International Journal of Industrial Electronics, Control and Optimization © 2021 IECO
Vol. 4, No. 2, pp. 181-190, April (2021)

RF Source Localization Using Obstacles Map and Reflections

Saeid Haidari [1,†], Hadi Moradi [2], Seyyed.M.M.Dehghan [3]

[1] Faculty of Engineering, University of Zabol, Iran.
[2] School of Electrical and Computer Engineering, University of Tehran, Iran.
[2] Intelligent Systems Research Institute, SKKU, South Korea.
[3] Malek-Ashtar University of Technology, Tehran.

ABSTRACT

This paper proposes radio frequency (RF) source localization in a non-line of sight condition using the map of obstacles. Received signal strength indicator (RSSI) and angle of arrival (AOA) measurements are observations obtained from the signal received on the unmanned aerial vehicles (UAV). In the proposed approach, AOA is used to determine the obstacle on the map from which the reflection has happened. Then, RSSI information is used to determine the location of the RF source. In the basic version of the approach, the RF source is located by triangulation. In the advanced approach, the reflection angle is also estimated to improve the localization accuracy. The estimation is done using the particle filter approach. In addition, it is shown analytically that the maximum localization error for the advanced approach is bounded, but the relative formation of the reflectors with respect to each other can increase the localization error for the basic approach.

Article Info

Keywords:
Obstacle Map, Particle filter, Reflection, RF source Localization, RSSI, UAV.

Article History:
Received 2020-10-28
Accepted 2021-02-02

I. INTRODUCTION

Cellphones can be used as RF sources to localize their users in different applications, especially in search and rescue missions over a large area. In some projects such as ARVA [1] and WISCOM [2], RF source localization in disastrous situations has been developed for search and rescue purposes in which the typical localization method based on BTS towers cannot be used. Moreover, in large open areas where network coverage is not available, such as a desert, RF source localization can be used for search and rescue missions. Using UAVs in outdoor search and rescue missions are very popular due to their maneuverability and fast coverage of the areas. UAVs can localize an RF source using RSSI [3], TOA [4], Time Difference Of Arrival (TDOA) [5], and Angle Of Arrival (AoA) measurements [6]. Hybrid methods have also been proposed, e.g., a combination of RSSI and AOA [7] and TDOA/FDOA measurements [8]. RF source localization is affected by different types of signal propagation including Line Of Sight (LOS) and Non-Line Of Sight (NLOS) propagations. Localization based on LOS signals, which is not usual in typical environments, is straightforward and already solved. In some conditions, LOS and NLOS signals happen at the same time. There are approaches proposed to mitigate the NLOS effect on localization [9-11]. Also, some approaches are proposed to consider the LOS and NLOS effects within a single model [12]. In a research paper on localization in the indoor environment using reflection and scattered signal, it is assumed that a LOS signal is also available in addition to a multipath signal. The locations of reflectors and scatters are determined using PSO as a searching algorithm [13]. If the signal path between an RF source and a receiver is blocked by an obstacle, the signal is received by the NLOS propagation.

For localization in the NLOS condition the fingerprinting approach can be used. In this approach, a database of received signals is required. It should be created using experimental data or propagation model in which each possible location of the RF source corresponds to a unique receiving signal pattern. This

[†]Corresponding Author: s.heidari@uoz.ac.ir
Tel: +98-32222023, University of Zabol
Faculty of Engineering, University of Zabol, Zabol, Iran.

approach is usually used in indoor applications [14-15]. For outdoor fingerprinting-based localization, a large database should be created [16]. This approach is not applicable for large outdoor localization as it is very time consuming and sometimes impossible to provide the required database.

RF source localization based on the NLOS propagation models has been investigated in the past few years. Dehghan et al. used the diffraction model for the knife-edge obstacles to localize an RF source and corresponding obstacle simultaneously. The diffraction model depends on the height of the obstacle that is located between the RF source and the receiver and on the distances of the obstacle from the RF source and the receiver [17]. Also, Song et al. have used a reflection-based propagation model, TOA-AOA, and the map of urban environments for localization in which the orientation of the buildings as reflectors are vertical to each other [18]. There is an approach that uses TOA/AOA measurements and a reflection model in a scenario in which a transmitter with a known location is used for self-localization of a receiver [19], but it is not applicable for target localization in a search and rescue scenario. In another research, TDOA/AOA-based RF source localization is performed using a reflection model in the NLOS condition. An expectation maximization algorithm is used to optimize the nonlinear localization equations. The accuracy of localization depends on the initial value of the parameters of the optimization including the reflection parameters [20].

In some new works, the localization is performed using reconfigurable intelligent surfaces (RISs) that can change the propagation environment for the reflection. The application includes robots and automated vehicles for the localization and communication system. The parameters of propagation in the RISs can be controlled by a microcontroller using feedback. RISs can be mounted on the wall of the building [21-22].

In another paper, AOA, angle of departure (AOD), and relative time of flight (rTOF) are used for localization. Multipath triangulation for localization of target by using AODs of multipath signals has become possible in which antenna array is required at the target side, but implementation is impossible for localizing a target in search and rescue operation [23].

These approaches employ time-based localization that needs time synchronization between the RF source and the receivers using dedicated devices. In addition, they are developed for urban environments and their assumptions are not suitable for large outdoor areas. In another work, the authors used fully reflected RSSI and AOA measurements for RF source localization by employing an RSSI reflection model. For localization, two steps are used. In the first step, parameters of reflection are obtained and in the second step, location of the RF source is estimated, using the reflection parameters [24-25]. Using RSSI measurement for localization is common due to its easiness of use and the availability of cheap sensors [26].

