Indoor Source Localization Using 2D Multi-Sensor Based Spatial Spectrum Fusion Algorithm

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***Abstract*— In a starving indoor environment where non-line of sight (NLOS) signals are strongly dominant, localization using traditional spatial spectrum estimation techniques easily fails due to low signal to noise ratio (SNR). Accordingly, in this paper, a novel 2-D multi-sensor Spatial Spectrum Fusion (2D-SSF) localization algorithm based on the multiple signal classification (MUSIC) method is proposed. The output data of each uniform rectangular array (URA) at each access point (AP) are first processed to get the noise subspace data. Then, after estimating the corresponding azimuth and elevation angles of each array using the MUSIC approach and finding the position of each point relative to each sensor in the search grid with the help of grid refinement algorithm, the parameters of interest of the target are estimated from a single spectrum that results from fusing all maximum noise subspaces where the position corresponding to the minimum error between the set of angles and every estimated point in the searching area is situated. Different simulation results of the proposed method in terms of RMSE as a function of SNR for various APs LOS/NLOS scenarios, the change in the number of antennas at each AP and the comparison with the MUSIC approach and the 1D localization based spatial spectrum fusion algorithm are carried out. The obtained results prove the significant performance of the proposed 2D-SSF localization algorithm with the strong presence of NLOS signals.**

Keywords—2-D Localization; Multi-Sensor; Spatial Spectrum Estimation Techniques; Data Fusion.

I. INTRODUCTION

In recent decades, the use of multi-sensor data fusion [1] for the purpose of localization has become a fundamental problem in modern signal processing and it has found wide applications in radar, sonar, wireless communications and acoustics [2][3].

In general, the localization of sources using multiple stations based spatial spectrum information at known locations is achieved by first exploiting the spatial information at each base station in order to estimate the direction of arrival (DOA) of the sources by employing an efficient direction finding (DF) estimator algorithm, such as the well-known Multiple signal classification (MUSIC) algorithm [4] .Then, the set of data (DOAs) will be sent to the fusion center where the positions of the sources are determined based on the appropriate approach in the fusion decision center like triangulation (e.g., as used in [5] and [6]) or other techniques that have been proposed in the literature [7].

However, in rush indoor environment, the propagation of the source signal is strongly attenuated by reflection when it hits the surface of an obstacle, which results in the high existence of NLOS signals arriving at the receiver through different paths. This multipath effect is even more severe where a ceiling, equipment, floor, and walls are present. Thus, the performance of the localization methods mentioned before is degraded under such starving environment with low SNR.

To overcome this problem, different methods have been proposed in the literature. In [8], the author proposed the use of the nonlinear PSO optimization algorithm to find the position of the target after the fusion process for a single moving array. A hybrid localization approaches with data fusion, like the employment of TOA/TDOA in [9]. There has also been comprehensive research work centering on fusion frameworks that rely on heterogeneous information, such as the proposed "MapSentinel" tracking system, which performs non-intrusive location sensing based on WiFi access points and ultrasonic sensors [10]. A system that exploits the acoustic properties of the room named as "SoundLoc" in [11] and indoor CO2 concentration based on the sensing by proxy methodology [12].

But, according to many previous types of research that rely on WiFi wireless network based indoor localization, to simplify the research conditions, such as time consumption and computation complexity, the arrays at the receiver sides were considered to be uniform linear array (ULA) geometry, which reduces the accuracy of the localization problem certainly in very low SNR.

In this paper, 2-D multi-sensor Spatial Spectrum Fusion (2D-SSF) localization algorithm based on WIFI signals is used for indoor localization. In the proposed work, the subspace-based MUSIC algorithm is used to estimate the azimuth and elevation angles at each URA array at the receiver side. Then,

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depending on known search grid dimension, 2D spectrum fusion process at the fusion center is used to estimate the DOAs or the coordinates of the target position.

