and section VI comments on the conclusions and future work.

II. Problem Overview and System Architecture

A. Problem Setup and Assumptions

This paper studies the problem of localization and tracking of an RF-emitting target using multiple UAVs, with the following assumptions:

- There is no prior information on target's location.
- Terrain is assumed to be 2-dimensional, hence target's position is completely determined by its longitude and latitude.
- The power of target's transmitter is not exactly known beforehand, however it is known that the actual signal power can only take finite number of different values (such as $10mW$, $100mW$ and $1W$).
- UAVs measure only signal strength, there is no time stamp or other meaningful data in the signal. No direction finding hardware is available onboard.
- The LOS between UAVs and the target is always clear.
- There are no communication constraints; UAVs may pass data in between them without loss of information.
- There are RF signal receiving constrains between UAVs and RF target for determined distance.
- Each UAV flies at a distinct, constant altitude.

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

B. System Architecture

The methodology developed in this paper to address the localization and tracking problem given in the previous subsection can be summarized as follows: After the initialization, UAVs follow precomputed trajectories for sweeping the area and receive signal from the RF emitting target. Once a UAV picks up the signal, the other UAVs are directed towards the location of signal receiving UAV. Once all the UAVs are receiving the RF signal, the distances from UAVs to the target are computed using the RSS values and a signal propagation model for various possible transmitter powers. Next, a previously trained neural network classification algorithm estimates the transmitter power from the input UAV-target distance data. Due to noise characteristics of the RSS, even after estimating the transmitter power and running the trilateration algorithm, target position cannot be determined with high accuracy. In order to increase the tracking performance, UAVs fly in circles with a fixed radius around the target while an EKF is ran based on UAV positions and measured distances from the RSS values. After calculations, flight manager generates the waypoints for each UAVs using calculated position of the target and receiving condition of RF signal. As UAVs continue to fly in loiter mode, tracking error decreases and converges to a fixed value. The system architecture is presented in Fig. 1 for a specific case where the team consists of 3 UAVs. Fig 2 summarizes the process given above.

III. Localization of the Target with Uncertain Transmitter Power

This section provides the details on how the measured RF signal strengths are converted into distances for a given signal transmitter power, multi UAV trilateration algorithm and neural network classification algorithm for estimating the transmitter power.

A. Signal Propagation Model

As it is explained in section II, the first step in the localization process is computing distances between the UAVs and target for all possible transmitter powers (which is a finite set as presented in the subsection II-A). Since the LOS between UAVs and the target is always clear (see subsection II-A), a free-space propagation model, such as Friis' Free Space Equation [13] can be used for computing the distances between the target and UAVs:

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

where d is the distance between receiver and 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.

The free-space propagation model is not an exact representation of the actual signal propogation, since it does not take into account effects such as reflection and received signal strength uncertainty [14]. In this work, these effects are modelled as a high magnitude Gaussian white noise added on the computed distance in Eq. 1.

