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A Semi Range-Based Iterative Localization Algorithm for Cognitive Radio Networks

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***Abstract*—In cognitive radio networks, knowledge of the position of the primary users is very important as it can be used to avoid harmful interference to the primary users, while at the same time be exploited to improve the spectrum utilization. In this paper, a semi range-based localization algorithm is proposed for the secondary users in cognitive radio networks to estimate the positions of the primary users. The basic idea of the proposed algorithm is to take advantage of the estimated detection probabilities, which can be obtained from the binary detection indictors of the secondary users, in order to estimate the distances between themselves and the primary users. The accuracy of the proposed localization algorithm is further improved by introducing an iterative least squares algorithm. The Cramer-Rao lower bound of the mean square error of the proposed localization estimator is also derived. Extensive simulations will then show that the actual mean square error achieved by the proposed localization algorithm is reasonably close to the lower bound, which demonstrates that the proposed method is near optimal.**

I. Introduction

In cognitive radio networks (CRN) [1] [2], there are primary users (PUs), who are licensed users and have priority in using the licensed bands, and secondary users (SUs), who are capable of sensing the spectrum holes in the licensed bands and seek chance to access them. Given the interference ranges of PUs, the SUs at different locations in the CRN may perceive different profiles of spectrum holes due to their varying distances from the PUs. Hence, knowledge of the position information of the PUs is important for the SUs to identify their spectrum access opportunities and to avoid harmful interference to the PUs. This can further facilitate higher-level designs such as multi-hop routing. Localization [3]–[5] is a methodology that can be adopted to obtain such position information. Localization algorithms can typically be classified into two classes, i.e., range-free algorithms [3], [5] and range-based algorithms [4]. In the range-free algorithms, not enough information can be exploited to estimate the exact distance. In the range-based algorithms, on the other hand, it is assumed that the necessary information to estimate the distance can be provided by some estimation parameters such as RSS (received signal strength) and TDOA (time difference of arrival).

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Compared with traditional networks, the key difference in CRN is that the SUs should be transparent to PUs, which implies that there is no cooperation between the two parties during the localization process. The new challenges presented by CRN imply that most of the existing localization algorithms fail in this case. A very limited number of related works can be found in the literature. In our previous work [11], a high order geometric range-free algorithm was proposed for all SUs in CRN to cooperatively estimate a target PU's position. Even though a high order geometric calculation is applied, the accuracy of the algorithm is limited by its range-free nature.

To overcome the weakness of pure range-free algorithms in estimation accuracy and to avoid the tough requirement of the conventional range-based algorithms on physical layer equipments, in this paper, we propose a semi range-based localization algorithm for CRN. The "semi range-based" highlights the two key features of our proposed algorithm. Firstly, only the binary sensing results of the SUs are required, as in the range-free algorithms. Secondly, the detection probabilities of each SU, which can be obtained from their binary detection indictors respectively, are exploited to estimate the distances from each SU to the target PUs. Establishing the relationship between the detection probability and distance is the key idea behind our algorithm which makes it perform like a range-based algorithm. In other words, the major advantage of the proposed semi range-based algorithm is achieving the localization accuracy of range-based algorithms without requiring additional information compared with range-free algorithms. Extensive simulations will show that the mean square error under the proposed localization algorithm is reasonably close to the Cramer-Rao lower bound derived theoretically.

The rest of this paper is organized as follows. In Section II, the system model is introduced. In Section III, the proposed semi range-based localization algorithm is described in detail. The theoretical Analysis of the localization accuracy is given in Section IV. In particular, the Cramer-Rao lower bound is derived. Simulation results are presented and discussed in

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Section V and Section VI concludes the whole paper.

II. System Model

Consider a cognitive radio network consisting of N SUs and M PUs. It is assumed that the primary users operate on orthogonal channels and the number of channels is also M. We assume that SU nodes are uniformly distributed in the network, and that the positions of both the PUs and SUs are stationary during the localization process. The SUs only need to report their binary sensing results to a common receiver in each time slot using the protocol described later in this section without additional information (e.g., the detected energy). This common receiver will utilize these sensing results to perform the localization algorithm proposed in this paper. The algorithm is focusing on locating a certain primary user and hence, the positions of M primary users will be separately located by the common receiver.