The presence of obstacles is a challenge in the robotic field research, such as obstacle avoidance [27]. Previously detected obstacles may be used as an aid in navigation. In this paper to improve the RF source localization, RSSI/AOA in a fully NLOS condition is used for localization based on the map of the obstacles and a reflection model. In the studied condition, the obstacles as reflectors have unknown directions as shown in Fig.1. In the first step of the proposed algorithm, the AOA of the signal and the map of the environment are used to determine the location of the reflection point on the map. The proposed approach has two versions. In its basic version, the RSSI and AOA measurements and the map are used for localization. In this case, three reflections are required for localization. In the advanced approach, the estimation of the reflection angle from the RSSI samples is also used. This version needs two reflections for localization and exhibits higher accuracy of localization than the basic one.

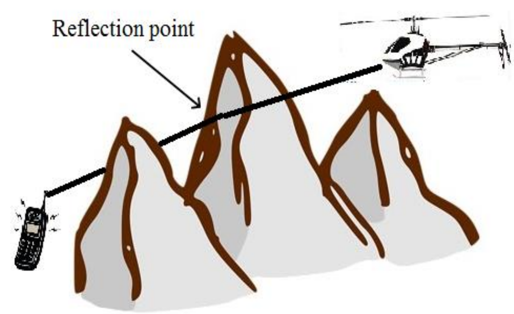

Fig.1. An illustration of the localization of an RF source using reflected signal in the outdoor environment.

The Bayes filter is the technique commonly used for localization in UAV and AUV and robotic field [28]. So, to estimate the RF source location, a particle filter is used because of the nonlinearity of the estimation equation and the motion of the UAV. Afterward, it is analytically shown that using the basic version may lead to a large localization error but using the advanced version has a bounded error.

In the next section, NLOS propagation from the reflector is explained. Then, the proposed approach for map-based localization is described, and the uncertainty of the localization for both versions is calculated. Finally, the simulation results show that the localization with the advanced approach has small uncertainty in comparison to the basic one.

II. REFLECTION PROPAGATION

RF signals propagate in the LOS or NLOS manner. The NLOS signals can be propagated by diffraction, reflection, and/or scattering mechanisms [26]. For a reflected signal, the strength of the signal depends on the path length between the receiver and the RF source. It also depends on the reflection coefficient magnitude, which is between 0 and 1. If it is equal to 1, the signal is reflected without any attenuation. If it is zero, the signal is absorbed. Path loss in dB for a reflection can be modeled by Equ.(1) [29]:

$$Path\ Loss = 20\log\left({}^{4\pi}/_{\lambda}\right) + 20\log(d) - 20\log(|\Gamma(\theta)|) \quad (1)$$

in which λ is the signal's wavelength, d is the path length between the RF source, the receiver, and θ is the reflection angle, $20\log(|\Gamma(\theta)|)$ is the reflection coefficient loss in dB, and $|\Gamma(\theta)|$ is the reflection coefficient magnitude, which is a function of the reflection angle. For a large reflection angle, the effect of roughness surface on the reflected signal is high and the reflection coefficient magnitude has a small amount. The reflection coefficient magnitude for two different frequencies including GSM frequencies and two different polarizations of the signal are shown in Fig. 2.

Generally, shadowing, which is a Gaussian random variable, is added to the path loss with standard deviation (SD) 2.2 to7.7 dB to show the unmolded part of the signal [30].

III. THE PROPOSED APPROACH

It is assumed that there is no LOS path between the RF source and the UAV. Thus, the signal is received using the reflection propagation mechanism. Furthermore, the problem is solved in 2D, and the effect of the UAV altitude is neglected because of the large distance between the UAV and the RF source in comparison with their altitude difference. Moreover, it is assumed that the reflected signals are based on a single bounce and the signals with two or more bounces are weak enough to be neglected. In the proposed approach, RSSI and AOA observations are used for localization.

The path loss of a reflected RF signal depends on the distance between the RF source and the reflector (d_{est}), the reflection angle (θ), and the distance between the reflector and the receiver (d_{obs}) as illustrated in Fig. 3.

In the first step of the proposed approach, the UAV moves in the direction of the received signal and starts to gather RSSI observations periodically. In this scenario, the angle of reflection is constant and the path length between the RF source and the UAV, i.e. $d_{obs} + d_{est}$ which is d in Eq. (2), can be estimated using the differential RSSI samples based on Eq. (2).

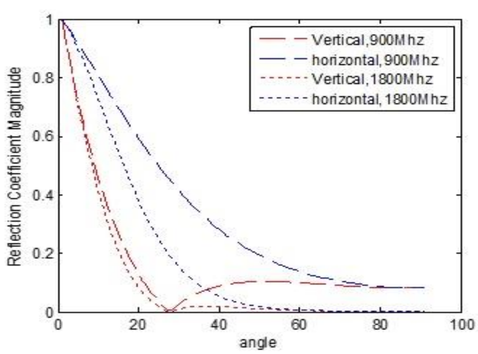

Fig. 2 The magnitudes of the reflection coefficients for a dry ground's surface with 4 cm SD of roughness [29].

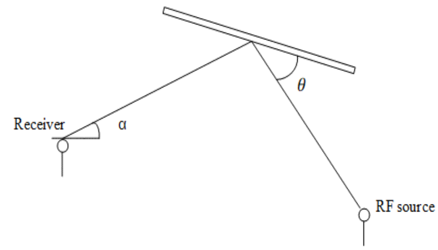

Fig.3. Reflected signal in 2D is illustrated by the RF source location and the reflector and receiver location

$$dPath\ Loss = 20\log\left({}^{4\pi}/_{\lambda}\right) + 20\log(d) - 20\log(|\Gamma|) - 20\,log\left({}^{4\pi}/_{\lambda}\right) - 20\log(d + \Delta d) + 20\log(|\Gamma|) = 20\log\left(\frac{d}{d+\Delta d}\right) \quad (2)$$

in which Δd is a constant distance step size between two consecutive waypoints in which the UAV takes observations. In the reflection-based RF source localization, the location and/or direction of the reflector are also unknown. As shown in Fig. 4, the loci of the possible locations of the RF source are circles. For each possible location of the reflector in the direction of the signal bearing, a circle can be considered as the locus of the RF source. It is shown in Fig. 4 that the intersection of these circles does not determine a unique location for the RF source even if two or more reflections are used. Consequently, more information is needed to obtain a unique location for the RF source in addition to the path length and the AoA of each reflection. In other words, the localization will not lead to a unique RF source location using the estimated path length and the angle of arrival even for different reflected signals.