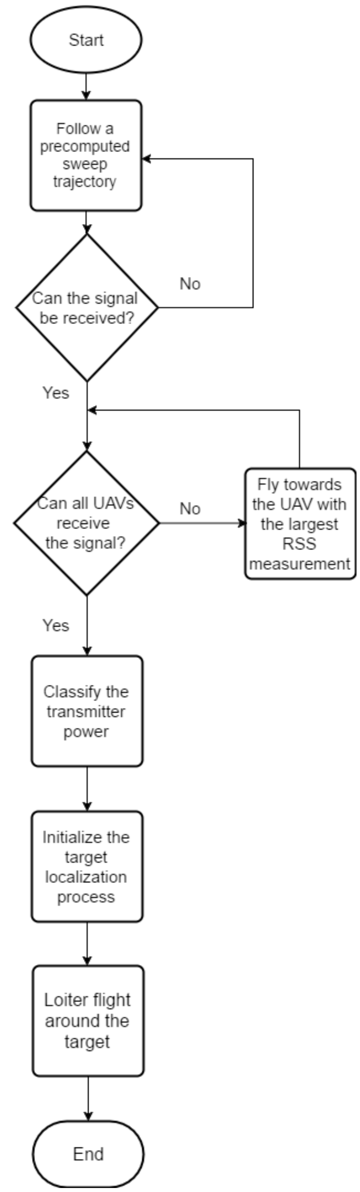


Fig. 2. *Flowchart of the system*

B. Localization Method

After computing the distances under various different transmitter powers, the trilateration algorithm is ran on each dataset for comparative analysis of localization results under different assumed transmitter powers. An East-North-Up (ENU) Cartesian coordinate system is used in the trilateration algorithm. At least 4 distinct measurements are required for 3-dimensional trilateration [15]. However, for the problem of interest in this paper, target lies on a 2-dimensional surface and UAVs fly at constant altitude (see subsection II-A), thus 3 distinct

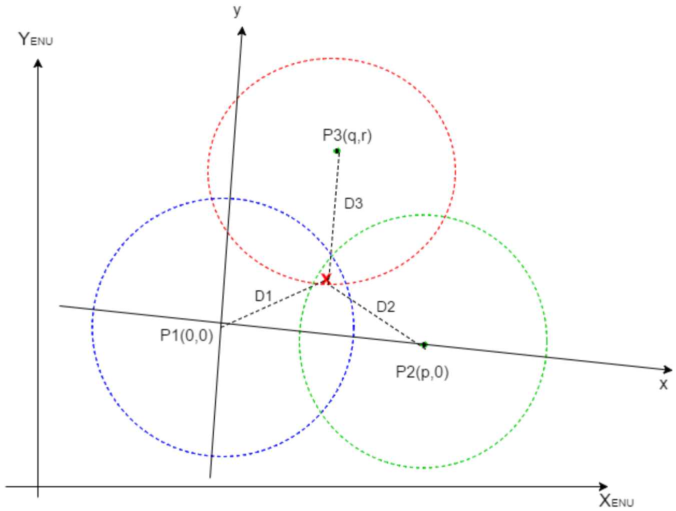


Fig. 3. *Modified axes for trilateration with 3 UAVs in the $z = 0$ plane.*

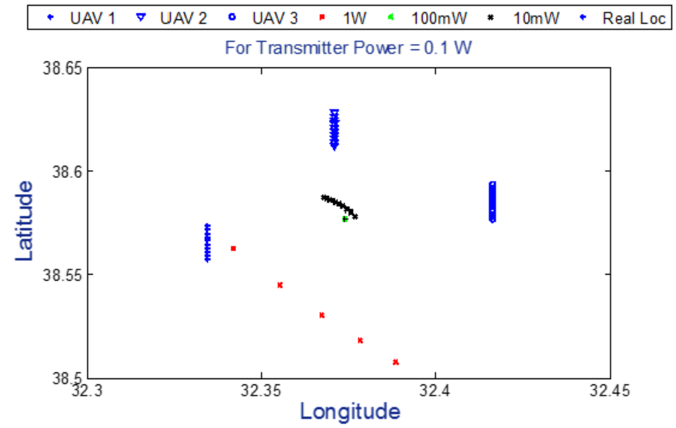


Fig. 4. *RSS values are modelled for* 100 *mW (the real power value) and localization algorithm is ran for all three transmitter power values (noise is not considered in these simulations). The search environment dimensions are* 10*km* × 10*km.*

