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A New Approach for Simultaneous Localization of UAV and RF Sources (SLUS)

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Abstract— **In this paper, a new approach for Simultaneous Localization of UAV and RF Sources (SLUS) is proposed. In the UAV-based localization of RF sources, such as a cell phone in a search and rescue mission, the UAV navigation errors are a significant source of localization error. Although the use of GPS can reduce UAV localization error significantly resulting in more accurate RF source localization, however, if the GPS is not available temporarily or permanently, the accuracy of UAV-based localization decreases rapidly. The proposed approach solves these two connected problems, i.e. UAV localization and RF source localization, simultaneously to decrease the error of UAV position estimation and the error of RF sources localization. The prediction of UAV pose is done in parallel to RF source position prediction first. Then the predicted states are augmented and the augmented predicted state information is corrected in SLUS using the range and bearing observations. The simulation results show that this method can reduce RF source's position estimation error and prevent the divergence of UAV navigation in latitude and longitude channels. In the other words, the RF features available in the environment can be used to improve the UAV navigation.**

Keywords—RF source localization; UAV navigation; SLAM; Kalman filter; RSSI; AOA

I. INTRODUCTION

Considering the fact that these days the majority of people carry a cell phone or dedicated devices such as ARVA, which propagates an electromagnetics signal [1], researchers and governments have realized the capacity in using RF signals for localization of the owner/user even if he or she is unconscious, especially for search and rescue tasks. For instance, Wireless Infrastructure over Satellite for Emergency Communications (WISECOM) aims to restore GSM (Global System for Mobile Communication) infrastructure over satellite for tracking rescue teams and victims [2]. WISECOM infrastructure will be used to provide essential information to the rescue workers, such as the number of victims involved, their health condition, and the way to reach them. I-LOV project [3] is another related project, focused on using a jammer for existent cell phone networks and setting up its own network to provide emergency communication and to localize victims.

A practical application of RF source localization is in the case of a person, which may be called the target, who is lost on a terrain. In such a case, a UAV may fly over the terrain and try to localize the RF signal emitted from the cell phone or any other dedicated handling device (Fig. 1).

One of the components of RF source localization error is the error of UAV position estimation by the navigation system. Although GPS has been widely used to provide fairly accurate position estimation, however, GPS may be not available for many reasons such as the failure of the onboard GPS system, low altitude flight of UAV, or bad weather. Consequently, it is important to propose methods to reduce UAV localization errors. To the best of our knowledge, despite the great importance of UAV navigation error in RF source localization, it has not been studied in any of the related researches. One of the methods that can be used for confronting this source of error is the use of simultaneous localization of UAV and RF source.

The localization of a robot and the features in an environment have already been addressed in Simultaneous Localization and Mapping (SLAM), in which the map of the environment is built while the robot moves around and localize itself. The problem in hand, i.e. localizing an RF source using a UAV with given position error, can be considered as a special case of SLAM, in which a limited number of features, which can be static or dynamic, exist in the map. In other words, we propose simultaneous Localization of the robot and the target which is called SLUS, i.e. Simultaneous Localization of UAV and RF Source(s). The used observations for SLUS correction stage are Received Strength Signal Indicator (RSSI) and

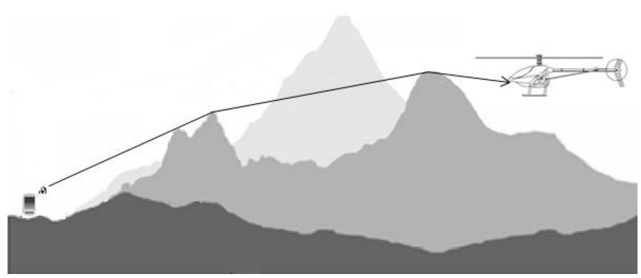

Fig. 1. A UAV hovers over a terrain searching for an RF signal which may falls into NLOS (Non Line Of Sight) propagation category that have different effects on the AOA and RSSI measurements. In this case, although the cell phone, shown on the left, has no LOS path to the UAV the UAV can receive its signal and estimate its range, assuming known transmitted power, and bearing).