In Subsection *A*, more information including the location of the reflector extracted from the obstacle map is used for

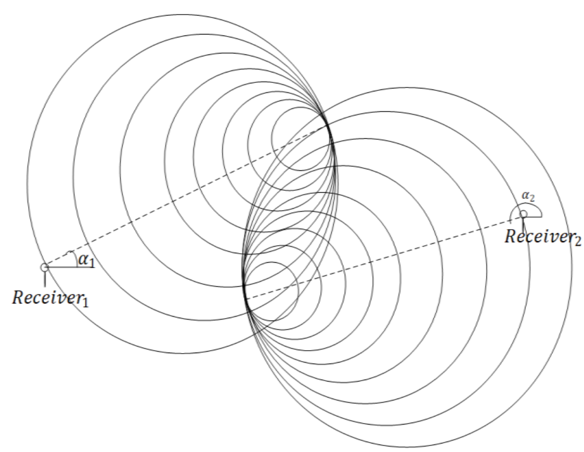

Fig.4. For two reflections, possible location of the RF source is a common area for the RF source locations.

localization. By this approach, the RF source location will be estimated uniquely.

A. Localization using map

Localization using the map of the obstacles and RSSI/AOA observations can lead to a unique location for the RF source. The intersection of the line of bearing with the obstacles map determines the location of the reflector. It should be noted that the orientation of the obstacles on the map are unknown because they are a natural obstacle (irregular terrain).

By using the reflector location, which is determined on the map, and the estimated reflection path length from RSSI samples, a circle is constructed as the RF source locus. In our basic version, the location of the RF source is estimated using the intersection of the three loci circles as shown in Fig. 5. It should be mentioned that the AOA of the signal has an error. This error leads to uncertainty in the reflection point detection. But the error is not large if the AOA is accurate.

It should be mentioned that the reflectors have roughness and the reflected signal with a large reflection angle has weak strength and it can be neglected. As such, localization using two reflections with a small reflection angle is also rendered possible.

To improve the map-based localization, the advanced approach is proposed, and Eq. (1) is used in which $|\Gamma|$ depends on the reflection angle. So, RSSI observation for a reflected signal is a function of the reflection angle in addition to the path length between the RF source and the receiver. As shown in Fig. 6, for a reflection angle (θ_1), there are two possible reflector orientations, so the RF source can be localized using two reflected signals and the estimated path length between the RF source and the receiver and the reflection angle (Fig. 6). The estimation of the RF source

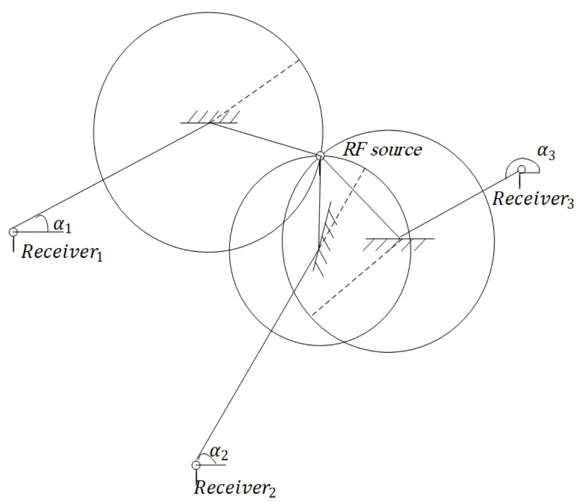

Fig.5. The localization of an RF source with the map and three reflections

location in 2D Cartesian space is performed using particle filter due to the nonlinearity and complications of Eq. (1).

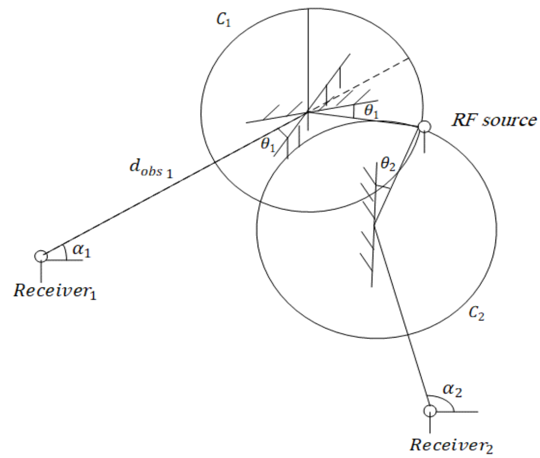

Fig.6. The localization with two reflections using map and reflection angle

1)Particle filter development for the map-based localization

As previously mentioned, the particle filter approach is used as the estimator for the RF source localization due to the nonlinearity of the reflection coefficient in the path loss equation. Particles include the location of the RF source in the Cartesian coordinate, i.e.,$(x^{[i]}, y^{[i]})$.

$$X^{[i]}(t) = < x^{[i]}, y^{[i]} > \quad (3)$$

The steps of the particle filter are presented below.

Particle initialization:

The elements of the particles, i.e. x and y, are uniformly distributed over the possible range, based on the geographical information of the search area.

Prediction of the next state:

The parameters of the particle are the locations of the RF source which are time invariant. It is assumed that the motion model of the UAV is accurate enough and the particles do not change in the prediction phase. The particles are augmented with a low SD in the perdition step to prevent the incorrect convergence of the filter.

