Detection of An Unknown Radio Transmitter Using Joint RSSD and AoA Information Based on Factor Graph

Liyang Zhang[1], Taihang Du[1], and Cheng-Xiang Wang[2]
[1]School of Control Science and Engineering, Hebei University of Technology, Tianjin 300130, China.
[2]Institute of Sensors, Signals and Systems, School of Engineering & Physical Sciences, Heriot-Watt University, Edinburgh, EH14 4AS, U.K.
Email: zlysghr@163.com, thdu@hebut.edu.cn, cheng-xiang.wang@hw.ac.uk

***Abstract*—This paper proposes a new geo-location algorithm to improve the accuracy of the positioning estimation of an unknown radio transmitter. We utilize received signal strength difference (RSSD) and angle of arrival (AoA) with the factor graph (FG) technique, the so-called RSSD-AoA-FG algorithm, to attain higher positioning accuracy. With the proposed algorithm, we can not only estimate the location of an unknown radio transmitter and eliminate the error effect from heterogeneous radio transmitting devices but also avoid ignoring the important AoA information of the radio transmitter. The simulation results show that RSSD-AoA-FG algorithm can obtain the best positioning performance compared with the RSSD-FG and AoA-FG techniques.**

***Index Terms*—Radio transmitter detection, received signal strength difference (RSSD), position location, factor graph, angle of arrival (AoA).**

I. Introduction

With the development of science and technology, mobile computing has been more and more popular. It has become a research hot-spot, and position location (PL) service is one of the services offered by mobile computing. Currently, the complex and various kinds of radio signals have existed in daily life. To strengthen the management of radio signals and make an orderly and efficient use of radio spectrum sources is urgently to be solved. Besides, it relates to the production security and privacy of country, enterprises and individuals.

Detection of unknown radio transmitter is an important work in radio management, which is an important link to protecting the rights of lawful users and cracking down on the illegally occupied radio resources. Currently, the positioning techniques are mainly based on measurements collected from the signal access point (AP) for example time of arrival (ToA) [1], time difference of arrival (TDoA) [2], [3], AoA [4], received signal strength (RSS) [5], [6] and their combination [7]– [9]. Among all of them, the RSS-based location fingerprint positioning technique is famous on the cost-effective without no extra equipment, an antenna array and time synchronization. Reference [10] proposed a robust RSSD location fingerprint to mitigate the effects of hardware variations when the testing devices are different from the training devices. However, due to the effect of multi-path and shadowing, only using the RSS or RSSD information has poor accuracy. This paper adopts joint RSSD-AOA approach to improve the PL accuracy.

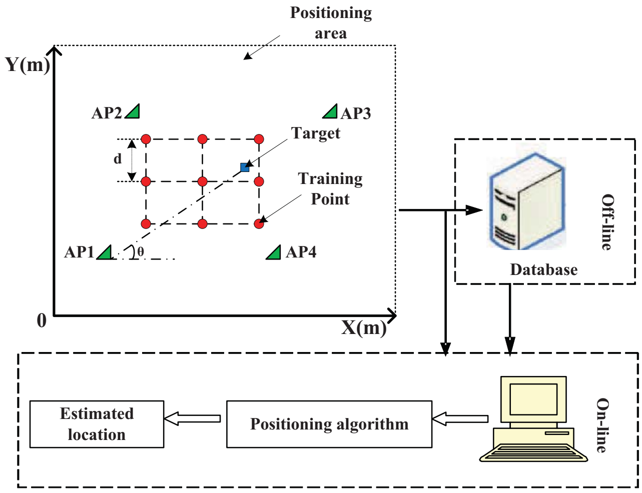

Fig. 1. The structure of proposed positioning system with 4 APs and an unknown radio tansmitter (target).