A. Primary User Traffic Model

Each channel has two states, "busy" and "idle" [7]. We assume that the channel states are i.i.d. If the channel is occupied by a PU, then it is considered as "busy". Otherwise, it is "idle". The SUs is allowed to transmit data in "idle" state [8]. The durations of both the "busy" and "idle" states are assumed to follow the negative exponential distribution, which is adequate to characterize the traffic process in practice [12]. Therefore, the channel state can be modeled by a discrete-time 2-state Markov chain. Denote $p(q)$ as the probability that the channel will remain idle (busy) after one-step transition. Hence, the degree of primary user's traffic is $\beta = q/(p+q)$. That is, during a period of time T, the average time that the PU occupies the channel is βT.

B. Signal Detection Model

In order to protect the primary users from harmful interference, the SUs have to sense the spectrum prior to their transmissions to make sure that it is available at that time instance. In this paper, we assume that the SUs use the widely-used energy detection method to detect the primary user's signal. So the objective of spectrum sensing is to decide between the following two hypotheses:

$$y_n(t) = \begin{cases} \mathcal{H}_1 : h_n x(t) + w(t) \\ \mathcal{H}_0 : w(t) \end{cases} \quad 0 < t \le T, n = 1, 2, ..., N \quad (1)$$

where H_0 and H_1 represent the absence and presence of a primary user, respectively, $y_n(t)$ is the received signal at the node n on a certain channel during time T, and $x(t)$ is the transmitted signal from the primary transmitter of power A^2, $w(t)$ is the zero-mean additive white Gaussian noise (AWGN) with variance σ^2 and h_n is the amplitude gain of the channel. We also denote by γ_n the signal-to-noise ratio (SNR) at the n-th secondary user as $\gamma_n = \frac{|h_n|^2 A}{\sigma^2}$. The power attenuation is characterized by

$$h = k d_n^{-\alpha}, \quad (2)$$

where k is a constant depending on the transmitter and receiver antenna gain as well as the wavelength, d_n is the distance between node n and the primary user, and α is the path loss factor.

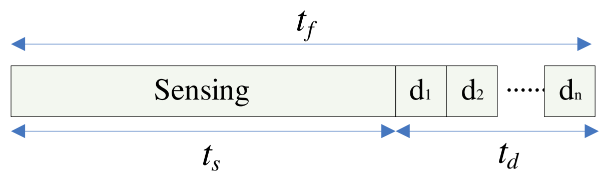

Fig. 1. Frame structure. t_f denotes the time length of a frame, and t_s and t_d denote the time length of the sensing and data transmission, respectively.

Let Y_n be the energy collected at the n-th receiver in a fixed bandwidth W during time T. Y_n can be shown to have the following distribution [10],

$$Y_n \sim \begin{cases} \mathcal{H}_0 : \chi^2_{2u} \\ \mathcal{H}_1 : \chi^2_{2u}(2\gamma_n) \end{cases}, \quad (3)$$

where $u = TW$, and χ^2_{2u} and $\chi^2_{2u}(2\gamma_n)$ denote the central and non-central chi-square distributions with $2u$ degree of freedom, respectively. And $2\gamma_n$ is the parameter for the latter one. where A_n is the square root of the received power at node n.

At the decision making stage of the energy detection, Y_n is compared with a pre-defined energy threshold λ. If $Y_n > \lambda$, the n-th secondary user assumes that the primary user is active on the spectrum sensed, i.e. the hypothesis $\mathcal{H}_1$ is true. Otherwise, $\mathcal{H}_0$ is assumed to be true.

The Rayleigh fading channel is considered in this paper. h_n includes both path-loss and small-scale Rayleigh fading coefficient g_n, i.e. $h_n = \sqrt{k d_n^{-\alpha}} g_n$, so the SNR at the n-th SU is $\gamma_n = \frac{k|g|^2 A}{d_n^\alpha \sigma^2}$, which is exponentially distributed with parameter

$$\bar{\gamma}_n = \frac{kA}{d_n^\alpha \sigma^2}. \quad (4)$$

In this case, the average probability of detection is hence given by [10]

$$\begin{aligned} P_D^{(n)} &= \mathbf{E}_{\gamma_n}\left[Pr\{Y_n > \lambda | \mathcal{H}_1\}\right] \\ &= e^{-\frac{\lambda}{2}} \sum_{k=0}^{u-2} \frac{1}{k!}\left(\frac{\lambda}{2}\right)^k + \left(\frac{1+\bar{\gamma}_n}{\bar{\gamma}_n}\right)^{u-1} \\ &\quad \times \left(e^{-\frac{\lambda}{2(1+\bar{\gamma}_n)}} - e^{-\frac{\lambda}{2}} \sum_{k=0}^{u-2} \frac{1}{k!}\left(\frac{\lambda\bar{\gamma}_n}{2(1+\bar{\gamma}_n)}\right)^k\right), \quad (5) \\ P_{FA}^{(n)} &= Pr\{Y_n > \lambda \mid \mathcal{H}_0\} \\ &= \frac{\Gamma\left(u, \frac{\lambda}{2}\right)}{\Gamma(u)}. \quad (6) \end{aligned}$$

Given the false alarm probability $P_{FA} = \epsilon$, the threshold γ is decided by (6). And then $P_D^{(n)}$ can be obtained.

