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# Sensor Set Selection for Cooperative Spectrum Sensing Based on Confidence Detection

Xiao Zhang, Jin-long Wang and Qi-hui Wu

***Abstract*—The problem of sensor set selection in cognitive radio networks (CRN) is considered in this paper. Although the method of cooperative spectrum sensing can greatly improve the sensing performance, the consumption of system resources will increase as the number of cooperative sensors increases, therefore, the number of cooperative sensors to use is a compromise between sensing performance and consumption of system resources. Firstly, based on the expression for the probability of detection which is characterized as a function of the number of cooperative sensors and the global average receiving signal to noise ratio, a sensor set selecting method is proposed; then, a confidence based trustless sensor detecting method is presented to delete the trustless sensors from CRN which would add negative effect on the sensor set selecting method; lastly, based on the two methods above, a confidence based sensor set selecting algorithm is proposed, which not only effectively delete the trustless sensors from CRN but also use fewest cooperative sensors to minimize the consumption of system resources, while still having enough for the sensing performance requirements. Analysis and numerical results illustrate the effectiveness and reliability of the proposed algorithm.**

***Index Terms*—Cognitive Radio; Sensor Set Selection; Confidence Distance; Confidence Degree**

## I. INTRODUCTION

Recently the radio spectrum is becoming exhausted because of the growing demands for the radio spectrum. In this regard, the paradigm shifts from the conventional exclusive use of frequency resources by the fixed allocation to the dynamic frequency utilization is indispensable for the future wireless networks. Cognitive Radio (CR) can greatly improve spectrum efficiency through allowing unlicensed users to dynamically access the unused primary spectrum while bring no harm to the primary users [1-3]. Spectrum sensing, as a key enabling functionality in cognitive radio networks (CRN), needs to reliably detect signals from licensed primary radios to avoid harmful interference. Generally speaking, spectrum sensing techniques fall into three categories: energy detection, coherent detection and cyclostationary feature detection. If the secondary user has limited information on the primary signals (e.g., only the local noise power is known), the energy detector is optimal. In this paper, we assume that the primary signal is unknown and we adopt energy detection as the building block for the proposed sensor set selecting algorithm.

The sensing performance are summarized in terms of two parameters: probability of detection, given by $p_d = p(H_1 | H_1)$, and probability of false alarm, given by $p_f = p(H_1 | H_0)$, where $H_0$ is the hypothesis that the channel is vacant and $H_1$ is the hypothesis that the channel is occupied. In CRN, a larger $p_d$ leads to less interference to primary users and a smaller $p_f$ results in higher spectrum usage efficiency [4]. FCC has set strict requirements on both of them, for example, in IEEE 802.22, the world's first international cognitive radio standard, primary users should be detected with $p_d \geq 0.9$ and $p_f \leq 0.1$ [5]. In this paper we assume primary users should be detected with $p_d \geq \beta$ and $p_f \leq \gamma$.

According to [6-8], due to the effects of channel fading/shadowing, a single sensor may not be able to reliably detect the existence of primary users. It is shown in [8] that Rayleigh fading and shadowing fading in energy detection scenarios produce a high $p_f$ for high $p_d$ and result in poor spectrum usage. To address this issue, cooperative spectrum sensing exploiting spatial diversity among several secondary users has been proposed by several authors [9-13]. In such scenarios, a network of cooperative cognitive radios, which experience different channel conditions from a primary user, would have a better chance of detecting the primary radio if they combine the sensing information jointly.

It is proven in [14] and [15] that, for a given $p_f$, $p_d$ increases as the number of cooperative sensors increases when sensors are assumed to be independent from each other. From the view of sensing performance, the number of cooperative sensors should be as large as possible, but the consumption of system resources, such as the total transmission power of the signal measurements and the amount of overhead traffic, grows approximately linearly with the number of cooperative sensors. In this sense, the number of cooperative sensors to use is a trade-off between having a high reliability of sensing and having a low consumption of system resources. Consequently, it is desirable to use as few cooperative sensors as possible to minimize the consumption of system resources, while still having enough for the sensing performance requirements.

A few trustless sensors may exist in CRN, for example, some sensors may receive "fake signals" coming from the spectrum leakage interference of an unknown wireless device (energy detector can not distinguish between interference and primary signals), and make the probability of false alarm extremely high. Now the problem has

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changed into how to choose a sensor set that has fewest trustful cooperative sensors to satisfy the sensing performance requirements, when some trustless sensors exist in CRN.

Based on the analysis above, the goal of this paper is to use fewest trustful cooperative sensors to minimize the consumption of system resources, while still having enough for the sensing performance requirements. The organization of this paper is given as follows: In Section Ⅱ, the system model is introduced in detail. The details of the confidence based sensor set selecting algorithm are given in Section Ⅲ. Simulation results and discussion are shown in Section Ⅳ. Section Ⅴ concludes this paper and suggests future work in this area.