The FG technique, which is first introduced by [11], has an advantage of high accuracy and low computational complexity among all the positioning algorithms. Since there are many kinds of measurements as described above, a variety of FG-based positioning techniques have been developed in recent years, such as ToA-FG [12], [13], TDoA-FG [14], AoA-FG [15] and RSS-FG [16]. The ToA-FG technique relies on the synchronic time between the signal transmitter and AP. The TDoA-FG technique can avoid the synchronization of target and AP, but it also needs the synchronization between reference nodes. And both of the two techniques are suitable for line-of-sight (LoS) scenario. The AoA-FG employs real-time measuring angles of the AP from the emitter without requiring appropriate synchronization, emitter power and time stamp. However, since none line-of-sight (NLoS) and multi-path influence, the positioning accuracy will be greatly affected. The RSS-FG is proposed to against this condition, because RSS contains the resultant information. While it not only ignores the important angle information from the emitter but also requires the knowledge of the radio transmit power. Due

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to the detecting target is an unknown radio transmitter, we cant obtain the power information in advance. Thus, the RSS-FG technique is unable to locate the unknown radio transmitters. Reference. [17] proposes RSSD-FG technique using RSSD measurements as the fingerprint to achieve the detection of unknown radio emitter, but it ignores the AoA information.

In this paper, instead of using either RSSD or AoA individually, we proposed a new factor graph model employing RSSD and AoA measurements to estimate the location of an unknown radio transmitter. Using RSSD as the fingerprint to construct the database can not only locate the unknown radio transmitter but also can eliminate the influence of heterogeneity from the different signal emitters which will be introduced in the next section. The basic structure of the proposed RSSD-AoA-FG positioning system is as shown in Fig. 1. First, the positioning area is divided into many equal squares which length of side is d. Then, we use a specific radio transmitter to collect the RSS samples with four APs at each training point to establish the off-line RSSD fingerprint database. Second, the real-time RSS and AOA measurements of the radio emitter are recorded in the on-line stage. Finally, we utilize the RSSD-AoA-FG algorithm to calculate and achieve the precise location of the target.

The structure of this paper is described as follows. We introduce the established joint RSSD-AoA-FG model in Section II. Next, the detail iteration of the proposed algorithm is derived in Section III. In Section IV, the positioning performance is compared with different PL algorithms.

II. PROPOSED RSSD-AoA-FG MODEL

In this section, we introduce how the proposed RSSD-AoA-FG model is used to calculate the location of an unknown radio transmitter. As shown in Fig. 2, the proposed factor graph model consists two kinds of nodes, the factor nodes (A_i, B_i, C_i, D_i, E_i, F_i, P_i, and P_j and the variable nodes (p_i, p_j, R_i, θ_i, d_x, d_y, x, and y) ,where i and j are the index of AP (i, j = 1, 2, ... , n). The combination of i and j is ”12, 23, 34, 41” in this paper. The input measurements, p_i, p_j, and θ_i, transport the information through the factor node by using the specific local functions. The result of estimated location will be achieved after a few iterations and the process is among the source factor nodes and the variable nodes. Finally, the root variable nodes, x and y, combine with the soft-information of all the connected factor nodes based on the sum-product algorithm.

We assume that (x,y) and (x_i,y_i) are the location of the unknown radio transmitter and AP respectively. Thus, dx_i and dy_i are the relative distances between the target and i-th AP, given by

$$\begin{bmatrix} dx_i \\ dy_i \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix} - \begin{bmatrix} x_i \\ y_i \end{bmatrix}. \tag{1}$$

In Fig. 2, p_i, p_j, and θ_i are the error-free measurements of RSS and AoA with i-th and j-th AP. They can be obtained by averaging a lot of sample values at each training point.

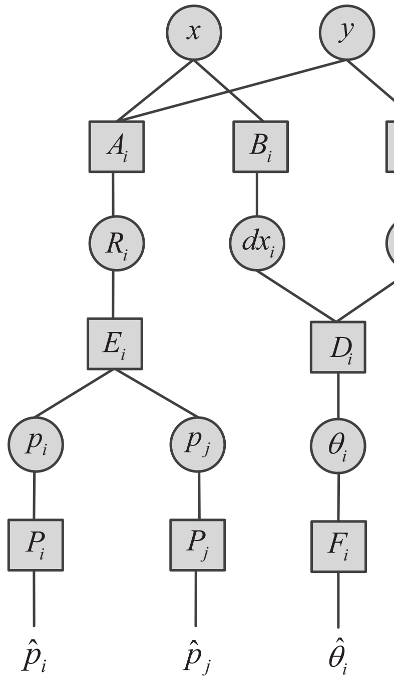

Fig. 2. The proposed RSSD-AOA-based factor graph model.