Updating particles weight:

The observation model is determined with the path loss equation (Equ. (1)) which is used to update the particles' weight. Considering the known transmitted power, the path loss can be measured using the power received by the UAV. Based on this description, the observation model can be shown by Equ.(4):

$$p\left(Z(t)\middle|X^{[i]}(t)\right) = p(PL_{msr}(t)| < x^{[i]}(t), y^{[i]}(t) >) = p(PL_{msr}(t)|PL_{cal}^{[i]}(t)) \quad (4)$$

in which $PL_{msr}(t)$ is the measured path loss and $PL_{cal}^{[i]}(t)$ is the path loss that is calculated based on the location of each particle. For each particle, $PL_{cal}^{[i]}(t)$ is calculated using Equ.

(5).

$$PL_{cal_1}^{[i]}(t) = 20\,log\left({4\pi}/{\lambda}\right) - 20log\,\Gamma(\theta) + 20log(d_{obs_1} + \sqrt{(x^{[i]}(t) - x_{obs_1})^2 + (y^{[i]}(t) - y_{obs_1})^2}) \quad (5)$$

in which x_{obs_1} and y_{obs_1} are the elements of the location of the first obstacle as the first reflector, which is obtained from the map, d_{obs_1} is the distance between the obstacle and the receiver, which is known, and θ is the reflection angle, which can be obtained based on the locations of the RF source, the receiver, and the reflector. It is calculated using Equ. (6).

$$\begin{aligned} a&=\sqrt{((x^{[i]}(t) - x_{obs_1})^2 + \left(y^{[i]}(t) - y_{obs_1}\right)^2} \\ b&=\sqrt{((x^{[i]}(t) - x_{r_1})^2 + \left(y^{[i]}(t) - y_{r_1}\right)^2} \\ \theta &= 90 - 0.5 * cos^{-1}\left(\frac{{d_{obs_1}}^2 + a^2 - b^2}{2*a*d_{obs1}}\right) \end{aligned} \quad (6)$$

in which (x_r, y_r) is the location of the UAV which is known considering an accurate navigation system. It is assumed that the path loss has Gaussian distribution, so Equ. (7) is used to update the particles' weights.

$$w_{t\ 1}^{[i]} = \frac{1}{\sigma_{sh} * \sqrt{2\pi}} e^{-\frac{\left(PL_{msr_1}(t) - PL_{cal_1}^{[i]}(t)\right)^2}{2{\sigma_{sh}}^2}} \quad (7)$$

Because two reflections are required for localization using the advanced approach, the particles' weights are updated using the weights of the measurements for two reflections (Equ. (8)).

$$w_t^{[i]} = w_{t\ 1}^{[i]} * w_{t\ 2}^{[i]} \quad (8)$$

Resampling:

The number of effective particles is named N_{eff}. When N_{eff} is smaller than a threshold, resampling is performed. Equ. (9) is used to obtain N_{eff} in which $\tilde{\omega}^{[i]}$ is the normalized weight of the particle i. After resampling, the particles weight will be 1/N.

$$N_{eff} = \frac{1}{\sum_{i=1}^{N} (\tilde{\omega}^{[i]})^2} \quad (9)$$

B. Analytical calculation of the RF source location uncertainty

The uncertainty of the RF source location depends on the geometry of the problem, the location of the reflector, and the variance of the observation noise. The location of the RF source can be obtained using the parameters of the reflection path loss including d and θ. These parameters have uncertainty around the true values due to the observation uncertainty and the presence of noise. If the observations have a bounded error, then the variance of these parameters is bounded too. To show the effectiveness of the approach, the uncertainty of the location is calculated based on the variance of the parameters of the path loss (Equ. (10)) [31].

$$VAR(x_{RF}) = \sum_i \left(\frac{\partial(x_{RF})}{\partial(parameter_i)}\right)^2 VAR(parameter_i) \quad (10)$$

$$VAR(y_{RF}) = \sum_i \left(\frac{\partial(y_{RF})}{\partial(parameter_i)}\right)^2 VAR(parameter_i)$$

1)Localization uncertainty of the basic version

In the basic version of the map-based localization, the path length between the RF source and the receiver, i.e. d, is the only parameter of the path. With this parameter and using the map, three reflections are required for localization. The intersection of three circles is the RF source location. The equations of the three circles are shown in Equ. (11) in which (x_{obs}, y_{obs}) and $(x_{obs'}, y_{obs'})$ and $(x_{obs''}, y_{obs''})$ are the location of the reflectors.

$$\begin{aligned} (x_{RF} - x_{obs})^2 + (y_{RF} - y_{obs})^2 &= (d - d_{obs})^2 \\ (x_{RF} - x_{obs'})^2 + (y_{RF} - y_{obs'})^2 &= (d' - d_{obs'})^2 \\ (x_{RF} - x_{obs''})^2 + (y_{RF} - y_{obs''})^2 &= (d'' - d_{obs''})^2 \end{aligned} \quad (11)$$

Thus, the trilateration method is used to the RF source location and the above nonlinear equations are converted to linear ones as follows:

$$\begin{aligned} y_{RF} &= a_1 x_{RF} + b_1 \\ y_{RF} &= a_2 x_{RF} + b_2 \\ a_1 &= \frac{x_{obs} - x_{obs'}}{y_{obs'} - y_{obs}} \\ a_2 &= \frac{x_{obs'} - x_{obs''}}{y_{obs''} - y_{obs'}} \end{aligned} \quad (12)$$

Eq. (12) shows two independent line equations that are obtained by differentiating the circles equations mentioned in Eq. (11). The intersection of the lines is shown by Equ. (13):

$$\begin{aligned} x_{RF} &= \left(\frac{b_1 - b_2}{a_2 - a_1}\right) \\ y_{RF} &= a_2\left(\frac{b_1 - b_2}{a_2 - a_1}\right) + b_2 \end{aligned} \quad (13)$$

Without the loss of generality, it is assumed that only one of the lines has uncertainty which is caused by the effect of the uncertainty of d on the path loss. To calculate the uncertainty of the localization, the derivative of the RF source location to this parameter is obtained by using the chain rule. Based on this description, the MSE of the location is obtained by using Equ. (14):

$$MSE|_{[x\ y]} = VAR(x_{RF}) + VAR(y_{RF}) = \frac{(d - d_{obs})^2}{(y_{obs'} - y_{obs})^2}\left[\left(\frac{1}{a_2 - a_1}\right)^2 + \left(\frac{a_2}{a_2 - a_1}\right)^2\right] VAR(d) \quad (14)$$

It is obvious that the MSE of the RF source location depends on the slope of the lines which are shown by a_1 and a_2. If these slopes are equal, then the error will be very large.