C. Proposed MAC Protocol for SUs

A dedicated channel for cognitive radio networks is not required in this paper. Secondary users can sense the states of the channels and transmit data only on idle channels. The cooperative protocol is shown in Fig. 1. The data transmission period is used for SUs to transmit the signal detection results. We use the TDMA model in the communication protocol and the time slots for secondary users are scheduled before establishing the network.

III. Localization Algorithm

In this section, we propose a semi range-based iterative localization algorithm using the detection probabilities. First, we present the basic idea of this semi range-based algorithm with the Least Square method. Second, we use an iterative algorithm to estimate the degree of primary user's traffic β.

A. The range-based localization algorithm

We assume that SU nodes are uniformly distributed in the cognitive radio network. The nodes should perform periodic sensing to avoid harmful interference to the primary system [**?**], [12]. The cooperative sensing method allows them to share their sensing results to each other in order to improve the sensing accuracy. So sending out the sensing results, in the form of binary bits, is much more practical than providing the energy information. The distance between SUs and PU can be estimated according to the signal detection model in Section II, since the detection probability can be obtained. During T time slots, node n sends out T_n indicator signals, where $T_n \leq T$ because there may be no available idle channels in some time slots to send out the sensing result. Given that the common receiver collects x_n times of "busy" information, the detection ratio is $p_n = x_n/T_n$. We assume that the false alarm probability P_{FA} is very low and can be ignored. Given that the degree of primary user's traffic is β. According to the *Law of Large Numbers* (LLN), the estimated detection probability can be obtained as

$$\hat{P}_D^{(n)} = \frac{p_n}{\beta} = \frac{x_n}{\beta T_n}. \quad (7)$$

The secondary users are transparent to the primary users. The primary users even do not know their existence and thus, the primary users can not cooperate with the secondary users. Hence, the value of β is unknown to the secondary users. We first assume that it is known to the secondary users at the current stage, and the details of how to estimate β will be provided later in this section.

According to (2) - (6), the detection probability P_D is a function of distance, namely, $P_D(d) \triangleq f(d)$.The distance from node n to the primary user can be estimated from $\hat{d}_n = f^{-1}(\hat{P}_D)$.

The primary user is assumed to have an interference range with radius r. Only the nodes inside the circle can detect the signals from the primary user. The algorithm does not work when there are fewer than 3 nodes in the range. Fig. 2 illustrates the basic idea of the localization algorithm. Denote the estimated distance from node n $(n = 1, 2, \cdots, N)$ to the primary user by d_n. We draw three circles with a radius of d_n and the position of node n as center. The expected position of the primary user is the intersect of these three circles. However, the three circles may not intersect at the same point or even

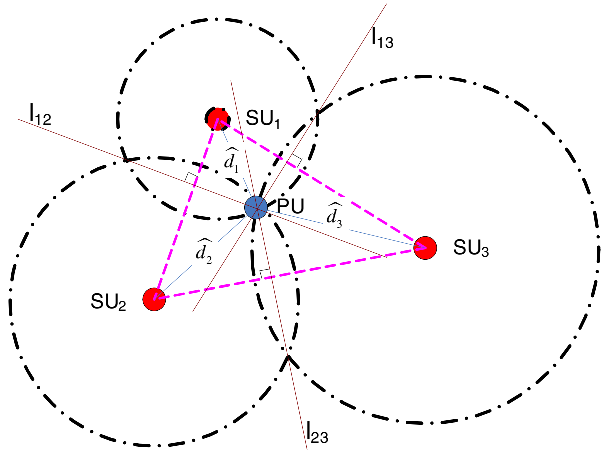

Fig. 2. Localization algorithm demonstration. In this example, there are three SUs locating the position of a certain PU. Three circles, with radii of the estimated distances between the SUs and PU are drawn, respectively. The expected position of the PU is the intersect of these three circles.