## II. System Model

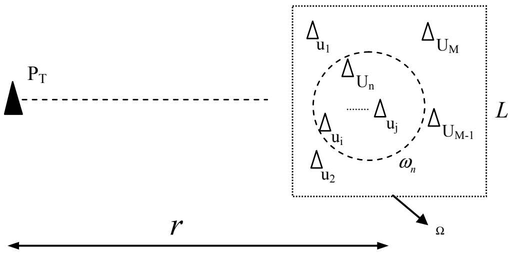


Fig. 1. System model

The system model is illustrated in Fig. 1. Consider a single-hop centralized CRN Ω of $M$ independent secondary users, denoted as $u_1$ through $u_M$, is randomly deployed in a $L\times L$ square area with the center of the square at distance $r$ from the primary transmitter $\mathrm{P_T}$. The transmitting power of $\mathrm{P_T}$ is $p_T$. We choose a sensor set $\omega_n$ of $n$ secondary users from Ω which employs a cooperative spectrum sensing protocol to detect signal transmissions of $\mathrm{P_T}$. The binary hypothesis test model of $u_i$ in $\omega_n$ for spectrum sensing at $k$th time instant is formulated as follows [4],

$$\begin{aligned} H_0 &: x_i(k)=v_i(k) \qquad\qquad i=1,2,\cdots,n \\ H_1 &: x_i(k)=h_i s(k)+v_i(k) \qquad i=1,2,\cdots,n \end{aligned} \tag{1}$$

where $s(k)$ denotes the signal transmitted by the primary user and $x_i(k)$ is the received signal by the $i$th secondary user. The signal $s(k)$ is distorted by the channel gain $h_i$, which is assumed to be constant during the detection interval, and is further corrupted by the zero-mean additive white Gaussian noise (AWGN) $v_i(k)$, i.e., $v_i(k)\sim N(0,\sigma^2)$ ( for ease of exposition, we assume that the noises at different secondary users have a same variance of $\sigma^2$ which are known *a priori*). Without loss of generality, $s(k)$ and $v_i(k)$ are assumed to be independent from each other.

Each secondary user in $\omega_n$ caculates a test statistic $y_i$ over a detection interval of $N$ samples, i.e.,

$$y_i=\sum_{k=0}^{N-1}|x_i(k)|^2 \qquad i=1,2,\cdots,n \tag{2}$$

where $N$ is determined from the time-bandwidth product. If the number of samples $N$ is large enough (e.g., $N\ge 10$ in practice), the test statistic $y_i$ is asymptotically normally distributed with mean

$$\mathrm{E}(y_i)=\begin{cases} N\sigma^2 & H_0 \\ (N+N\eta_i)\sigma^2 & H_1 \end{cases} \tag{3}$$

and variance

$$\mathrm{Var}(y_i)=\begin{cases} 2N\sigma^4 & H_0 \\ 2(N+2N\eta_i)\sigma^4 & H_1 \end{cases} \tag{4}$$

where

$$\eta_i=\frac{P_i}{\sigma^2}=\frac{E_s|h_i|^2}{N\sigma^2} \tag{5}$$

is the local average receiving signal to noise ratio (ARSNR) at the $i$th secondary user and the quantity $E_s=\sum_{k=0}^{N-1}|S(k)|^2$ represents the transmitted signal energy over a sequence of $N$ samples during each detection interval. The received primary signal power $P_i$ can be calculated as the total power at the RF front-end minus the noise power $\sigma^2$. Further more, the exact local ARSNR can be estimated if $P_i$ and $\sigma^2$ are known.

## III. The Sensor Set Selecting Algorithm Based on Confidence Detection

### A. The sensor set selecting method

Let $\mathbf{y}=[y_1,y_2,\cdots,y_n]^T$ denote the vector containing all of the test statistics of $\omega_n$, then cooperative spectrum sensing can be formulated as the following binary hypothesis testing problem:

$$\begin{aligned} H_0 &: \ \mathbf{y}\sim N(\boldsymbol{\mu}_\mathbf{0},\boldsymbol{\Psi}_\mathbf{0}) \\ H_1 &: \ \mathbf{y}\sim N(\boldsymbol{\mu}_\mathbf{1},\boldsymbol{\Psi}_\mathbf{1}) \end{aligned} \tag{6}$$

where $\boldsymbol{\mu}_\mathbf{0}$ and $\boldsymbol{\Psi}_\mathbf{0}$ are the mean vector and covariance matrix of $\mathbf{y}$, respectively, when $H_0$ is true; $\boldsymbol{\mu}_\mathbf{1}$ and $\boldsymbol{\Psi}_\mathbf{1}$ are the mean vector and covariance matrix of $\mathbf{y}$, respectively, when $H_1$ is true. They can be respectively expressed as follows,

$$\boldsymbol{\mu}_\mathbf{0}=[N\sigma^2,\cdots,N\sigma^2]^T{}_{n\times 1} \tag{7}$$