The derivative-based optimization of the MSE function, which is demonstrated by Equ. (15), leads to $a_2 = -1/a_1$. This means that if the second line is vertical to the first one, then the uncertainty of localization will be minimal. The minimum value of the MSE is calculated by Equ. (15).

$$\min(MSE|_{[x\,y]}) = \frac{(d-d_{obs})^2}{(y_{obs'}-y_{obs})^2}\frac{1}{1+{a_1}^2}VAR(d) = \left(\frac{d-d_{obs}}{d_{reflectors}}\right)^2 VAR(d) \quad (15)$$

in which $d_{reflectors}$ is the distance between two centers of the locus circles that are determined by the reflector locations. When the reflectors are close to each other, the minimum of the uncertainty of the RF source location will be large even if $VAR(d)$ has a bounded value.

2)Localization uncertainty of the advanced version

In the advanced version of the map-based localization, the RF source localization is performed using the path loss parameters and AOA as Equ. (16).

$$x_{RF} = d_{obs}cos(\alpha) + (d-d_{obs})cos(\alpha-2\theta) + x_r$$
$$y_{RF} = d_{obs}sin(\alpha) + (d-d_{obs})sin(\alpha-2\theta) + y_r \quad (16)$$

in which it is assumed that the error of the parameters has a known variance. The derivatives of Equ. (16) with respect to the parameters of the path loss, i.e. d and θ, are shown in Equ. (17).

$$\frac{\partial x_{RF}}{\partial d} = \cos(\alpha-2\theta)$$
$$\frac{\partial y_{RF}}{\partial d} = \sin(\alpha-2\theta) \quad (17)$$
$$\frac{\partial x_{RF}}{\partial \theta} = 2(d-d_{obs})\sin(\alpha-2\theta)$$
$$\frac{\partial y_{RF}}{\partial \theta} = -2(d-d_{obs})\cos(\alpha-2\theta)$$

The uncertainty of the RF source location, which is caused by the variance of the distance, can be calculated using Equ. (18):

$$MSE|_{[x\,y]}(d) = VAR(x_{RF}) + VAR(y_{RF}) = VAR(d) \quad (18)$$

Equ. (18) shows that the uncertainty of the localization is equal to the error of d. Also, it shows that the geometric relation of the reflectors has no effect on the uncertainty of the localization.

The error of the RF source location caused by $VAR(\theta)$ is calculated using Equ. (19).

$$MSE|_{[x\,y]}(\theta) = VAR(x_{RF}) + VAR(y_{RF}) = 4(d-d_{obs})^2VAR(\theta) \quad (19)$$

In this equation, it is shown that the uncertainty of the RF source location, which is caused by the reflection angle uncertainty, depends on the distance between the obstacle and the RF source. If $VAR(\theta)$ has a bounded value, the uncertainty of the RF source localization will be bounded. It should be mentioned that the above calculation is done for one reflection. If two or more reflections are used for the localization, the localization uncertainty will be equal or lower than the above-calculated value. In other words, the summation of the uncertainties calculated by Eq. (18) and (19) is the maximum uncertainty of the localization by the advanced approach, which is a bounded error.

The above calculation shows that the maximum uncertainty of the RF source localization by the advanced approach is bounded if the errors of its parameters are bounded, but the minimum localization error of the basic approach for a bounded error of the path loss parameters can be large when the reflectors are near each other.

IV. SIMULATION AND RESULTS

In the simulations, it is assumed that the obstacles map is available. Also, the locations of the reflectors are previously determined using this map and the AOA of the received signals. After receiving the first reflected signal, the UAV moves in the direction of the signal and takes several RSSI samples. Furthermore, the reflection surface is considered large enough to use the mentioned propagation equation and the reflector's material is assumed to be dry soil. Finally, only horizontal polarization is used for localization.

In the first simulations, for the localization using the basic version, it is assumed that three reflections are determined as shown in Fig.7. The RF source is localized, using the map, considering three reflections, and employing a least-square estimator. For each configuration, different SDs of the noise are applied in which the main part of the noise is shadowing. In each simulation, it is assumed that the location of the obstacle or reflector has no error or there is a 400-meter SD error caused by the map or AOA error. Monte-Carlo simulation is run with an average of 100 consecutive runs whose results are presented in Table.I.

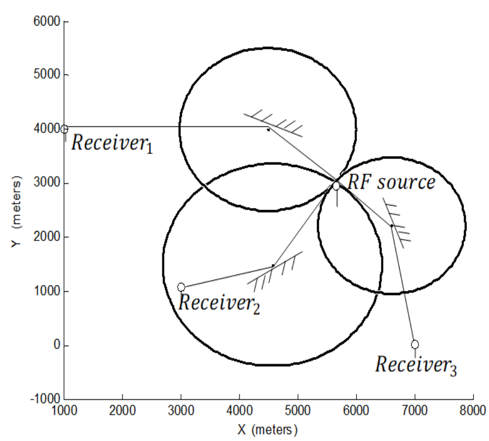

Fig.7. Localization using the basic approach in the first configuration of the reflectors

TABLE. I. RMSE OF THE LOCALIZATION OF THE BASIC APPROACH FOR THE FIRST CONFIGURATION

	SD of Noise(dB)				
	1	2	3	4	5
RMSE in meter (obstacles locations do not have errors)	153	302	483	679	764
RMSE in meter (obstacles locations have errors)	450	489	539	689	881

In the second simulation, the third reflector is considered closer to the second reflector as shown in Fig. 8. The results are presented in Table II.