We select 100 samples in this paper. When an unknown radio transmitter enters the positioning area, the AP will record the RSS and AoA measurements and they can be expressed as

$$\hat{p}_i = \tilde{p}_i + e_{p_i} \ , \tag{2}$$

$$\hat{R}_i = \hat{p}_i - \hat{p}_j, \tag{3}$$

and

$$\hat{\theta}_i = \tilde{\theta}_i + e_{\theta_i}. \tag{4}$$

where $\widehat{R}_i$ is the subtraction of any i-th AP and j-th AP in terms of any one training point. In equation (2) and (4), e_{p_i} and e_{θ_i} are zero-mean Gaussian random variables. They follow normal distribution $N(0, \sigma_{p_i}^2)$ and $N(0, \sigma_{\theta_i}^2)$ respectively. Due to the multi-path effect, small scale fading, system hardware influence, and measurement errors, σ_{p_i} and σ_{θ_i} represent the measurement errors. We assume that the $\hat{p}_i$ and $\hat{\theta}_i$ follow the normal distribution so as do in [10]. Then, $\hat{p}_i$ and $\hat{\theta}_i$ obey the normal distribution $N(\tilde{p}_i, \sigma_{p_i}^2)$ and $N(\tilde{\theta}_i, \sigma_{\theta_i}^2)$, where $\tilde{p}_i$ and $\tilde{\theta}_i$ are the mean of measurement samples. In addition, there is a geometric relationship between the relative distances dx_i, dy_i, and θ_i in the factor node D_i as

$$\begin{bmatrix} dx_i \\ dy_i \end{bmatrix} = \begin{bmatrix} dy_i \cdot \cot(\theta_i) \\ dx_i \cdot \tan(\theta_i) \end{bmatrix}. \tag{5}$$

According to the log-normal shadowing model [18], we denote that $P(d_0)$, $P(d_i)$, and $P(d_j)$ in units of dBm are the RSS at distance d_i and d_j from the radio emitter to i-th and j-th AP. d_0 is a reference distance. The relationship between the $P(d_0)$, $P(d_i)$, and $P(d_j)$ can be written as

$$P(d_i) = P(d_0) - 10 \cdot \alpha \cdot \log\left(\frac{d_i}{d_0}\right) + \chi_i \tag{6}$$

and

$$P(d_j) = P(d_0) - 10 \cdot \alpha \cdot \log\left(\frac{d_j}{d_0}\right) + \chi_j \tag{7}$$

where α is the pass loss component, χ_i and χ_j represent the variations of RSS, which obey zero-mean Gaussian distribution. Considering the free space propagation model [19] as follows

$$P(d_0) = 10\log(\frac{P_t G_t G_i \lambda^2}{(4\pi)^2 {d_0}^2 L_i}) \tag{8}$$

where P_t is the power of radio transmitter, G_t is transmitted antenna gain, G_i is the i-th AP's antenna gain, L_i is the system loss factor, and λ is the emitter carrier's wavelength. According to (6) and (7), we can get the RSS of i-th AP and j-th AP respectively as

$$P(d_i) = 10\log(\frac{P_t G_t G_i \lambda^2}{(4\pi)^2 {d_0}^2 L_i}) - 10 \cdot \alpha \cdot \log(\frac{d_i}{d_0}) + \chi_i \tag{9}$$

and

$$P(d_j) = 10\log(\frac{P_t G_t G_j \lambda^2}{(4\pi)^2 {d_0}^2 L_j}) - 10 \cdot \alpha \cdot \log(\frac{d_j}{d_0}) + \chi_j. \tag{10}$$

From (9) and (10), the RSSD from i-th and j-th AP can be calculated by

$$P(d_i) - P(d_j) = 10\log(\frac{G_i L_j}{G_j L_i}) + 10\log(\frac{d_j}{d_i}) + (\chi_i - \chi_j). \tag{11}$$

As we can see from (11), the RSSD does not suffer from the influence of diverse radio transmitters. Therefore, if the AP remains the same, we do not need to establish the location fingerprint database again in terms of radio emitters. Moreover, it can greatly reduce the workload.