no intersect due to the detection errors. Denote the position of the primary user and the position of the secondary user n by (θ_x, θ_y) and (a_n, b_n), respectively. We have these equations

$$\sqrt{(\hat{\theta}_x - a_v)^2 + (\hat{\theta}_y - b_v)^2} = \hat{d}_v = f^{-1}\left(\frac{x_v}{\beta T_v}\right), \quad (8)$$

for $v = 1, 2, ..., u$. Assuming that we have u users in the interference range, we can obtain u equations with errors, with β, θ_x, θ_y being unknown variables. The linear *Least Squares* method can yield estimation with the minimum MSE. Nonetheless, the equations are not linear. So we should find a way to implement them.

Consider two nodes i and j that form two detection circles. If they have two intersects (in the case the distance between the two nodes $d_{ij} < d_i + d_j$), the line passing through these two intersects is l_{ij} as shown in Fig. 2. The cases wherein they have one or no intersect are similar. The number of such lines is $l = \frac{u(u-1)}{2}$. The equations representing the lines can be calculated from ith equation minus jth of (8) as follows:

$$-2(a_i - a_j)\hat{\theta}_x - 2(b_i - b_j)\hat{\theta}_y = (\hat{d_i^2} - \hat{d_j^2}) - (a_i^2 - a_j^2) - (b_i^2 - b_j^2). \quad (9)$$

The estimated position $\hat{\boldsymbol{\theta}}$ ($\hat{\boldsymbol{\theta}} = [\hat{\theta}_x, \hat{\theta}_y]^T$) can be obtained from these linear equations in order to achieve the minimum MSE

$$\hat{\boldsymbol{\theta}} = (\mathbf{A}^{\mathrm{T}}\mathbf{A})^{-1}\mathbf{A}^{\mathrm{T}}\boldsymbol{\rho}, \quad (10)$$

where

$$\mathbf{A} = \begin{bmatrix} \xi_{12} & \cdots & \xi_{1u} & \xi_{23} & \cdots & \xi_{(u-1)u} \\ \zeta_{12} & \cdots & \zeta_{1u} & \zeta_{23} & \cdots & \zeta_{(u-1)u} \end{bmatrix}^{\mathrm{T}} \quad (11)$$

$$\boldsymbol{\rho} = \begin{bmatrix} \rho_{12} & \ldots & \rho_{1u} & \rho_{23} & \ldots & \rho_{(u-1)u} \end{bmatrix}^{\mathrm{T}}. \quad (12)$$

$$\begin{array}{r}\xi_{ij} = 2(a_i - a_j) \\ \zeta_{ij} = 2(b_i - b_j) \\ \rho_{ij} = (a_i^2 - a_j^2) + (b_i^2 - b_j^2) - (\hat{d}_i^2 - \hat{d}_j^2)\end{array} . \tag{13}$$

B. The Iterative Algorithm

The algorithm described above is based on the knowledge of β, which is generally an unknown variable. We shall use an iterative method to obtain β. The basic idea of the iteration steps is first decide an initial value of β, and then run the algorithm, the updated value of β can be obtain from the localization result, are finally use the updated value of β to run the algorithm again until the stopping criterion is satisfied.

Algorithm 1: The Iterative Localization Algorithm

```
Set the initial value of β. Let β^(0) = max_n p_n;
for (n = 1 to N) do
    if (x_n > 0) then
        this node can detect PU, put it into the set ℂ;
    end
end
for (s = 1 to S) do
    for (n = 1 to N) do
        Calculate the detection probability by (7);
        P̂_D(n) = x_n / (β T_n);
        Calculate the distances from each node to the
        primary user by (4)(5); d̂_n = f^{-1}(P̂_D(n));
    end
    Estimate the position of primary user θ̂^(s) by (10) ;
    if ( |θ̂^(s) − θ̂^(s−1)| < ε) then
        Stop iteration;
    end
    for (n = 1 to N) do
        if (n ∈ ℂ) then
            Calculate the iterative distance d̂_n^(s) by (8);
            d̂_n^(s) = f^{-1}( x_n / (β T_n) ) ;
            Calculate the iterative detection probability
            P̂_D(n)^(s) by (5); P̂_D(n)^(s) ≜ f( d̂_n^(s) ) ;
            Calculate β_n^(s) = x_n / (P̂_D(n)^(s) T_n) ;
        end
    end
    Set the average iterative β; β̂^(s) = (1/|ℂ|) Σ_{n∈ℂ} β_n^(s) ;
end
```

IV. Theoretical Analysis

The Cramer-Rao Lower Bound (CRLB) is commonly used in estimation and detection theory to evaluate the effectiveness of an algorithm and to indicate the margin for improvement. The CRLB is derived in this section.