TABLE. II. RMSE OF THE LOCALIZATION OF THE BASIC APPROACH FOR THE SECOND CONFIGURATION

	SD of Noise(dB)				
	1	2	3	4	5
RMSE in meter (obstacles locations do not have error)	174	364	560	784	855
RMSE in meter (obstacles locations have error)	503	579	893	899	932

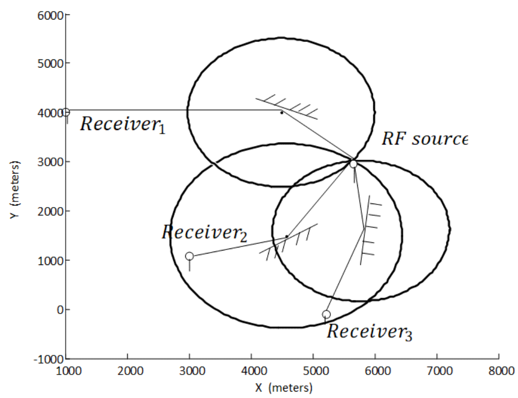

Fig. 8. Localization using the basic approach in the second configuration of the reflectors.

In the third simulation configuration, the third reflector is close to the second reflector in Fig. 9. The results of the localization are presented in Table III.

TABLE. III. RMSE OF LOCALIZATION OF THE BASIC APPROACH FOR THE THIRD CONFIGURATION

	SD of Noise(dB)				
	1	2	3	4	5
RMSE in meter (obstacles locations do not have errors)	209	513	857	922	1150
RMSE in meter (obstacles locations have errors)	694	679	807	1151	1099

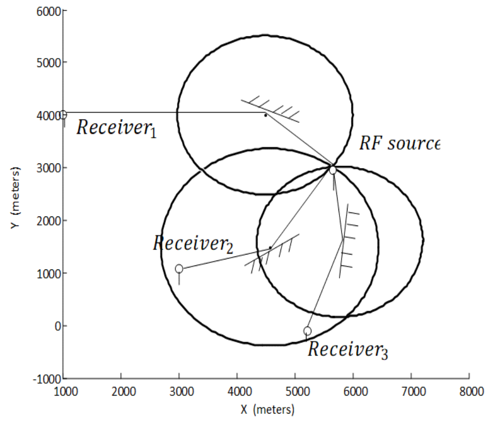

Fig.9. Localization using the basic approach in the third configuration of the reflectors

The above simulations show that if one of the reflectors is close to the other one, the localization error will be large. In the second set of simulations, the advanced approach for the localization with the map is evaluated. The localization is done by using two reflections as shown in Fig. 10. A particle filter is used for localization. In these simulations, 500 particles are used to achieve enough estimation accuracy. The Monte-Carlo simulation is done using an average of 100 consecutive runs. The results are presented in Table IV.

TABLE. IV. RMSE OF LOCALIZATION USING THE ADVANCED APPROACH

	SD of Noise(dB)				
	1	2	3	4	5
RMSE in meter (obstacles location does not have errors)	89	107	130	175	213
RMSE in meter (obstacles location has errors)	420	483	554	602	637

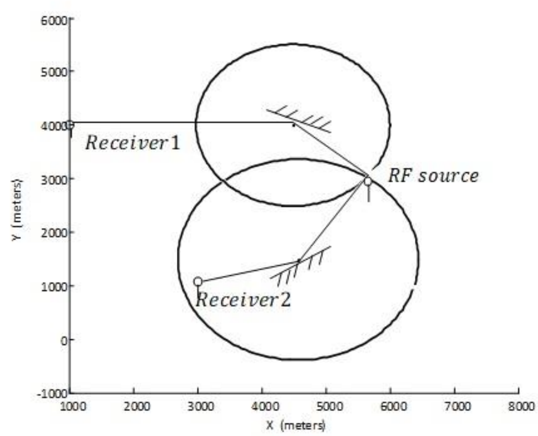

Fig.10. Configuration of the two reflectors for the localization using the advanced approach

The above simulation shows that the error of the localization, using the advanced approach, is low when the location of the reflector has a low error. If the location of the obstacle has a large error, the error of the RF source localization will be noticeable though it will be still lower in comparison to that of the basic version.

Using the advanced approach for one reflection results in two possible locations of the RF source, the error for localization with one reflection in the final simulation is obtained. It is assumed that the localization area is bounded to one of the possible RF source locations for one reflection. This is possible when the orientation of the obstacle is determined without enough accuracy. This simulation shows the maximum error of the localization using the advanced approach when the noise variance has a known amount in Table V.

TABLE V. RMSE OF LOCALIZATION USING THE ADVANCED APPROACH AND ONE REFLECTOR

	SD of Noise(dB)				
	1	2	3	4	5
RMSE in meter (obstacles location does not have errors)	271	287	294	343	382
RMSE in meter(obstacles location has errors)	462	465	515	607	655

The above simulations show that map-based localization has a lower error in all configurations when the advanced approach is used and the noise has bounded variance. In contrast, the basic approach could have a large error in some configurations because of the geometric relation of the reflectors.

The advanced approach is compared with the proposed approach below for localization in [25] in which two reflections are needed and the RSSI and AOA are the observations similar to the advanced approach. The approach proposed in [25] is simulated in the scenario that is shown in Fig. 10. In this approach, a fingerprinting is created using the reflection propagation equation and it is used to estimate the reflection parameter, i.e., the reflection angle and path length between the RF source and the receiver. Then, the RF source localization is done by placing the estimated parameter in the linear equation of possible locations of the RF source and solving this equation. Table.VI presents the results of the simulation using this approach. In this table the errors of the parameters estimation are also presented which are obtained in the step one of the approach.