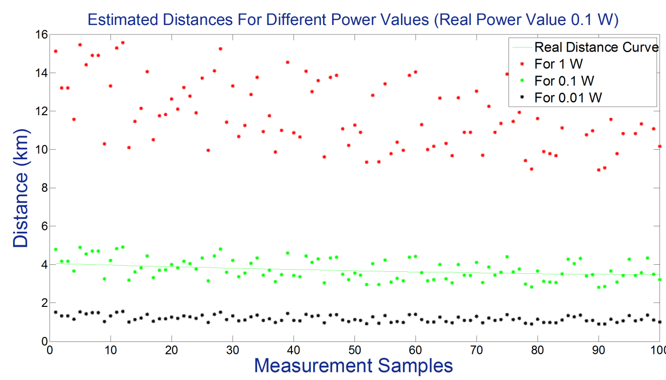


Fig. 5. *Distances between the target and UAV$_1$ for all transmitter powers. Noise in the signal is incluided in these simulations.*

measurements are sufficient [16]. Fig. 3 shows how three distinct measurements and a modified coordinate axes can be utilized for localization of the target. In the modified axes, origin of the coordinate system coincides with the first UAV and the x-axis is oriented towards the second UAV.

Steps of trilateration algorithm are given below for a team consisting of 3 UAVs. In equations below (see Eq. 2-11), $\mathbf{P}_k$ is the position vector of UAV$_k$ and D_k is distance between the target and UAV$_k$ where $k = 1, 2, 3$, $\mathbf{e}_x$, $\mathbf{e}_y$ and $\mathbf{e}_z$ are the basis unit vectors, output of the algorithm is the position of the target $\mathbf{P}_{target}$,

$$\mathbf{e}_x = (\mathbf{P}_2 - \mathbf{P}_1) \,/\, \|\mathbf{P}_2 - \mathbf{P}_1\|, \tag{2}$$

$$a = \mathbf{e}_x(\mathbf{P}_3 - \mathbf{P}_1), \tag{3}$$

$$\mathbf{e}_y = (\mathbf{P}_3 - \mathbf{P}_1 - a\mathbf{e}_x) \,/\, \|\mathbf{P}_3 - \mathbf{P}_1 - a\mathbf{e}_x\|, \tag{4}$$

$$\mathbf{e}_z = \mathbf{e}_x \times \mathbf{e}_y, \tag{5}$$

$$d = \|\mathbf{P}_2 - \mathbf{P}_1\|, \tag{6}$$

$$b = \mathbf{e}_y(\mathbf{P}_3 - \mathbf{P}_1), \tag{7}$$

$$x_{new} = (D_1^2 - D_2^2 + d^2)/2d, \tag{8}$$

$$y_{new} = \left[(D_1^2 - D_3^2 + a^2 + b^2)/2b\right] - (a x_{new}/b), \tag{9}$$

$$z_{new} = \sqrt{\mid D_1^2 - x_{new}^2 - y_{new}^2 \mid}, \tag{10}$$

$$\mathbf{P}_{target} = \mathbf{P}_1 + x_{new}\mathbf{e}_x + y_{new}\mathbf{e}_y + z_{new}\mathbf{e}_z, \tag{11}$$

Fig. 4 plots the results of trilateration process under different assumed transmitter powers ($10mW$, $100mW$ and $1W$), where the actual transmitter power is $100mW$. Examining Fig. 4 reveals that when the assumed transmitter power is less than the actual value, there is a considerable deviation in estimated target locations (black dots in Fig. 4) despite the fact that there was no noise in the simulations. In addition, estimated locations are relatively close to each other and follow a distinct curved pattern. On the other hand, when the assumed transmitter power is greater than the actual value, estimated locations (red dots in Fig. 4) at each step vary significantly over the search area.

Next, we analyze the effect of including noise in the assumed transmitter power-actual transmitter power mismatch. Fig. 5 shows computed distances between the target and UAV$_1$ for different assumed transmitter powers. From the figure it can be observed that the dispersion pattern in the estimated distance varies significantly across different power transmitter assumptions. For instance, when the assumed value is greater than the actual value (red dots in 5), estimated distances vary greatly, whereas the dispersion among the estimated locations where assumed value is less than the actual value is relatively smaller.