We assume that the region of cognitive radio networks is within the unit circle with radius 1. The estimation target is the position of the primary user $\hat{\boldsymbol{\theta}}$ ($\hat{\boldsymbol{\theta}} = [\hat{\theta}_x, \hat{\theta}_y]^T$). The measurements are the accumulative binary detection results vector $\mathbf{x} = x_n, 1 \le n \le N$. We assume that $T_n = T(\forall n)$ and β is a known constant. The region of cognitive radio networks is symmetrical and the primary and secondary nodes are uniformly distributed in the network. Thus, we have $\mathrm{E}[\hat{\boldsymbol{\theta}}] = \boldsymbol{\theta}$. That is, we have an unbiased estimator.

$p(\boldsymbol{x}, \boldsymbol{\theta})$ is the joint probability density function. The detection process is independent between different time slots for each node. We have

$$P\{x_n = \tau\} = \binom{T}{\tau} \left(P_D^{(n)}\right)^{\tau} \left(1 - P_D^{(n)}\right)^{T-\tau} . \tag{14}$$

According to the *Central Limit Theorem*, the *Binomial* distribution can be approximated by the *Gaussian* distribution as

$$p_0(x_n, \boldsymbol{\theta}) = \frac{1}{\sqrt{2\pi\sigma_n^2}} e^{-\frac{(x_n - \mu_n)^2}{2\sigma_n^2}}, \tag{15}$$

where $\mu_n = TP_D^{(n)}$, $\sigma_n^2 = TP_D^{(n)}(1 - P_D^{(n)})$.

Only the users who are in the interference range with radius r of the primary user can detect it. So,

$$p(\boldsymbol{x}, \boldsymbol{\theta}) = \prod_{n=1}^{N} p_0(x_n, \boldsymbol{\theta})^{I(n)}, \tag{16}$$

where

$$I(n) = \begin{cases} 1, & d_n \le r \\ 0, & d_n > r \end{cases}, \tag{17}$$

$$d_n = \sqrt{(a_n - \theta_x)^2 + (b_n - \theta_y)^2}, \tag{18}$$

and

$$\mathrm{E}[I(n)] = r^2. \tag{19}$$

We define

$$\begin{aligned} q(\boldsymbol{x}, \boldsymbol{\theta}) &= \ln(p(\boldsymbol{x}, \boldsymbol{\theta})) \\ &= -\sum_{n=1}^{N} \left(I(n) \left(\frac{1}{2} \ln(2\pi\sigma_n^2) + \frac{(x_n - \mu_n)^2}{2\sigma_n^2} \right) \right) . \end{aligned} \tag{20}$$

The Fisher Information [9] is

$$J(\boldsymbol{\theta}) = \begin{bmatrix} -E\left[\frac{\partial^2 q(\boldsymbol{x},\boldsymbol{\theta})}{\partial\theta_x^2}\right] & -E\left[\frac{\partial^2 q(\boldsymbol{x},\boldsymbol{\theta})}{\partial\theta_x \partial\theta_y}\right] \\ -E\left[\frac{\partial^2 q(\boldsymbol{x},\boldsymbol{\theta})}{\partial\theta_y \partial\theta_x}\right] & -E\left[\frac{\partial^2 q(\boldsymbol{x},\boldsymbol{\theta})}{\partial\theta_y^2}\right] \end{bmatrix}, \tag{21}$$

where the expectation operator E[·] is taken with respect to $\mathbf{x}$.

The *Cramer-Rao Lower Bound* is defined as

$$var(\hat{\boldsymbol{\theta}}) \ge \mathrm{CRLB} = \mathrm{E}[g_{11} + g_{22}], \tag{22}$$

where $\mathbf{G} = \{g_{ij}, i, j = \{1, 2\}\} \triangleq J^{-1}(\boldsymbol{\theta})$, and the expectation operator E[·] is taken with respect to the positions of all the nodes and the position of the primary user. Since they are uniformly scattered in an unit circle, the PDF of their distance is $f_d(r) = 2r$.