The remainder of this paper is organized as follows: In Section II, we present the data model and we formulate the main problem. The proposed 2D spatial spectrum fusion algorithm is demonstrated in Section III. Thereafter, in Section IV, different simulation results of the RMSE of the proposed method as a function of SNR are carried out for various APs LOS/NLOS scenarios, the change in the number of antennas at each AP and the comparison with the MUSIC approach and the 1D localization based spatial spectrum fusion algorithm used in [13]. The paper is concluded in Section V.

II. Data Model And Problem Formulation

Consider an indoor environment composed of P Access point (AP) each has URA geometry with M= $N_x \times N_y$ number of antennas impinged by Q multi-path source signal in the far field of the antenna array, see Figure 1. Suppose that the direction of the waves is Φ and ϴ. Then, the received signal at the p-th AP, with *p = 1,…,P* is given by:

$$X_p(t) = A_p(\Phi,\Theta)S(t) + N_p(t) \qquad (1)$$

Also is equal to

$$X_p(t) = a_p(\Phi_p,\Theta_p) * S_p(t) + \sum_{k=1}^{Q} \gamma_k(t)\ a_p(\Phi_k,\Theta_k)\ S_p(t-\tau_k) + N_p(t) \qquad (2)$$

Where; S(t) is the source signal, $\gamma_k(t) = \alpha_k e^{-j2\pi f_c \tau_k}$. α_k , f_c, τ_k , Φ_k, Θ_k , Φ_p, Θ_p are the correlation coefficient, carrier frequency, delay of travel time, azimuth and elevation angles of the k-th multipath signal with k = 1, 2,…, Q, azimuth and elevation angles of the direct signal respectively. N(t) is white Gaussian additive noise with mean 0 and variance σ^2 . $a_p(\Phi,\Theta) \in ₵^{M\times P}$ is the steering vector of the URA at each receiver point. We can observe from (2) that the received signal at each array consists of direct path signals and multipath signals. So, the transfer vector corresponding to the LOS signal at the p-th array is equal to:

$$a_p(\Phi_p,\Theta_p) = \left[1\ \ e^{j\frac{2\pi}{\lambda}\Delta(p,2)}\ \ e^{j\frac{2\pi}{\lambda}\Delta(p,3)}\ \ \dots\dots\dots\ e^{j\frac{2\pi}{\lambda}\Delta(P,M-1)}\right]^T \qquad (3)$$

Here, $(.)^T$ denotes the transpose operator, where the inter-element delay $\Delta_{(p,m)}$ is given by:

$$\Delta_{(p,m)} = e^{j\frac{2\pi}{\lambda}(m-1)\, d_x\, \sin(\Theta_p)\cos(\Phi_p)} + e^{j\frac{2\pi}{\lambda}(m-1)\, d_y\, \sin(\Theta_p)\sin(\Phi_p)} \qquad (4)$$

In general, the steering matrix corresponding to the direct path signals can be expressed as:

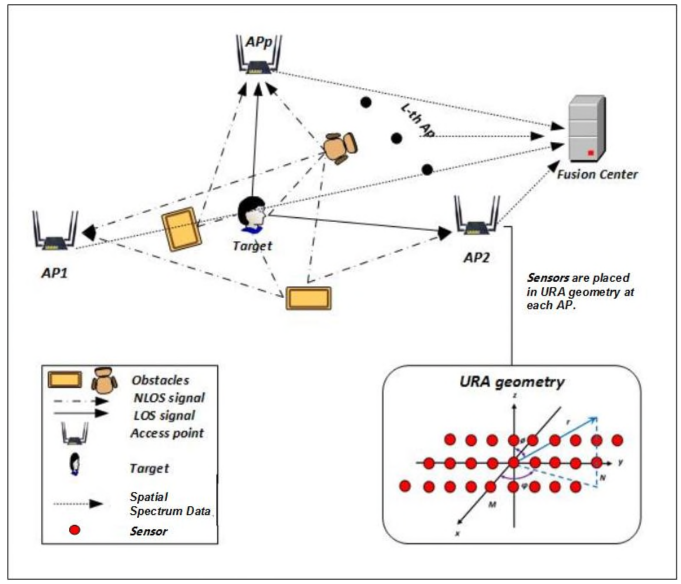

Figure 1. 2D-Multi-sensor spatial spectrum fusion target localization in an indoor environment.