C. Neural Network Classification and Results

The analysis in subsection III-B suggests that actual transmitter power can be identified by examining computed distance dispersion data from trilateration. This result motivates the use of machine learning algorithms for estimating/classifying the actual transmitter power. In this subsection,

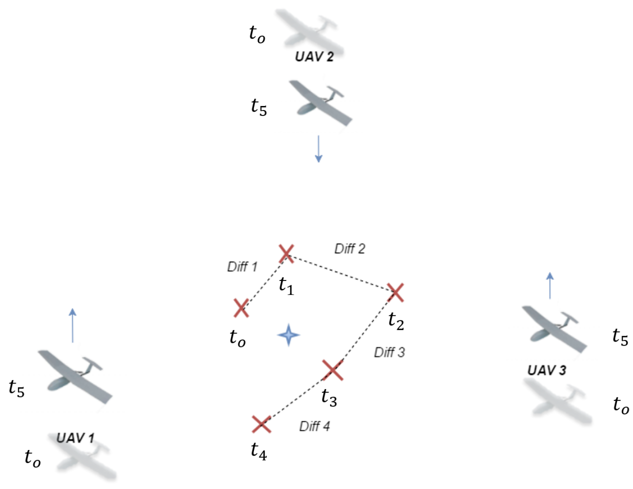


Fig. 6. *Explanation of collecting data input for the neural network classifier. UAVs are flying from step t_0 to t_5 and estimated locations of the target are shown as red crosses and real location of the target is shown as the blue star.*

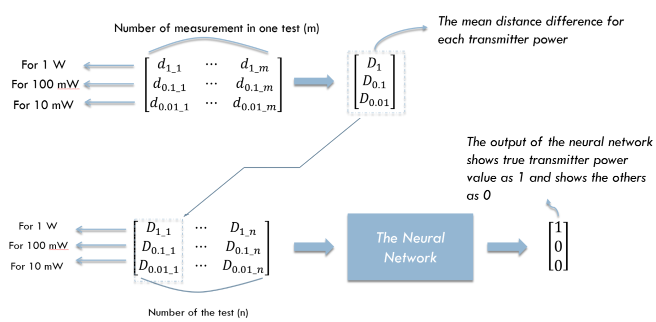


Fig. 7. *Structure of the neural network classifier*

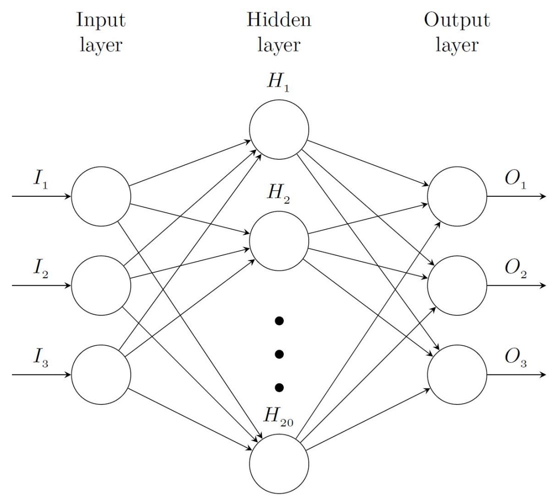


Fig. 8. *Diagram of the neural network in Fig 7*

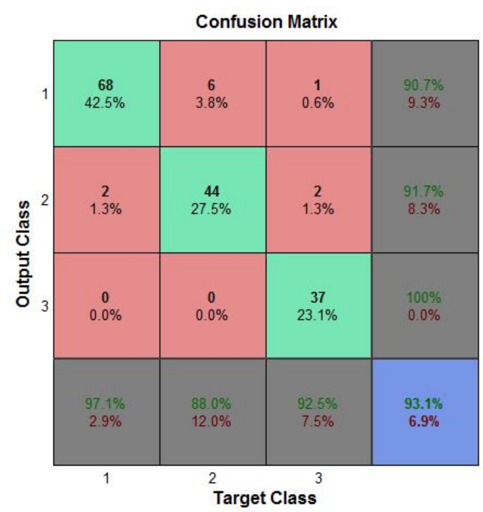


Fig. 9. *Confusion Matrix of Classification*

we show that a such classification problem can be solved by using neural networks [17].