Angle of Arrival (AOA) measurements, which are used to calculate range, assuming that the transmitted power is known, and bearing of the RF transmitter. The known RF source power assumption can be easily removed using DRSSI based localization; however it is considered to help with simpler presentation of the main approach. This approach can be used in any application in which there is at least one visible RF source, directly or indirectly (i.e. LOS or NLOS respectively), in the area to improve INS based localization.

II. RELATED WORKS

Using UAVs for localization of RF sources in wide open areas requires solving various issues such as optimal localization point(s) selection [4], path planning [5-6], cooperation to benefit from triangulation of UAVs [7-8], and multiple-target localization [6]. The localization techniques based on RSSI and AOA measurements are developed in the previous articles by the authors [9-10] assuming to have accurate UAV position.

The localization of an RF source using a UAV with given pose error, can be considered as a special case of SLAM, in which the RF source is considered as a feature on the map to be built. There are many studies about simultaneous localization of moving agents (receivers) on a surface and mapping of static wireless devices based on the RF signal measurements [11-16]. In these studies, a moving agent can be a pedestrian [11] or a mobile robot [12-14], and the static nodes can be access points in Wi-Fi networks [11], RFID tags [15], or any other active beacon which are fixed in the indoor environment. The map of available static nodes can be used to decrease the robot localization error or improve the tracking the moving humans in an indoor space. The main limitation of these studies is in reliance on available and uniquely recognizable features to create a proper map for localization which are not available in wide open environments. Furthermore, most of these studies are done for 2D environments, except a few such as the proposed approach by Kleiner et al. [15]. Localization in sensor networks can also be solved as an SLAM problem [16] which is similar to the described RF signal-based SLAM.

There are many studies using vision for SLAM of UAVs which rely on visual environmental features for both localization and mapping [17-18]. In this study, the problem of simultaneous localization of a UAV and RF source(s) is approached similar to SLAM. However, due to the limited number of RF source(s), the possible dynamics in the RF source(s) location(s), the special observation model (having NLOS condition), and the wide area of localization, the Simultaneous Localization of UAV and RF Sources (SLUS) approach is proposed.

A. *NLOS propagation*

One of the important issues in the localization of an RF source is the difference between direct visibility of the source of signal, i.e. being Line Of Sight (LOS), and indirect visibility of the source of signal, i.e. Non Line Of Sight (NLOS). In NLOS condition, the RF signals propagate due to reflection, diffraction, and scattering mechanisms.

Consequently, in this study, two observation models are used to represent NLOS propagation for RSSI and AOA. The RSSI model for signal attenuation due to the distance is the general path loss model. Signal attenuation due to shadowing in decibel is modeled by a normal distribution with zero mean and adjustable standard deviation (SD).

The basic components of an appropriate model to simulate AOA propagation are local scattering, probability of blockage, and a method for merging these. In this paper, the probability of blockage is assumed negligible. It should be noted that this assumption has been considered to ease up the presentation of SLUS. Although this assumption is true for cases such as a source in a wide open area, the proposed approach can be applied to cases that include blockage using multi-step Gaussian filtering [10] or particle filter [9]. The details of the used propagation model for RSSI and AOA can be found in the [10].

III. ARCHITECTURE OF SLUS

Fig. 2 shows the general structure of SLUS. The UAV and RF source location prediction is done separately. Then the predicted states are augmented to form the augmented state. The augmented predicted state is then passed to the correction module in which the RSSI and AOA signals are used to improve the localization of the UAV and the target. It should be noted that due to the higher sample rate of IMU compared to AOA and RSSI observations, the UAV navigation module has its own filtering process to improve the navigation.

After passing correction phase and during the de-augmentation process, the estimated mean and covariance matrix for navigation state parameters, and also the estimated mean and covariance for RF source(s) location parameters are extracted from SLUS's mean and covariance and are used for solving new localization and navigation equations.