TABLE VI. RMSE OF THE PARAMETERS ESTIMATION BASED ON THE RSSI OBSERVATION AND LOCALIZATION OF THE RF SOURCE USING THE PROPOSED APPROACH IN [25]

SD of Noise(dB)	RMSE of θ (deg.)	RMSE of d in meter	RMSE of localization(meters)
1	1.98	391	489
2	2.53	447	545
3	3.77	583	623
4	4.03	653	722
5	4.69	731	810

In Table.VII, RMSE of localization for the proposed approach in this paper and the proposed approach in [25] is compared. It is shown that the localization accuracy of the advanced approach when obstacles location has no error or has error, is more than the basic approach in the best configuration of the obstacle and the proposed approach in [25] (with out map) for different SD's of noise.

TABLE .VII. RMSE OF LOCALIZATION FOR THE PROPOSED APPROACH IN [25], THE ADVANCED APPROACH AND THE BASIC APPROACH.

SD of Noise(dB)	approach in [25] (meter)	basic approach (meter)	basic approach (meter) (obstacle location has error)	Advanced approach (meter)	advanced approach (meter) (obstacles location has error)
1	489	153	450	89	420
2	545	302	489	107	483
3	623	483	539	130	554
4	722	679	689	175	602
5	810	764	881	213	637

V. CONCLUSION AND FUTURE WORKS

This paper analyzes the localization in the NLOS condition using a map of the obstacles in a large outdoor environment. The RSSI and AOA observations are used and two approaches are proposed for localization. In the basic approach, RSSI is used for range estimation and localization is performed using three reflections. To improve the localization in the advanced approach, the reflection angle and two reflections are used. It is shown in the simulation and analytical calculation that the localization with the advanced approach has a lower error in comparison to the basic approach for different configurations of the reflectors.

In future works, an approach can be proposed to obtain the optimal reflector on the map for improving localization. In addition, the RF source beacons can be used to obtain the obstacle map, and localization can be done using the estimated map. Also, an optimal UAV path should be determined for taking the RSSI sample and improving localization. In the NLOS condition, the diffracted signal may also be available. Using the map in the NLOS condition can be extended for reflected and diffracted signals simultaneously.

VI. REFERENCES

[1] S. Zorn, M. Gardill R. Rose, A. Goetz, and R. Weigel Alexander Koelpin, "A Smart Jamming System for UMTS/WCDMA Cellular Phone Networks for Search and Rescue Applications," *2012 IEEE MTT-S International Microwave Symposium Digest*, pp. 1-3, 2012.

[2] M. Berioli, J. M. Chaves, N. Courville, P. Boutry, J. Fondere, H. Skinnemoen, H. Tork, M. Werner and M. Weinlich, "WISECOM: A rapidly deployable satellite backhauling system for emergency situations," *International Journal of Satellite Communications and Networking, Special Issue on Emergency Telecommunications via Satellites*, Volume 29, Issue 5, pp. 419–440, 2011.

[3] S. Ferreira, G. Carvalho, F. Ferreira, J. Sousa," Assessing the capacity of man-portable UAVs for network access point localization, using RSSI link data," *In 2014 International Conference on Unmanned Aircraft Systems (ICUAS)*, IEEE, pp. 355-364.2014,

[4] Z. Ma, K.C. Ho, " TOA localization in the presence of random sensor position errors," *In 2011 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, IEEE, pp. 2468-2471, 2011.

[5] M. Yang, D. R. Jackson, J. Chen, Z. Xiong & J. T. Williams, "A TDOA localization method for nonline-of-sight scenarios," *IEEE Transactions on Antennas and Propagation*, vol.67, issue. 4, 2666-2676, 2019.

[6] J.R. Jiang , C.M. Lin , F.Y. Lin and S.T. Huang, "ALRD: AoA localization with RSSI differences of directional antennas for wireless sensor networks," *International Journal of Distributed Sensor Networks*, vol. 9, issue.3, p.52,2012.

[7] S.Tomic, M. Beko, R. Dinis, "Distributed algorithm for target localization in wireless sensor network using RSS and AoA measurement", *Pervasive and Mobile Computing*, vol.37, pp. 63-77, pp. 63-77, 2017.

[8] S.K. Han, W.S. Ra, J.B. Park, "TDOA/FDOA based target tracking with imperfect position and velocity data of distributed moving sensors", *International Journal of Control, Automation and Systems*, vol.15, issue.3, pp 1155–1166, 2017.

[9] S. Venkatraman and J. Caffery, " H. -R. You," Location using LOS range estimation in NLOS environments," *In Vehicular Technology Conference. IEEE 55th Vehicular Technology Conference. VTC Spring 2002 (Cat. No. 02CH37367)*, vol.2, pp 856 – 860, 2002.

[10] P. Closas, C. Fernández-Prades, and J. A. Fernández-Rubio, "A Bayesian approach to multipath mitigation in GNSS receivers," *IEEE J. Sel. Topics Signal Process*, vol. 3, isuee. 4, pp. 695–706, Aug. 2009.

[11] M. Gholami, and R.W. Brennan, "Comparing two clustering-based techniques to track mobile nodes in industrial wireless sensor networks," *Journal of Systems Science and Systems Engineering*, vol.25, no.2, pp.177-209. 2016.

[12] X. Zhang, Y. Sun, and J. Xiao, "A novel radio source search algorithm using force field vectors and received signal strengths," *International Journal of Mechatronics and Automation*, vol.3, isuue.1, pp.25-35, 2013.

[13] Z. Li, Z. Tian, Z. Wang, and Z. Zhang, "Multipath-assisted Indoor Localization Using a Single Receiver," *IEEE Sensors Journal*, vol.21, issue.1, pp. 692 – 705, 2020.

[14] S. He, S.H. Gary Chan, "Wi-Fi Fingerprint-base Indoor Positioning: Recent Advanced and Comparisons," *IEEE Communication Survey & Touturials*, vol.18 ,pp.466-490, 2015.