The differences of computed distances between UAVs and the target are used as the main feature for training the classifier. Since the distance differences of different transmitter power values have significant variance, the data input for the training and test stages are selected as distance differences of the estimated locations (see Fig. 6).

To obtain the data inputs, while UAVs are flying and measuring RSS values, the estimated locations of the target are calculated for each measurement step (t). This process is repeated for all three possible transmitter power values. At the end of the measurement stage, distance differences from one estimated location to another are calculated for all three power values and the data input for neural network is prepared (see Fig. 7).

Neural network was trained using a multilayer feedforward network structure and Levenberg-Marquardt training function [18]. Diagram of the neural network is shown in Fig. 8. The formulation for the neural network structure is presented as follows:

$$I_j^i(t) = \sum_{k=1}^{n_i} w_{jk}^i(t) O_k^{i-1}(t), \tag{12}$$

$$O_j^i(t) = f(I_j^i(t)), \quad j = 1, 2, ..., n_i, \tag{13}$$

where f is the activation function (sigmoid function), n_i is the number of neurons in the i^{th} layer, $I_j^i(t)$ is the input of the j^{th} neuron in the i^{th} layer and $O_j^i(t)$ is the output of the j^{th} neuron in the i^{th} layer. The training was performed using data from 160 different simulations, where each simulation consists of 100 measurement steps from UAVs. There were 20 neurons in neural network hidden layer. The classification results, for the case where the transmitter power admits only three different values ($10mW$, $100mW$ and $1W$), are shown in the confusion matrix format in Fig. 9). From the figure it can be seen that the total success rate of the classification is 93.1%.

IV. Estimation and Tracking Algorithm

Because of the noise of RSS, trilateration can only estimate target location to a certain level in large-scale environments. For instance, Fig. 5 shows that even when the power of transmitter is determined correctly, localization errors might be in the order of kilometres. In this section, we present an EKF structure for increasing the tracking accuracy of the target. The main idea is to use first result of trilateration as an initial condition for the EKF and let the filtering algorithm improve the accuracy of the tracking performance.

Since the target is assumed to be stationary, the filter states consist solely of the location of the target:

$$X_{k+1} = f_k(X_k) = AX_k, \tag{14}$$

$$X_k = \begin{bmatrix} x_k \\ y_k \\ z_k \end{bmatrix}, \tag{15}$$

where X_k represents the state of system $X_k = [x_k, y_k, z_k]$; the location of the target in Cartesian coordinates. The measurement model consists of locations of UAVs relative to the target, note that UAV locations are measured using onboard sensors (inertial sensors and GPS).

$$r_k = \sqrt{(x_{uk} - x_k)^2 + (y_{uk} - y_k)^2 + (z_{uk} - z_k)^2}, \tag{16}$$

where x_{uk}, y_{uk}, z_{uk} are position of k*th* UAV and r_k is distance between RF target and k*th* UAV. Using this equation, the Jacobian matrix can be computed as follows:

$$H_k = \begin{bmatrix} \frac{\partial r_1}{\partial x} & \frac{\partial r_1}{\partial y} & \frac{\partial r_1}{\partial z} \\ \frac{\partial r_2}{\partial x} & \frac{\partial r_2}{\partial y} & \frac{\partial r_2}{\partial z} \\ \frac{\partial r_3}{\partial x} & \frac{\partial r_3}{\partial y} & \frac{\partial r_3}{\partial z} \end{bmatrix} \tag{17}$$