A. *UAV Localization*

The UAV's position includes latitude (Lat_t^V) and longitude ($Long_t^V$) which is calculated solving the navigation equations. UAV is navigating by IMU and altimeter sensors. In each iteration of navigation loop, new values of state variables and their covariance would be predicted based on the measured values by IMU and by solving the navigation equations. Navigation equations in NED (North East Down) coordinate system can be summarized as (1), which is a discretized version of time continuous equations in [19]:

$$X_t^V = f_t^V(X_{t-1}^V, u_t^{IMU}, w_t^{IMU}) \tag{1}$$

in which UAV state variable at time t (X_t^V) includes the attitude, the speed, and the position of the UAV consisting of latitude, longitude, and height from the surface of the geodetic earth according to the WGS-84 standards. The input (u_t^{IMU}) includes the IMU angular rate and acceleration measurements at time t given in the body frame. These measurements include the measurements errors such as the additive accelerometer and gyro noises and the accelerometer and gyro biases. The matrix w_t^{IMU}

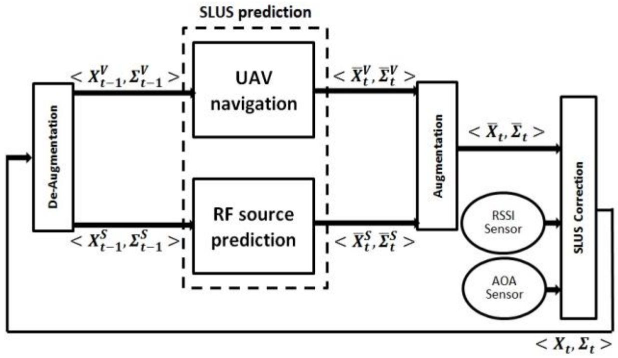

Fig. 2. Architecture of SLUS

models IMU error processes as zero-mean white Gaussian with known covariance Σ_t^{IMU}.

The navigation equations can be solved by the fourth-order Runge-Kutta method, or any other method suitable to solve differential equations numerically, for obtaining an estimation of the values of the state variables.

If valid GPS data is available, the prediction from solving navigation equations can be corrected in a correction phase according to the GPS data and the altimeter observations which is called an integrated GPS/INS/Alt navigation algorithm [20]. UAV localization in this situation is accurate enough and there is no need for using SLUS approach. SLUS approach is used when GPS data is not available. In this case, the correction phase within navigation block will be done only based on the altimeter observations. It should be noted that the navigation equations in altitude channel are naturally unstable and it is necessary to integrate the results of solved equation with a barometric altimeter to prevent the increase of navigation error in altitude channel.

The predicted error covariance of the inertial navigation system ($\bar{\Sigma}_t^V$) calculated by (2). In this equation, the effects of noisy status of IMU measurements have been added to the noise of the process. $\nabla_{X^V} f_t^V$ and $\nabla_{u^{IMU}}$ are respectively the Jacobian of the navigation equation with respect to the state variables (X^V) and IMU inputs (u^{IMU}). These Jacobians would be calculated using $\bar{X}_t^V$ and u_t^{IMU} values.

$$\bar{\Sigma}_t^V = \nabla_{X^V} f_t^V \, \Sigma_{t-1}^V \, \nabla_{X^V} {f_t^V}^T + \nabla_{u^{IMU}} f_t^V \, \Sigma_t^{IMU} \, \nabla_{u^{IMU}} {f_t^V}^T \qquad (2)$$

As mentioned, the prediction of the covariance of the inertial navigation system is corrected according to the altimeter observation using an extended Kalman filter (EKF). The resulted covariance matrix will be used in the SLUS correction stage. It should be noted that an altimeter observation mainly affects the UAV altitude state variable and has negligible effect on AOA and RSSI due to the large ratio of the distance of the UAV to the RF source to the flight altitude. Therefore, it has been used in the UAV navigation module.

B. *RF Source(s) Localization*

After receiving the first RF signal from a source, over a given RSSI threshold, the RF source localization is initialized. Assuming that the UAV is circulating around the candidate search area, the center of the search area is considered as the first estimation of RF source position. In addition, the covariance matrix for the new target is set such that the entire search area is covered. This initial estimation can be corrected according to AOA and RSSI observations. It should be mentioned that in this paper the targets are assumed to be static and no update is performed on their position in the prediction phase.