Next, we derive the relationship between the RSSD and the location coordinate of training points (x_l,y_l), where l is the index of training point. For any one of the AP sensors at each training point, the approximated hyperplane equation of (x_l,y_l) and $\hat{R}_i$ is expressed as

$$k_x \cdot x_l + k_y \cdot y_l + k_p \cdot \hat{R}_i = c \tag{12}$$

where k_x, k_y, and k_p are the coefficients and c is a non-zero constant set to one in this paper. Thus, this equation can be solved by using least square (LS) approach as in [16]. To determine the needed four training points, we utilize 4-Nearest Neighbor technique to seek the appropriate training points in this work. Since the error-free RSSD measurements and the location of the four training points are known, coefficients of the equation can be easily calculated by

$$\begin{cases} k_x \cdot x_1 + k_y \cdot y_1 + k_p \cdot \hat{R}_1 = 1 \\ k_x \cdot x_2 + k_y \cdot y_2 + k_p \cdot \hat{R}_2 = 1 \\ k_x \cdot x_3 + k_y \cdot y_3 + k_p \cdot \hat{R}_3 = 1 \\ k_x \cdot x_4 + k_y \cdot y_4 + k_p \cdot \hat{R}_4 = 1 \end{cases}. \tag{13}$$

Hence, the coefficients can be obtained by (13), and we can replace the (x_l,y_l,$\widehat{R}_i$) with the location coordinate of target (x,y) and real-time relevant measurement R_i of the unknown radio transmitter with i-th and j-th AP. It can be expressed as

$$k_x \cdot x + k_y \cdot y + k_p \cdot R_i = 1. \tag{14}$$

However, we need initial value of dx_i and dy_i, which are corresponding to the location of target (x, y). The entire iteration will be introduced in next section.

III. SOFT-INFORMATION CALCULATION AND ITERATION PROCESS

In this section, we introduce that how to calculate the soft-information and the detail of iteration process. We denote $SI(a, b)$ being the soft-information from node a to node b, which represents the statistical properties of the estimated variables and measurement errors in the form of a Gaussian PDF in this paper. The mean and variance of $SI(a, b)$ are $m_{a,b}$ and $\sigma^2_{a,b}$ respectively. Note that the variable nodes (x and y) to factor nodes (A_i, B_i, and C_i) which process the initial soft-information should be calculated at first. According to the sum-product algorithm [20], $SI(x, A_i)$, $SI(x, B_i)$, $SI(y, A_i)$), and $SI(y, C_i)$ are given by

$$SI(x, A_i) = \prod\nolimits_{j \neq i}^{n} (A_j, x) \prod\nolimits_{i=1}^{n} (B_i, x), \tag{15}$$

$$SI(x, B_i) = \prod\nolimits_{j \neq i}^{n} (B_j, x) \prod\nolimits_{i=1}^{n} (A_i, x), \tag{16}$$

$$SI(y, A_i) = \prod\nolimits_{j \neq i}^{n} (A_j, y) \prod\nolimits_{i=1}^{n} (C_i, y), \tag{17}$$

and

$$SI(y, C_i) = \prod\nolimits_{j \neq i}^{n} (C_j, y) \prod\nolimits_{i=1}^{n} (A_i, y). \tag{18}$$