$$= \begin{bmatrix} -\frac{(x_{u1}-x)}{r_1} & -\frac{(y_{u1}-y)}{r_1} & -\frac{(z_{u1}-z)}{r_1} \\ -\frac{(x_{u2}-x)}{r_2} & -\frac{(y_{u2}-y)}{r_2} & -\frac{(z_{u2}-z)}{r_2} \\ -\frac{(x_{u3}-x)}{r_3} & -\frac{(y_{u3}-y)}{r_3} & -\frac{(z_{u3}-z)}{r_3} \end{bmatrix} \tag{18}$$

$$Z_{k+1} = \begin{bmatrix} D_1 \\ D_2 \\ D_3 \end{bmatrix} \tag{19}$$

EKF update equation is given as:

$$X_{k+1} = X_k + K_{k+1}[Z_{k+1} - H_{k+1}], \tag{20}$$

$$R_k = \begin{bmatrix} \sigma^2_{D_1} & 0 & 0 \\ 0 & \sigma^2_{D_2} & 0 \\ 0 & 0 & \sigma^2_{D_3} \end{bmatrix} \tag{21}$$

where K_{k+1} is the gain matrix computed using EKF design equations and R_k is measurement noise covariance matrix computed by $\sigma^2_{D_{uk}}$ which represents precalculated variances of each distance [19]. Note that the initialization of the filter is set from the results obtained from the trilateration algorithm.

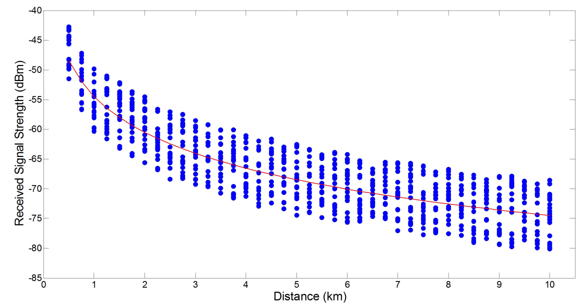


Fig. 10. *RSS-distance relation*

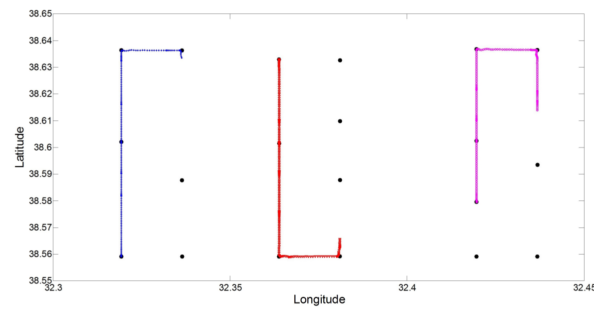


Fig. 11. *UAVs follow precomputed waypoints until at least one of UAVs senses the RF emitting target's signal.*

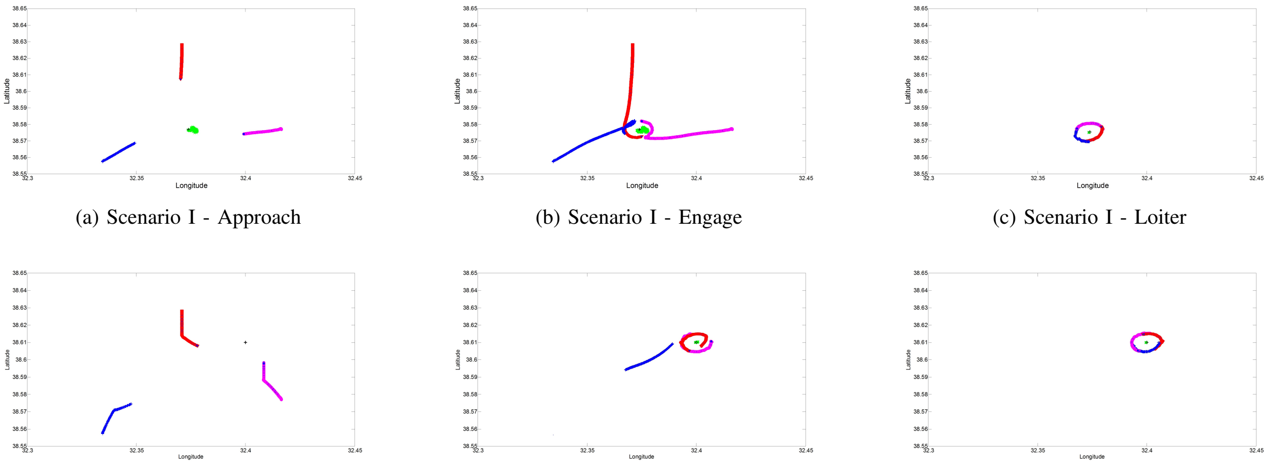
After the localization of the target is achieved up to a certain level, UAVs start to circle the target by flying in the loiter mode. The radius of the circle is a parameter of the system that can be selected beforehand, based on the desired level of accuracy and the constraints on UAV dynamics.