$$A_s(\Phi,\Theta) = [a_1(\Phi_1,\Theta_1)\ a_2(\Phi_2,\Theta_2)\dots\dots\dots\ a_p(\Phi_p,\Theta_p)] \qquad (5)$$

However, for simplicity, we can obtain the steering matrix corresponding to the NLOS signals from [14].

Our task is to estimate the position of the target p using the spatial spectrum fusion (SSF) approach starting from estimating the azimuth and elevation of each URA, i.e., two-dimensional search, based on the observations obtained from (2) under an environment mixed with LOS and NLOS signals. It can be briefly demonstrated in Figure 1.

III. Localization Algorithm

A. Spatial spectrum estimation for every array

A.1 Construct the covariance matrix

The first step is to construct the covariance matrix of the received spatial data at each array and then decompose it into signal and noise subspaces. At a certain array p, the covariance matrix of the observed data $X_p(t)$ can be expressed as:

$$R_{X_p} = \frac{1}{L} X_p(t){X_p}^H(t)\ \in ₵^{M\times M} \qquad (6)$$

$$= U_p \Sigma_p {U_p}^H = [{U_p}^{(s)}{U_p}^{(n)}]\, \Sigma_p [{U_p}^{(s)}{U_p}^{(n)}]^H \qquad (7)$$

Here, $(.)^H$symbolizes to the Hermitian Transpose.

${U_p}^{(s)} \in ₵^{M\times 1}$ denotes the eigenvector spanning the signal subspace.

${U_p}^{(n)} \in ₵^{M\times M-1}$denotes the eigenvector spanning the noise subspace.

$\Sigma_p \in \mathbb{C}^{M\times M}$ is a diagonal matrix containing the decreasing order of the associated eigenvalues.

A.2 MUSIC algorithm

After obtaining the covariance matrix, DOA based subspace estimation method is used to estimate the spatial spectrum of each array. Here, we use the MUSIC algorithm due to its reliable performance compared to the traditional spatial spectrum estimation algorithms certainly in low SNR [15]. The power spectrum of the MUSIC algorithm is given by:

$$P_p(\Phi,\Theta) = \frac{1}{\text{norm}\,[A^H(\Phi,\Theta)\, U_p{}^{(n)}]} \quad (8)$$

The used MUSIC algorithm explores the searching area ($-\pi < \Phi < \pi$) and ($0 < \Theta < \pi$) to look around the spectrum peak of (8) where the azimuth and elevation of each URA is located.

B. Spatial spectrum fusion

B.1 Calculate the set of angles of each position p in the search grid

Before starting the data fusion procedure, the fusion center needs to know the position of each point relative to each sensor in the search grid. The search grid is set to vary between $(x_{g_0}, y_{g_0}, z_{g_0})$ and $(x_{g_f}, y_{g_f}, z_{g_f})$. Assuming that the reference AP is placed in the position $G_0(x_0, y_0, z_0)$ where the p-th sensor array coordinates is $G_p(x_p, y_p, z_p)$ proportional to the reference sensor in the search grid. The set of each angle in the whole scanning grid corresponding to each array can be calculated as follows:

for $i = x_{g_0} : x_{g_f}$
  for $j = y_{g_0} : y_{g_f}$
    for $l = z_{g_0} : z_{g_f}$

$$set\_\Phi_p = \arctan\frac{y_j - y_p}{x_i - x_p} \quad (9)$$

$$set\_\Theta_p = \arccos\frac{z_l - z_p}{\Delta r_p} \quad (10)$$

$$\Delta r_p = \sqrt{(x_i - x_p)^2 + (y_j - y_p)^2 + (z_l - z_p)^2} \quad (11)$$

    end
  end
end

Where Δr_p is the distance between the p-th sensor and the i-th position of the grid.