Knowing the power of the transmitter, the state variable of an RF source consists of its latitude and longitude.

$$X_t^S = \begin{bmatrix} Lat_t^S \\ Long_t^S \end{bmatrix} \qquad (3)$$

Considering the fixed position of the RF source, it is obvious that its position's mean and covariance would not change in the prediction phase.:

$$\bar{X}_t^S = X_{t-1}^S \;\; and \;\; \bar{\Sigma}_t^{SS} = \Sigma_{t-1}^{SS} \qquad (4)$$

C. *Augmented state*

As mentioned earlier, the SLUS approach is used for simultaneous correction of the output of UAV navigation and RF source predictions. In the correction phase, the predicted states are augmented and EKF is used to correct the augmented state using RSSI and AOA observations. The augmented state variable consists of the UAV navigation parameters and RF source[1] position parameters:

$$X_t = \begin{bmatrix} X_t^V \\ X_t^S \end{bmatrix} \qquad (5)$$

The augmented covariance matrix at time *t* is shown in (6). Σ_t^{VV} corresponds to the covariance matrix of UAV navigation and Σ_t^{SS} corresponds to the covariance of the RF source localization. The correlation between the UAV navigation and the RF source localization errors (Σ_t^{VS} and Σ_t^{SV}) are zero at the beginning. It should be noticed that $\Sigma_t^{VS} = {\Sigma_t^{SV}}^T$ at any time.

$$\Sigma_t = \begin{bmatrix} \Sigma_t^{VV} & \Sigma_t^{VS} \\ \Sigma_t^{SV} & \Sigma_t^{SS} \end{bmatrix} \qquad (6)$$

By this explanation and the fixed target assumption, the augmented motion model is described as:

$$X_t = f_t^A(X_{t-1}, u_t^A, w_t^A) = \begin{bmatrix} f_t^V(X_{t-1}^V, u^{IMU}, w^{IMU}) \\ X_{t-1}^S \end{bmatrix} \qquad (7)$$

D. *Augmented Predictions*

The predicted augmented state is represented by:

$$\bar{X}_t = \begin{bmatrix} \bar{X}_t^V \\ \bar{X}_t^S \end{bmatrix} \qquad (8)$$

The augmented predicted covariance matrix correspondent with the last prediction of the value of augmented system state variables can be calculated as:

[1] Only one target is considered for the sake of easier presentation. However, the equations can be extended for more targets.

$$\bar{\Sigma}_t = \nabla_X f_t^A \ \Sigma_{t-1} \nabla_X f_t^{A^T} + \nabla_u f_t^{A^T} R_t \nabla_u f_t^A \quad (9)$$

In this equation, $\nabla_X f_t^A$ and $\nabla_u f_t^A$ are the Jacobian of the augmented process model with respect to the state X and u^A evaluated at $\bar{X}_t$ and u_t^A, respectively.

The covariance matrix of the process noise would be calculated using (10) based on the fixed position assumption of the RF source.

$$R_t = \begin{bmatrix} \Sigma_t^{IMU} & 0 \\ 0 & 0 \end{bmatrix} \quad (10)$$

By plugging (6) and (10) in the (9), the predicted covariance matrix for SLUS is simplified as:

$$\begin{aligned} \bar{\Sigma}_t = &\begin{bmatrix} \nabla_{X^V} f_t^V & 0 \\ 0 & I \end{bmatrix} \begin{bmatrix} \Sigma_{t-1}^{VV} & \Sigma_{t-1}^{VS} \\ \Sigma_{t-1}^{SV} & \Sigma_{t-1}^{SS} \end{bmatrix} \begin{bmatrix} \nabla_{X^V} f_t^{V^T} & 0 \\ 0 & I \end{bmatrix} \\ &+ [\nabla_{u^{IMU}} f_t^V \quad 0] \begin{bmatrix} \Sigma_t^{IMU} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \nabla_{u^{IMU}} f_t^{V^T} \\ 0 \end{bmatrix} \end{aligned} \quad (11)$$

Based on the (2), (11) can be written as[1]:

$$\bar{\Sigma}_t = \begin{bmatrix} \bar{\Sigma}_t^V & \nabla_{X^V} f_t^V \Sigma_{t-1}^{VS} \\ \Sigma_{t-1}^{SV} \nabla_{X^V} f_t^{V^T} & \bar{\Sigma}_t^S \end{bmatrix} \quad (12)$$