In order to gain a better insight the relationship between the RSS noise, estimated distances and EKF, we can look at how the RSS varies as a function of distance. Fig. 10 displays the variation of the noisy RSS versus distance. Note that, as the relative distance between the target and UAV gets smaller, EKF is expected to perform better since the signal to noise ratio of the signal gets larger.

V. Simulation and Test Results

Localization and tracking of a target in a $10 \times 10\text{km}^2$ search area was considered for simulation studies. 3 DOF models were used and aircraft were guided using cross-track guidance algorithm to track waypoints [20] for simulating UAV dynamics. RF emitting target was chosen to be randomly located in all test scenarios.

In the first phase of the mission, UAVs fly a precomputed trajectory to sweep the search area, looking for the RF signal. Trajectories of the search patterns are given in Fig. 11. In the second phase, trilateration and transmitter power estimation/classification algorithms are ran (see section III) to



(a) Scenario I - Approach (b) Scenario I - Engage (c) Scenario I - Loiter

(d) Scenario II - Approach (e) Scenario II - Engage (f) Scenario II - Loiter

Fig. 12. *EKF results are shown with green dots and it can be seen that all UAVs close the distance between the target to improve the performance of EKF. After the distance between UAVs and the target reduces below a certain level, UAVs start flying in loitering mode with a fixed radius. It can be seen that EKF performance gets better with time and estimated location of the target (green dots) are close to RF emitting target's location.*

estimate the location of the target. Next, this estimation is used as an input to the initial condition of EKF. EKF tracking performance results are presented in Fig. 12, where the blue, red and magenta lines represent trajectories of UAV_1, UAV_2 and UAV_3 respectively. The black point represents the real location of the RF target and the green points are EKF state outputs, which are the estimated location of the RF target.

TABLE I
AVERAGE ERROR DISTANCE ACCORDING TO LOITER RADIUS

Loiter Radius (m)	Average Error Distance (m)
800	57.3
600	42.8
400	28.3

Finally, we examine the relationship between the loiter radius and tracking performance. Table I displays the loiter radius versus distance error (averaged over 100 simulation results with random target and UAV locations). From these results it can be seen that decreasing the loiter radius indeed improves the tracking performance. However, it should be noted that decreasing the radius beyond a limit might not be possible in a realistic scenario, due to structural and aerodynamic limits of the aircraft. Note that average error distance can be reduced down to 28.3 meters in a search environment of $10 \times 10\mathrm{km}^2$ area.

VI. Conclusion and Future Works

In this paper we developed an architecture and presented a collection of localization, classification and tracking algorithms that can be used for solving RF emitting target localization and tracking problems in large scale environments. In particular, the developed system can work when the signal power is uncertain, and the combination of trilateration and EKF enables accurate tracking of the target in large-scale environments.

For future work, based on the problem setup and assumptions in subsection II-A, the architecture and algorithms will be improved for more realistic cases such as communication loss cases. Also, improving trajectory planning performance by using information based algorithms and validating the algorithms with outdoor flight tests are considered.

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