B.2 Spectrum Fusion

From (9) and (10), we can observe that the set of angles set_Φ_p and set_Θ_p represents matrices that contain the azimuth and elevation angles for all possible points in the search grid corresponding to the position of each AP.

Now, the target position estimating problem comes down to find the maximum of the spectrum, which is a combination of spatial spectrums of (8) $(P_1(p), P_2(p), \ldots, P_P(p))$, where the position coinciding to the minimum error between each estimated point in the search grid and every angle in the searching area ($-\pi < \rho < \pi$) is situated.

The target position estimation can be expressed by the following formula:

$$p_{target_{est}} = \arg\max_{p}\left\{\arg\min_{p}\left(\sum_{p=1}^{P} P_p\left(P_{err_{\Phi_p}}, P_{err_{\Theta_p}}\right)\right)\right\} \quad (12)$$

$$P_{err_{\Phi_p}} = \text{abs}\left(set_{\Phi_p} - \Phi_\rho\right) \le \varepsilon \quad (13)$$

$$P_{err_{\Theta_p}} = \text{abs}\left(set_{\Theta_p} - \Theta_\rho\right) \le \varepsilon \quad (14)$$

Where $P_{err_{\Phi_p}}$ and $P_{err_{\Theta_p}}$ are the errors between each set position and every azimuth and elevation angles respectively in the searching area. ε is the threshold. The 2D-SSF can be generalized along the lines shown in Figure 2.

1. ***Compute the covariance matrix of the observed spatial output data at each sensor using (6).***
2. ***Decompose (1) into signal and noise subspaces using (7).***
3. ***Use MUSIC algorithm in (8) to get the azimuth and elevation angles of each array.***
4. ***Calculate the set of each position p in the search grid.***
   for $i = x_{g_0} : x_{g_f}$
     for $j = y_{g_0} : y_{g_f}$
       for $l = z_{g_0} : z_{g_f}$
         $\boldsymbol{set\_\Phi_p = Use\ (9)}$
         $\boldsymbol{set\_\Theta_p = Use\ (10)}$
         $\boldsymbol{with\ \Delta r_p\ in\ (11)}$
       end
     end
   end
5. ***Transfer the obtained data to the fusion center and compute the minimum errors between each set position and every azimuth and elevation angles respectively in the searching area using (13) and (14).***
6. ***Get the position of the target using (12).***

Figure 2. The 2D-SSF procedures needed for target positioning.

IV. SIMULATION RESULTS AND DISCUSSION

We consider an indoor environment with dimensions length=20m, width=20m and height=20m contain four APs such that each consists of 4 antenna arrays with half wavelength distance and uniform rectangular geometry is placed inside. The reference sensor is positioned at $A_1(0,0,0)$ whereas the remaining three sensors placed at $A_2(20,0,0)$, $A_3(0,20,0)$ and $A_4(20,20,20)$.The position of

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the target is P (11, 20, 5) and the number of multipath signals Q= 6. Some obstacles are taken to be placed in the middle of the AP and the target such that no LOS signal exists whereas the others are placed away from the middle. SNR = 5 dB and the sample number is set to be 200 samples. All simulation results obtained using MATLAB R2015a.

Firstly, we consider the case where all APs are able to see the target directly, i.e., the LOS signal between the source signal and each array exists. From Figure 3, the resulting angles (Φ, Θ) of each array are (76.6°, 60.8°), (-3.2°, 23°.4), (-51.8°, 66.4°) and (-0.4°, 120.8°). Compared with the actual angles in Figure 3, the highest error difference between the azimuth ones is in array 2 (about 3 degrees difference) whereas almost 1 degrees error difference in elevation corresponding to array1 and this can improve the additional support of the elevation angle for more target position estimation accuracy during the application of the fusion process.