Taking an example of $SI(x, A_i)$, its mean and variance can be obtained by

$$\sigma^2_{x,A_i} = 1/(\sum_{i=1}^{n} \frac{1}{\sigma^2_{B_i,x}} + \sum_{j \neq i}^{n} \frac{1}{\sigma^2_{A_j,x}}) \tag{19}$$

and

$$m_{x,A_i} = \sigma^2_{x,A_i}(\sum_{i=1}^{n} \frac{m_{B_i,x}}{\sigma^2_{B_i,x}} + \sum_{j \neq i}^{n} \frac{m_{A_j,x}}{\sigma^2_{A_j,x}}). \tag{20}$$

In the same way, the soft-information $SI(x, B_i)$, $SI(y, A_i)$ and $SI(y, C_i)$ can also be calculated. According to (13), the factor node A_i to variable node x passes the message $SI(A_i, x)$ can be calculated by

$$m_{A_i,,x} = (1 - k_y \cdot m_{y,A_i} - k_p \cdot m_{R_i,A_i})/k_x \tag{21}$$

and

$$\sigma^2_{A_i,x} = (k_y^2 \cdot \sigma^2_{y,A_i} + k_p^2 \cdot \sigma^2_{R_i,A_i}). \tag{22}$$

With the similar manner, $SI(A_i, y)$ can be obtained. The message passing from variable node R_i to factor node A_i is equal to E_i to variable node R_i, where $m_{R_i,A_i} = m_{E_i,R_i}$, $\sigma^2_{R_i,A_i} = \sigma^2_{E_i,R_i}$.

From (3), the calculation of $SI(E_i, R_i)$ is given by

$$m_{E_i,R} = m_{p_i,E_i} - m_{p_j,E_i} \tag{23}$$

and

$$\sigma^2_{E_i,R_i} = \sigma^2_{p_i,E_i} + \sigma^2_{p_j,E_i}. \tag{24}$$

The node P_i and P_j directly forwards the message to node E_i respectively, where $m_{p_i,E_i} = m_{P_i,p_i}$, $\sigma^2_{p_i,E_i} = \sigma^2_{P_i,p_i}$ and $m_{p_j,E_j} = m_{P_j,p_j}$, $\sigma^2_{p_j,E_j} = \sigma^2_{P_j,p_j}$. $SI(P_i, p_i)$ and $SI(P_j, p_j)$ can be directly obtained by (2). In the same way, $SI(p_j, E_i)$ can be obtained.
From (1), the message contained in the node B_i and C_i are converted to the variable node by

$$\begin{cases} m_{B_i,x} = m_{dx_i,B_i} + x_i, \sigma^2_{B_i,x} = \sigma^2_{dx_i,B_i} \\ m_{C_i,y} = m_{dy_i,C_i} + y_i, \sigma^2_{C_i,y} = \sigma^2_{dy_i,C_i} \end{cases}. \tag{25}$$

Next, the factor node D_i transports the soft-information to nodes B_i and C_i, where $m_{d_x,B_i} = m_{D_i,d_x}$, $\sigma^2_{d_x,B_i} = \sigma^2_{D_i,d_x}$ and $m_{d_y,C_i} = m_{D_i,d_y}$, $\sigma^2_{d_y,C_i} = \sigma^2_{D_i,d_y}$. According to (5), $SI(D_i, d_x)$ and $SI(D_i, d_y)$ can be calculated using the first-order Taylor series approximation and the product of two independent random variables by

$$\begin{cases} m_{D_i,dx_i} \approx m_{dy_i,D_i} \cdot \cot(m_{\theta_i,D_i}) \\ \sigma^2_{D_i,dx_i} \approx m^2_{dy_i,D_i} \cdot \sigma^2_{\theta_i,D_i} \cdot \csc\left(m_{\theta_i,D_i}\right)^4 \\ \qquad + \sigma^2_{dy_i,D_i} \cdot \sigma^2_{\theta_i,D_i} \cdot \csc\left(m_{\theta_i,D_i}\right)^4 \\ \qquad + \sigma^2_{dy_i,D_i} \cdot \cot\left(m_{\theta_i,D_i}\right)^2 \end{cases} \tag{26}$$