[15] E. Kupershtein, M. Wax, and I. Cohen, "Single-site emitter localization via multipath fingerprinting," *IEEE Trans. Signal Process*, vol.61, issue.1, pp. 10–21, Jan. 2013.

[16] D. Zimmermann, J. Baumann, A. Layh, F. Landstorfer, R. Hoppe and G. Wolfle, "Database Correlation for Positioning of Mobile Terminals in Cellular Networks using Wave Propagation Models," *IEEE Vehicular Technology Conference*, pp 4682 – 4686, Fall. 2004.

[17] S. M. M. Dehghan, S. Haidari and H. Mordi, "Toward aerial simultaneous target localization and obstacle estimation using RSSI observations," *3rd RSI International Conference on Robotics and Mechatronics (ICROM), Tehran*, pp.517 – 522, 2015.

[18] H. B. Song, H. G. Wang, K. Hong, and L. Wang, " A novel source localization scheme based on unitary esprit and city electronic maps in urban environment," *Progress In Electromagnetics Research*, pp.243-262, 2009.

[19] C. Gentner, T. Jost, W. Wang, S. Zhang, A. Dammann, and U.C. Fiebig, "Multipath Assisted Positioning with Simultaneous Localization and Mapping," *IEEE Transaction on Wireless Communication*, vol. 15, issue.9 , 2016.

[20] W. Xu, F.Quitin, M. Leng, W.P.Tay and S. G. Razul,"Distributed Localization of a RF target in NLOS Environments," *IEEE Journal on Selected Areas in Communications*, pp.1317 – 1330, 2015.

[21] J. He, H. Wymeersch, T. Sanguanpuak, O. Silvén, and M. Juntti, "Adaptive beamforming design for mmwave RIS-aided joint localization and communication," *IEEE Wireless Communications and Networking Conference Workshops IEEE. Korea*, pp. 1-6, 2020

[22] T. Ma, Y. Xiao, X. Lei, W. Xiong, and Y. Ding, "Indoor Localization with Reconfigurable Intelligent Surface," *IEEE Communications Letters*, PP.1-6, 2020.

[23] E. Soltanaghaei, A. Kalyanarnman, and K. Whitehouse, "Multipath triangulation: decimeter-level WiFi localization and orientation with a single unaided receiver," *in Proceedings of ACM MobiSys*, 2018.

[24] S. Haidari, H. Moradi, M.Shahabadi, S.M. M. Dehghan, "RF source Localization using Reflection Model in NLOS Condition,"*In 4rd RSI International Conference on Robotics and Mechatronics (ICROM)*, Tehran, 2016.

[25] S. Haidari, H. Moradi, M. Shahabadi, S.M. M. Dehghan, "A reflection-based rf source localization algorithm," *International Journal of Robotics and Automation*, vol.34, issue.3, 2019.

[26] R. Zekavat and R. M. Buehrer, H*and book of position location,Wiley* IEEE Press , 2011.

[27] F. Sabahi, "Robot Action Space of Tractable Subsumption Architecture," *International Journal of Industrial Electronics, Control and Optimization*, vol.2, issue.4, pp.297-304, 2019.

[28] R.P. França, G.A. Pimentel, and A.T.Salton, "Parametric and Nonparametric Bayesian Filters for Autonomous Underwater Vehicle Localization," *Journal of Control, Automation and Electrical Systems*, vol.31, issue 1, pp.40-

51, 2020.
[29] H. Budiarto, K. Korihata, k. Haneda and J. Takada, “Experimental study of non-specular wave scattering from building surface roughness for the mobile propagation modeling,”*IEICE transaction Communications*, vol.87, issue.4, pp.958-966, 2004.
[30] D.Tassetto, E.H. Fazli and M. Werner, “ A novel hybrid algorithm for passive localization of victims in emergency situations,” *IEEE 4th Advanced Satellite Mobile Systems*, pp. 320–327, 2008.
[31] D. M. Hamby,”A review of techniques for parameter sensitivity analysis of environmental models,” *environmental Monitoring and Assessment, Volume 32*, Issue 2, pp 135-154, September 1994.

Saeid Haidari received his B.Sc. in Electrical Engineering from Nikbakht University, Iran in 2003 and M.Sc. in Control Engineering from University of Kerman, Iran in 2007, and Ph.D. degrees in robotic and AI from University of Tehran. Currently he is an assistant professor at university of Zabol, Iran. His research interests include autonomous aerospace systems, aerial robotics, RF source localization, complex and Multi-agent systems, evolutionary computation, UAVs cooperation.

Hadi Moradi is an associate professor at the Electrical and Computer Engineering Department of the University of Tehran. He is also a member of Control and Intelligent Processing Center of Excellence. He received his BSc in Electrical Engineering from the University of Tehran and his MS and PhD degrees in Computer Engineering (Robotics), respectively, in 1994 and 1999 from the University of Southern California. Before joining the Tehran University in 2008, he spent several years in industry as a research scientist. He joined USC at 2000 as a faculty at the Computer Science Department. In 2004, he spent two years at the Intelligent Systems Research Center at Sungkyunkwan University, in South Korea till 2006. His current research interests include motion planning, manipulation, service robotics, educational robotics, and intelligent tutoring system, especially game-based teaching.

S.M. Mehdi Dehghan received his B.Sc. in Electrical and Computer Engineering, M.Sc. in Artificial Intelligence and Robotics, and Ph.D. in Control, respectively, in 1999, 2002, and 2015 from the University of Tehran. His research interests include autonomous aerospace systems, aerial robotics, navigation, complex and Multi-agent systems, UAVs cooperation, SLAM of RF sources and attitude determination and control. He is now an assistant professor at the Department of Control Engineering at the Malek-Ashtar University of Technology.active and hybrid filters, the application of power electronics in renewable energy systems and electrified railway systems, reactive power control, harmonics, and power quality compensation systems such as SVC, UPQC, FACTS devices.