Figure 4 presents spectrums resulted from the fusion of the spatial spectra of Figure 3. The maximum values of the obtained spectra represent the estimated position of the source signal. From the left side of Figure 4, we can observe that the obtained horizontal coordinates are 10.4 m and 19.4 m while the vertical position (height) of the target is 5.2 m

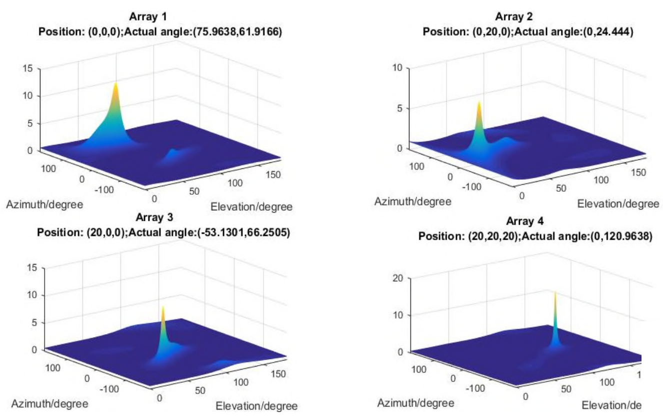

Figure 3. Music spectrums for the four arrays, SNR=5 dB, N=4 antennas.

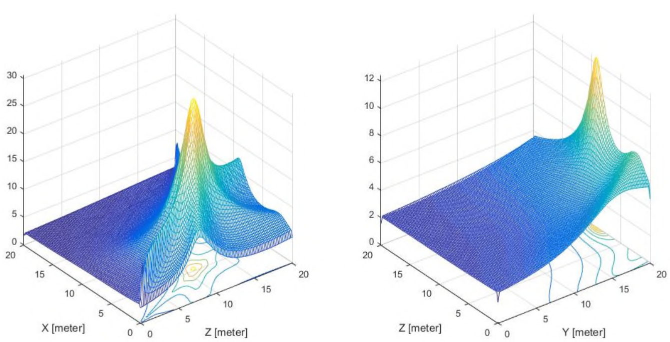

Figure 4. The estimated (x,y,z) coordinates of the target position using the 2D-SSF method. SNR=5 dB, N=4 antennas.

according to the right part of Figure 4. Compared to the actual location of the source (11, 20, and 5) m, the location estimation error is reliable thus can prove the important localization accuracy achievement of the 2D-SSF algorithm certainly in Low SNR.

Now we examine the performance of the 2D-SSF in terms of root mean square error (RMSE) in different LOS and NLOS scenarios (Figure 5). 50 Monte Carlo simulations were carried out. We observe that the RMSE decreases with the increasing number of the LOS APs. For low SNR (-10 dB) the RMSE of the 5 cases varies between 2 and 2.5 meters whereas in high SNR (20 dB) the localization performance improved until 0.1373 m error when the LOS signals can be seen by the whole APS whilst the difference gap between the first and the last case is still reliable (almost 1 meter). When a group of arrays is disorganized with the NLOS signals, the aid of the Aps, which consider the LOS signal is used, we can remark that for the cases of 1AP LOS, 2AP LOS and 3AP LOS with RMSE below than 1 meter and this gives an important point in real applications when a couple of WiFi systems are blocked with massive obstacles, so the placement of the APS should be reliable such that the chance of the LOS signal between the WiFi systems and the user would be dominant.