and

$$\begin{cases} m_{D_i,dy_i} \approx m_{dx_i,D_i} \cdot \tan(m_{\theta_i,D_i}) \\ \sigma^2_{D_i,dx_i} \approx m^2_{dy_i,D_i} \cdot \sigma^2_{\theta_i,D_i} \cdot \csc\left(m_{\theta_i,D_i}\right)^4 \\ \qquad + \sigma^2_{dx_i,D_i} \cdot \sigma^2_{\theta_i,D_i} \cdot \sec\left(m_{\theta_i,D_i}\right)^4 \\ \qquad + \sigma^2_{dx_i,D_i} \cdot \tan\left(m_{\theta_i,D_i}\right)^2. \end{cases}. \tag{27}$$

In (26) and (27), m_{θ_i,D_i} and $\theta^2_{\theta_i,D_i}$ are from the measurements of AoA. The variable node dx_i directly forwards the soft-information to the node x ,where $SI(B_i, x) = SI(dx_i, B_i)$. And the node dy_i forwards the message to y, where $SI(C_i, y) = SI(dy_i, C_i)$.
As mentioned above, all the soft-information has been calculated with the sum-product algorithm and the entire iteration process will be repeated until the precise location of target is obtained. Finally, the soft-information of $SI(x)$ and $SI(y)$ can be updated by

$$\sigma^2_x = 1/\left(\sum_{i=1}^{n} \frac{1}{\sigma^2_{A_i,x}} + \sum_{i=1}^{n} \frac{1}{\sigma^2_{B_i,x}}\right), \tag{28}$$

$$m_x = \sigma^2_x \cdot \left(\sum_{i=1}^{n} \frac{m_{A_i,x}}{\sigma^2_{A_i,x}} + \sum_{i=1}^{n} \frac{m_{B_i,x}}{\sigma^2_{B_i,x}}\right), \tag{29}$$

$$\sigma^2_y = 1/\left(\sum_{i=1}^{n} \frac{1}{\sigma^2_{A_i,y}} + \sum_{i=1}^{n} \frac{1}{\sigma^2_{C_i,y}}\right), \tag{30}$$

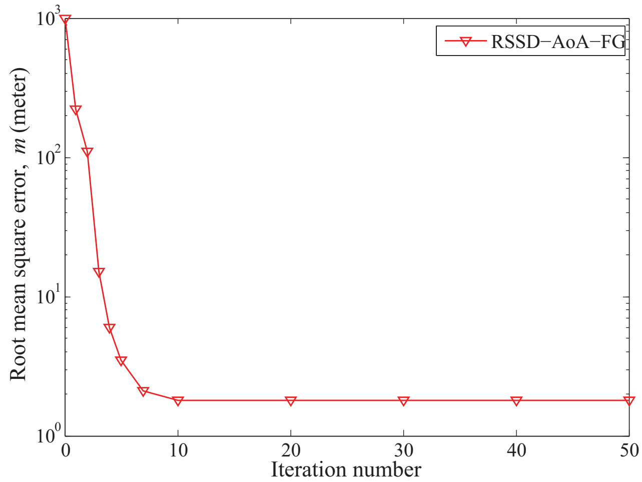

Fig. 3. Root mean square error of RSSD-AoA-FG with the iteration changing from 0 to 50 times with fixed power at 1.2×10^{-5} watt and angle at 27°.

and

$$m_y = \sigma^2_y \cdot \left(\sum_{i=1}^{n} \frac{m_{A_i,y}}{\sigma^2_{A_i,y}} + \sum_{i=1}^{n} \frac{m_{C_i,y}}{\sigma^2_{C_i,y}}\right). \tag{31}$$

From (28) to (31), the estimated location of the unknown radio transmitter is determined by m_x and m_y.

IV. SIMULATION RESULTS

The positioning performance of proposed algorithm is verified through the computer simulation. In order to achieve the better comparison, we select two algorithms RSSD-FG and AoA-FG. The simulation scenario covers 1000 random target locations within 100×100 m^2. We use four APs (AP1-AP4) which locate at (17, 25) m, (43, 75) m, (67, 25) m, and (83, 75) m respectively. And the total iteration is 50 times.