E. *Measurement Update (Correction phase)*

In the correction phase, the RSSI and AOA measurements are used to improve the UAV and target localization. The observation model based on the explanation presented for the NLOS propagation are written as (13).

$$Z_t = \begin{bmatrix} h_{RSSI}(X_t^V, X_t^S) \\ h_{AOA}(X_t^V, X_t^S) \end{bmatrix} + \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix} \quad (13)$$

Observation model for the RSSI measurement is:

$$h_{RSSI}(X_t^V, X_t^S) = Pt - PL_{d0} - 10\alpha \log_{10} \frac{d_t}{d_0} \quad (14)$$

in which PL_{d0} is the path loss in the reference distance d_0 and d is the distance of the UAV to the RF source which is calculated using (15). Pt is the transmitted power in decibel and R_0 is the radius of earth in kilometer.

$$\begin{aligned} d_t^2 = &(R_0(Lat_t^S - Lat_t^V))^2 \\ &+ (R_0 \cos(Lat_t^V)\,(Long_t^S - Long_t^V))^2 \end{aligned} \quad (15)$$

The AOA observation model is defined as:

$$h_{AOA}(X_t^V, X_t^S) = \tan^{-1}\left(\frac{Long_t^S - Long_t^V}{Lat_t^S - Lat_t^V}\right) \quad (16)$$

δ_1 , in (13), is a normal distribution with the shadowing effect SD (σ_{Sh}) and δ_2 is a normal distribution with the local scattering SD (σ_{LS}). Here it is assumed that the noises are Gaussian and independent and their SD to be time invariant. So the covariance of the observation noise is:

$$Q = \begin{bmatrix} \sigma_{Sh}^2 & 0 \\ 0 & \sigma_{LS}^2 \end{bmatrix} \quad (17)$$

Observation model is a non-linear function so the Jacobian of observation model with respect to the state X_t , i.e. H_t , is computed for using EKF. The Jacobian is evaluated at $\bar{X}_t$, i.e. the estimated UAV state $\bar{X}_t^V$, and the estimated RF source position $\bar{X}_t^S$. H_t is calculated as follows in which $a_t = \frac{10\alpha}{d_t^2 \ln 10}$ is used for better readability of the equations. h_{11}, h_{12}, h_{13}, and h_{14} are derivation of h_{RSSI} with respect to Lat_t^V , $Long_t^V$, Lat_t^S , and $Long_t^S$, respectively.

$$\begin{aligned} h_{11} = &a_t R_0^2((Lat_t^S - Lat_t^V) \\ &+ \sin(Lat_t^V)\cos(Lat_t^V)(Long_t^S - Long_t^V)^2) \end{aligned} \quad (18)$$

$$h_{12} = a_t(R_0 \cos(Lat_t^V))^2(Long_t^S - Long_t^V) \quad (19)$$

$$h_{13} = -a_t R_0^2\,(Lat_t^S - Lat_t^V) \quad (20)$$

$$h_{14} = -a_t\,(R_0 \cos(Lat_t^V))^2(Long_t^S - Long_t^V) \quad (21)$$

Also, h_{21}, h_{22}, h_{23}, and h_{24} are derivation of h_{AOA} with respect to Lat_t^V , $Long_t^V$, Lat_t^S , and $Long_t^S$, respectively.

$$h_{21} = (Long_t^S - Long_t^V)/r \quad (22)$$

$$h_{22} = -(Lat_t^S - Lat_t^V)/r \quad (23)$$

$$h_{23} = -(Long_t^S - Long_t^V)/r \quad (24)$$

$$h_{24} = (Lat_t^S - Lat_t^V)/r \quad (25)$$

in which *r* is used for readability and is defined as;

$$r = (Lat_t^S - Lat_t^V)^2 + (Long_t^S - Long_t^V)^2 \quad (26)$$

It has to be noted that the observation model does not depend on the attitude, linear speed, and flight altitude of the UAV; but it just depends on the UAV and the RF source latitude and longitude. Therefore, H_t would be as follows:

$$H_t = \begin{bmatrix} \mathbf{0_{1*6}} & h_{11} & h_{12} & 0 & h_{13} & h_{14} \\ \mathbf{0_{1*6}} & h_{21} & h_{22} & 0 & h_{23} & h_{24} \end{bmatrix} \quad (27)$$