In order to compare the performance of the 2D-SSF with the traditional approaches, we test the estimation of angles relative to each antenna arrays by using the classical MUSIC algorithm and the 2D-SSF algorithm in terms of RMSE. We consider the case where the target is able to be seen by 2 APs. According to Figure 6, it is obvious that the advocated method outperforms the MUSIC algorithm. From SNR= -10dB to SNR= 20 dB, the RMSE for 2D-SSF decreases slightly and tend to 0 dB in very high SNR while although the SNR is high the MUSIC method cannot give reliable angles estimation for both azimuth and elevation (about 3° error) and this is due to the NLOS environment. Moreover, the error estimation for angles of the 2D-SSF in low SNR (2.5°, 2.1°) is even better than

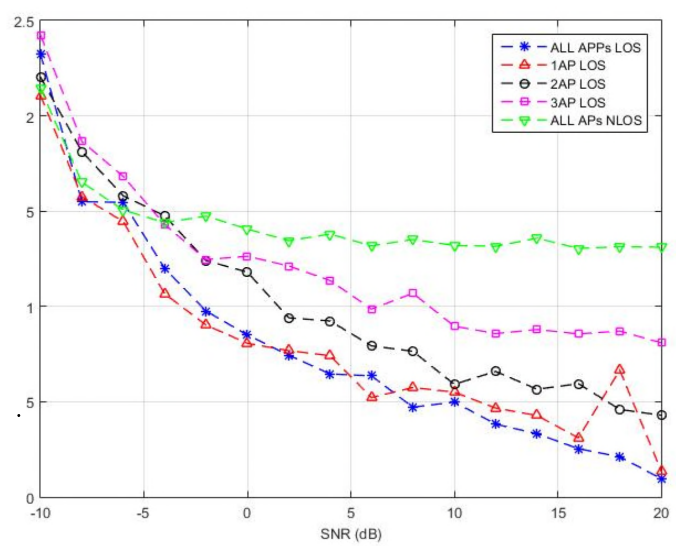

Figure 5. RMSE (distance) for different APs LOS/NLOS scenarios using the 2D-SSF method.

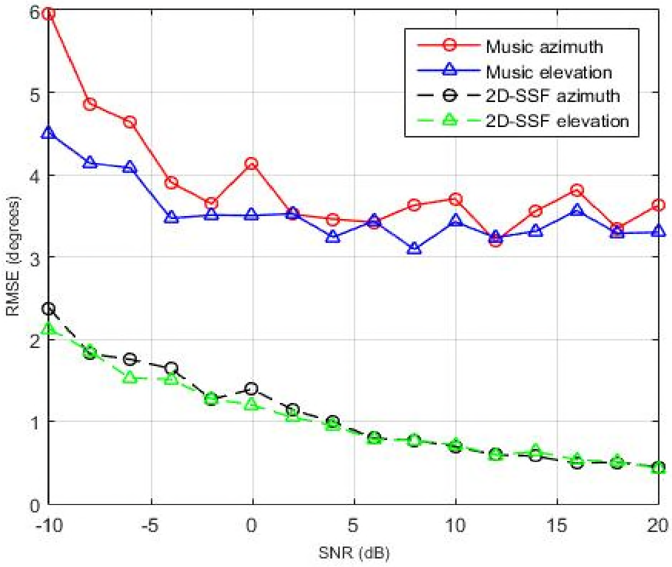

Figure 6. Angles (azimuth and elevation) estimation comparison between MUSIC and the 2D-SSF method.

the estimation of the MUSIC in High SNR (3.4°, 3.1°).

The outperformance of the advocated method is represented in the usage of multi-sensor in addition of that the estimation of the elevation angles of each array that enhance the accuracy of the location of the sensor, hence, the target position.

Here, the performance of the 2D-SSF approach is tested according to the change in the number of antennas at the sensors. The same situation for the target and the sensors is taken as before. It is evident from Figure 7 that the increase in the number of antennas at each AP gives a significant enhancement for the target localization. At SNR=-10 dB there is a considerable decrease in the estimated distance error from 2.3 meters using 4 antennas to 0.7 meters using 16 antennas While the RMSE for using 16 antennas tends to 0 meters at high SNR.