At the beginning, a round target-location is obtained by using 4-Nearest Neighbour technique since the RSS-FG and RSSD-FG algorithms need the initial guess. However, our proposed algorithm only need to set the initial location optionally, which is (1, 1) m in this paper. In this simulation, we use the log-normal shadowing model to emulate the off-line random RSS measurement p from the i-th AP to each training point and the real-time RSS as [16]. The mean of the AoA measurements can be obtained by the geometric relationship between the target and AP. In addition, there are two types of standard measurement errors are needed, which are standard variance of RSS measurement errors ranging from 0.5×10^{-5} watt to 1.5×10^{-5} watt and standard variance of AoA measurement errors ranging from 0 to 45°.

As it is shown in Fig. 3, the proposed RSSD-AoA-FG algorithm obtains good accuracy performance. And with the increase of the number of iterations, positioning accuracy can be rapidly increased and convergence at fixed power 1.2×10^{-5} W and at fixed angle 27°.

When the standard deviation (STD) of AoA measurement error is stationary and STD of RSS changing within a

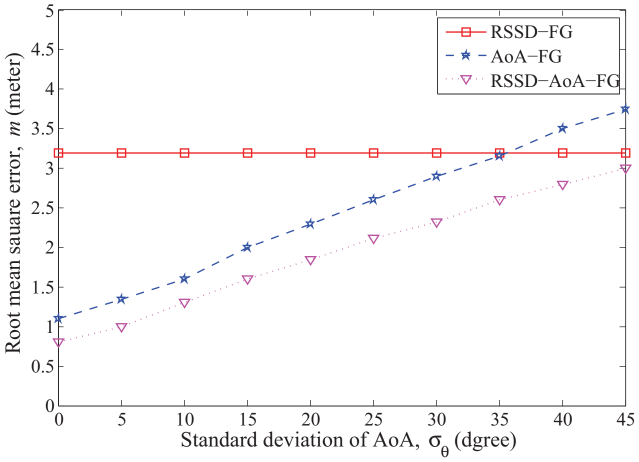

Fig. 4. Root mean square error comparison among RSSD-FG, AOA-FG, and RSSD-AoA-FG with fix standard deviation power at 0.7×10^{-5} watt.

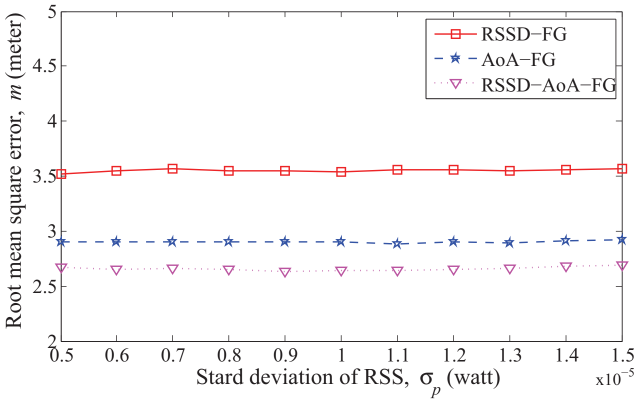

Fig. 5. Root mean square error comparison among RSSD-FG, AOA-FG, and RSSD-AoA-FG with fix standard deviation angle at 27°.

certain range, the RSSD-AoA-FG has the better positioning performance than the RSSD-FG and AoA-FG techniques. Fig.5 shows that the proposed technique also has higher stability and position accuracy than the other two algorithms at fixed power.

V. CONCLUSIONS

In this paper, we have proposed a novel RSSD-AoA-FG technique to estimate the location of an unknown radio transmitter based on factor graph and sum-product algorithm. A new joint RSSD-AoA positioning model has been established with factor graph to simplify the detection of the unknown radio transmitter issue. Considering the stochastic properties of RSS and AoA measurement errors, RSSD-AoA-FG method can achieve better position performance than RSSD-FG and AoA-FG when only using one of the measured parameters.

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