IV. SIMULATION RESULTS

To test the proposed approach, the following search scenario, around the global 0.6043 radian longitude and 0.7921 radian latitude which is a suburb of Tehran, Iran, has been simulated. A UAV flies at a fixed altitude on a circular path, with the radius of 10km, at constant linear velocity of 100m/s. The UAV starts at the longitude of 0.6043 radian and latitude of 0.7902 radian. The simulation parameters of IMU are adjusted according to a

[1] It should be mentioned that this equation is simplified, for the sake of simplification in presentation, by not showing the effect of altimeter which is applied in the navigation phase. This is done due to the independency of the SLUS's correction phase from the altimeter readings.

class of low-cost MEMS. The target is placed randomly at different positions in the search area. The SD of shadowing effect and local scattering are set 3dB and 0.1 radian respectively.

To include the effects of spherical nature and the rotation of the earth, which are important in large area search scenarios, the raw values of linear acceleration and angular velocity of the UAV in a given path are updated according to Coriolis accelerations and rotational velocity of the earth. The resulted values are the inputs of simulation of IMU sensors. It should be noted that the effect of the autopilot (controller) is not considered in these simulations.

The presented results are based on the Root Mean Square (RMS) of the target and the UAV localization errors in 100 consecutive runs according to the condition of Monte-Carlo simulation. Figs. 4 and 5 show the results of target localization without and with using SLUS approach respectively. The square points are the main path of the UAV, the small empty circles are the results of the UAV localization, the red star demonstrates the real position of the target, and the triangles represent the results of localization in each one of the UAV's waypoints. The oval shapes corresponds to the error covariance value of the UAV localization.

A. *Basic Target Localization*

To show the importance of the proposed approach, a basic approach is used to localize the target in two steps, i.e. first the UAV is localized and then the target is localized based on the UAV's estimated position (Fig. 3).

The UAV's pose is estimated by the UAV navigation module and the localization of the target is done using an EKF filter based on the AOA and RSSI observations [10]. Table I shows the results of target localization considering different UAV navigation scenarios.

TABLE I. : THE RMSE OF UAV AND RF SOURCE LOCALIZATION USING BASIC TARGET LOCALIZATION.

	RMSE of UAV localization (km)	RMSE of target localization (km)
Ideal Navigation	0	0.1895
GPS/INS/Alt Navigation	0.0185	0.1831
INS/Alt Navigation	4.9424	2.9067

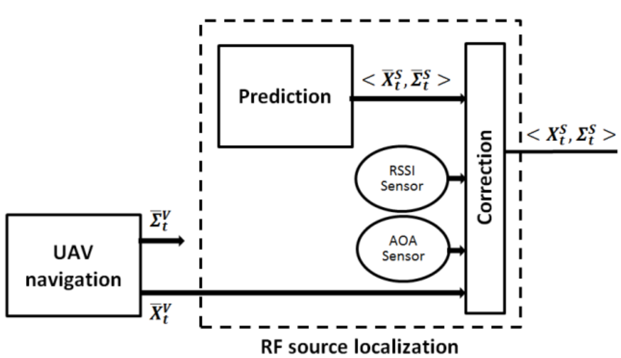

Fig. 3.The architecture of the basic approach for target localization.

Fig. 4 shows that lack of GPS can cause a fast increase of UAV localization error. The increase of the UAV localization error increases the error of the target localization and also prevents its convergence.

B. *SLUS based Target Localization*

As shown in table I, target localization is fairly accurate when GPS is available. However, the target localization has huge error when GPS is not available. Consequently, the importance of SLUS should be presented in cases in which GPS is not present.

Fig. 5 shows the result of using SLUS approach when the target is at longitude of 0.6046 radian and latitude of 0.7928 radian. In such a case, which is similar to the last row of Table I, the RMSE of the UAV and the target localization, has reduced to 0.9624km and 0.7155km, respectively. As it can be seen in Figs. 4 and 5, the basic approach suffers from divergence of the UAV localization which results in the divergence of the target localization. In contrast, in 100 runs of the SLUS approach, a few cases could not converge in the given time and the localization had to be re-initialized to converge. It should be mentioned that multi-target localization using SLUS will improve the performance of the proposed approach.