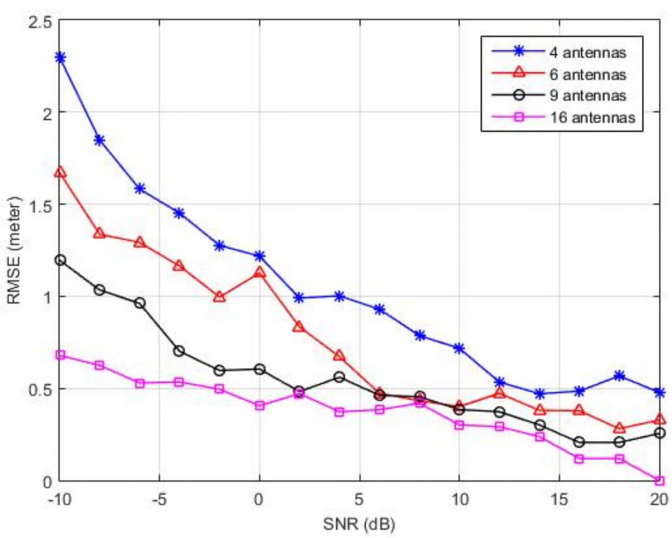

Figure 7. RMSE (distance) for a different number of antennas at each sensor using the 2D-SSF method.

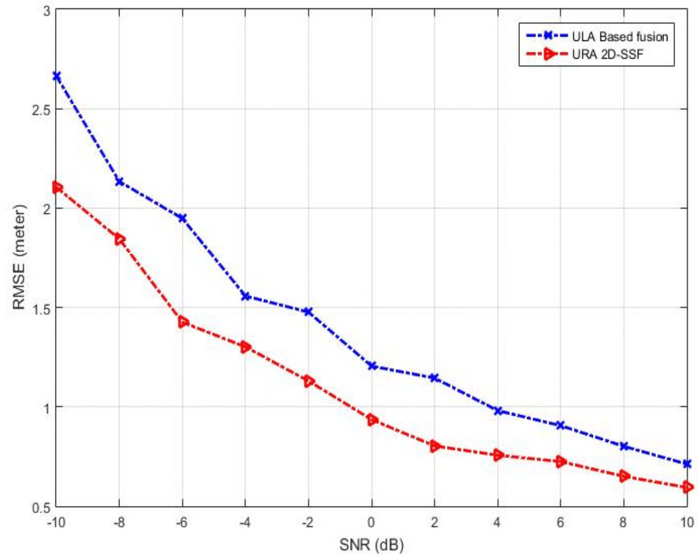

Figure 8. Comparison between ULA based fusion method [13] and the 2D-SSF localization method.

In the final part, the 2D-SSF is compared with the 1-D localization algorithm based fusion method used in [10]. We use the same parameters for the two algorithms during the source location estimation process. According to Figure 8, the change in the geometry of antennas to the 2-D array at each AP results in considerable enhancement of the error difference between the RMSE of the two used algorithms such that in SNR=-10 dB the difference error between the two curves is about 56 centimeters. However, the performance of the two methods attends to be the same as the SNR is higher, obviously, when SNR=10 dB the difference in error reaches 20 centimeters.

V. CONCLUSION

In this paper, 2D multiple sensors based on spatial spectrum fusion estimation algorithm was investigated. Under an indoor environment, the use of multiple sensors with the proposed fusion method in addition of that the change in the geometry of the antennas to URA at each sensor gave a significant improvement in source localization. Simulation results showed that the performance of the 2D-SSF method can be changed according to the used number of antennas at each sensor, the placement of the APs in the monitoring area, and the selected SNR. Moreover, the considerable outperformance of the 2D-SSF compared with traditional and 1-D based source localization methods has been proved.

As future work, the proposed algorithm will be implied to the real environments along with real data and extra massive obstacles, which can lead to the elimination of most LOS signals. Also, the modification of the 2D-SSF might be done by considering the Time of Arrive (TOA) based localization approach for more positioning accuracy.

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