V. Simulation Results

The primary and secondary nodes are uniformly distributed in the considered system. The network topology is taken as a unit circle. Given that the false alarm probability P_{FA} is 0.01 and power attenuation constant $k = 0.01$, SNR is 10 dB. The radius of interference range of primary user is set to $r = 0.3$. The upper bound of number of iteration times $S = 3$. We also assume that $p = 0.5$ and $q = 0.5$. Thus, the degree of primary user's traffic $\beta = 50\%$, but it is unknown to the secondary users.

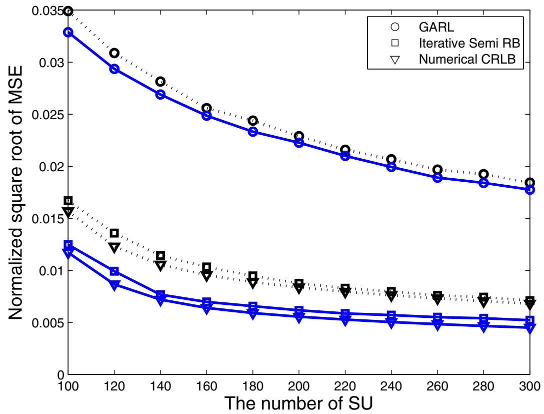

Fig. 3. MSE Comparison and CRLB. The dashed and solid lines represent $T = 100$ and $T = 400$, respectively.

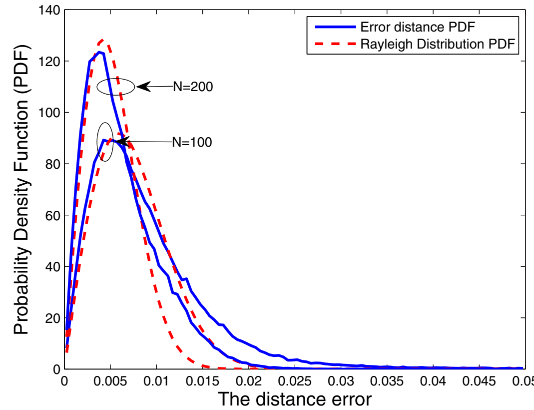

Fig. 4. The PDF of the distance between the estimated position and actual position vs. the Rayleigh Distribution

A. Comparison of the MSE of Algorithms and CRLB

We set the number of detection periods $T = 100$ and $T = 400$, respectively. In Fig. 3, the x-axis is the number of SUs and the y-axis is the root of the mean square localization error. The solid curves are under $T = 400$, while the dashed curves are under $T = 100$. We can see that increasing the number of SU nodes will reduce the localization error. The GRL algorithm (with 2 orders) is our previous range free localization algorithm [11]. The weighted iterative algorithm can reduce the MSE significantly compared with GRL. Furthermore, the gap between the numerical CRLB and our proposed algorithm is almost indistinguishable, which validates the great potential of the proposed approach. When N equals 200, the normalized MSE is approximately 0.006 using the proposed algorithm. This means, for example, that if there are 200 secondary users randomly located within a circle of radius 1km, then with a very high probability the primary user will fall within a circle with radius 6m, around the estimated position.

B. Analysis of the Distribution of Estimation Target

This part will discuss the distribution of the distance between the estimated position $\hat{\boldsymbol{\theta}}$ and the actual position $\boldsymbol{\theta}$. That is, $\triangle d = |\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}| = \sqrt{(\hat{\theta_x} - \theta_x)^2 + (\hat{\theta_y} - \theta_y)^2}$. Define $\triangle x = \hat{\theta_x} - \theta_x$, $\triangle y = \hat{\theta_y} - \theta_y$. The distributions of $\triangle x$ and $\triangle y$ are the same due to the unbiasedness of the estimation algorithm. $\triangle x$ is obtained by combining lots of measurements. According to the *Central Limit Theorem*, $\triangle x$ will approach a normal distribution with very high probability. Since $\triangle x$ and $\triangle y$ approach the normal distribution, $\triangle d = \sqrt{\triangle x^2 + \triangle y^2}$ will probably follow a Rayleigh distribution. Fig. 4 shows the comparisons.

VI. Conclusion

In this paper, an accurate semi range-based iterative localization algorithm was proposed to estimate the position of the primary users in cognitive radio networks. The non-cooperative nature of the primary user entails the design of an iterative procedure to further and gradually improve the localization accuracy. The proposed method was verified through extensive simulations. In particular, significant performance gains over the range-free algorithm were observed. More importantly, the proposed localization algorithm was found to approach CRLB very well, which indicates that the proposed approach is near optimal.

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