Since the performance of the RF source localization mainly depends on the SD of shadowing and local scattering, the sensitivity of SLUS to these parameters is tested by increasing them to 7dB and 0.3radian, respectively. Table II shows the result of the basic target localization and the target localization using SLUS approach in this situation.

TABLE II. : COMPARISON OF BASIC TARGET LOCALIZATION AND SLUS APPROACH WHEN $\sigma_{Sh} = 7dB$ AND $\sigma_{LS} = 0.3\,radian$.

	RMSE of UAV localization (km)	RMSE of target localization (km)
Basic approach	4.9096	3.0015
SLUS approach	1.7114	1.3514

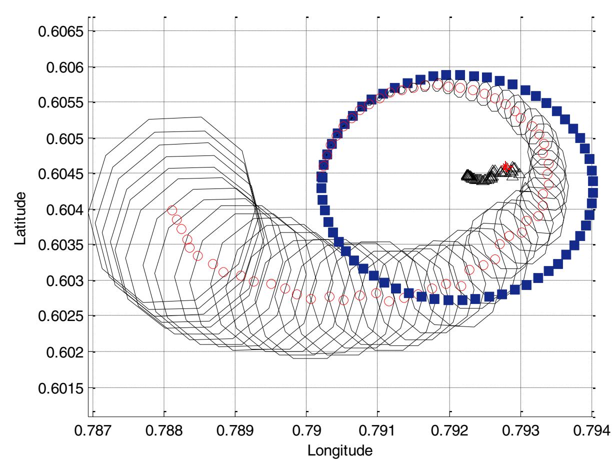

Fig. 4. The UAV and the target localization without using SLUS, i.e. the basic approach shown in Fig. 3, when GPS is not available. The UAV starts from global position of 0.6043 radian longitude and 0.7902 radian latitude.

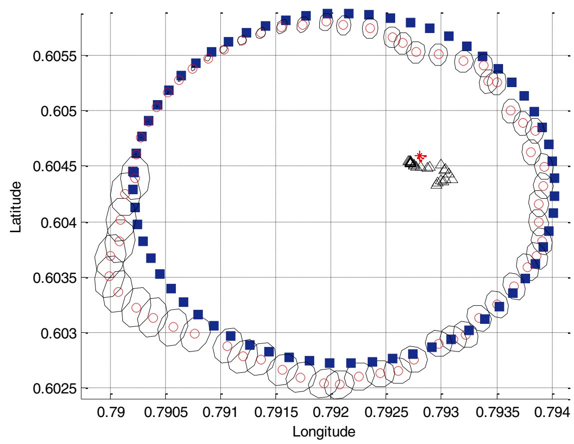

Fig. 5. The UAV and target localization using SLUS approach. The UAV starts from global position of 0.6043 radian longitude and 0.7902 radian latitude.

V. CONCLUSION AND FUTURE WORKS

In this paper, a new approach is presented for simultaneous localization of a UAV and an RF source. Generally, in UAV-based RF source localization, the UAV localization error causes the increase of the RF source localization error. If the GPS is available, the UAV localization has enough accuracy and has very small effect on the RF source localization. On the other hand, if GPS is not available, the error of localization by INS/Alt navigation system would increase over time and has great effect on the localization of the target. For such a situation, the use of SLUS approach is suggested to simultaneously decrease the error of the UAV and the RF source localization. The results of using this approach show the great effect of SLUS on the results of these two localization problems, especially on the convergence of these localizations.

The future work would focus on addressing the effects of noise of RSSI and AOA observations in the performance of the proposed approach. In other words, it is necessary to present an analysis about the effect of SD of shadowing and local scattering on the performance of the SLUS approach. The effect of uncertainty of transmitter power on the performance of SLUS is another subject that should be investigated.

In addition, the use of multi-step Gaussian filtering [10] or particle filter [9] should be investigated for a condition that the probability of blockage is not negligible. Finally, multi-target localization using SLUS is currently under investigation which may improve the performance of the proposed approach.

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