$$\boldsymbol{\Psi}_\mathbf{0}=2N\sigma^4\times\mathbf{I}_{n\times n} \tag{8}$$

$$\boldsymbol{\mu}_1=[(N+N\eta_1)\sigma^2,\cdots,(N+N\eta_n)\sigma^2]^T{}_{n\times 1} \tag{9}$$

$$\boldsymbol{\Psi}_\mathbf{1}=\begin{bmatrix} 2N(1+2\eta_1)\sigma^4 & 0 & \cdots & 0 \\ 0 & 2N(1+2\eta_2)\sigma^4 & \cdots & 0 \\ 0 & \vdots & \ddots & 0 \\ 0 & 0 & \cdots & 2N(1+2\eta_n)\sigma^4 \end{bmatrix}_{n\times n} \tag{10}$$

where $\mathbf{I}_{n\times n}$ represents the identity matrix.

For ease of exposition, we adopt the equal gain combining rule. Then the decision variable can be expressed as

$$\Lambda=\mathbf{y}^T\mathbf{1} \tag{11}$$

where $\mathbf{1}=[1,1,\cdots,1]^T{}_{n\times 1}$ denotes the unit vector. The means and variances of Λ under different hypotheses are respectively given by

$$\begin{aligned} \mathrm{E}(\Lambda \mid H_0) &= \boldsymbol{\mu}_0{}^T \mathbf{1} = nN\sigma^2 \\ \mathrm{E}(\Lambda \mid H_1) &= \boldsymbol{\mu}_1{}^T \mathbf{1} = nN\sigma^2 + nN\sigma^2\Gamma \end{aligned} \tag{12}$$

and

$$\begin{aligned} \mathrm{Var}(\Lambda \mid H_0) &= \mathbf{1}^T \boldsymbol{\Psi}_0 \mathbf{1} = 2nN\sigma^4 \\ \mathrm{Var}(\Lambda \mid H_1) &= \mathbf{1}^T \boldsymbol{\Psi}_1 \mathbf{1} = 2nN\sigma^4 + 4nN\sigma^4\Gamma \end{aligned} \tag{13}$$

with $\Gamma = \sum_{i=1}^{n} \eta_i / n$ which represents the global ARSNR of $\omega_n$.

According to the Neyman-Pearson Lemma [16], $p_f$ and $p_d$ can be respectively given by

$$p_f = p(H_1 \mid H_0) = Q\left(\frac{\lambda - \mathrm{E}(\Lambda \mid H_0)}{\sqrt{\mathrm{Var}(\Lambda \mid H_0)}}\right) \tag{14}$$

and

$$p_d = p(H_1 \mid H_1) = Q\left(\frac{\lambda - \mathrm{E}(\Lambda \mid H_1)}{\sqrt{\mathrm{Var}(\Lambda \mid H_1)}}\right) \tag{15}$$

with $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} e^{-t^2/2} dt$.

By letting $p_f = \gamma$, the decision threshold can be get as

$$\lambda = Q^{-1}(\gamma)\sqrt{2nN\sigma^4} + nN\sigma^2 \tag{16}$$

With this threshold setting, the expression for the probability of detection becomes

$$p_d = Q\left(\frac{Q^{-1}(\gamma)\sqrt{2nN} - nN\Gamma}{\sqrt{2nN + 4nN\Gamma}}\right) \tag{17}$$

Note that in (17), $p_d$ is characterized as a function of $\Gamma$ and $n$ for given $N$ and $\gamma$. In Fig. 2, we plot $\Gamma$ against $n$, with $N = 100$, $p_f = \gamma = 0.01$ and $p_d = \beta = 0.99$. From Fig. 2, we can see that the required global ARSNR $\Gamma$ decreases as $n$ increases.

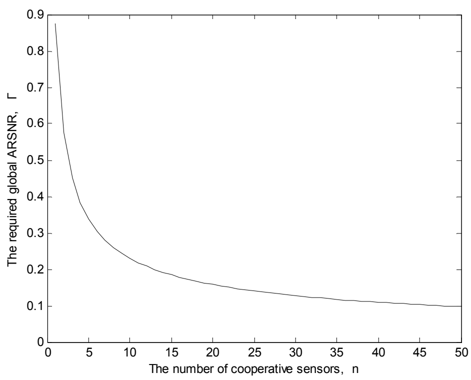


Fig.2 The relationship between $\Gamma$ and $n$.

The goal of this paper is to use fewest trustful cooperative sensors to minimize the consumption of system resources, while still having enough for the sensing performance requirements. Therefore, the operations of the sensor set selecting method are as follows: Firstly, obtain a queue denoted by $\Re$ by sorting the sensors of the CRN in decreasing order of local ARSNR. Secondly, choose the first $n$ ($1 \le n \le M$) sensors of $\Re$ to form the chosen sensor set $\omega_c$. Finally, increase $n$ until $n$ and $\Gamma$ of the current $\omega_c$ satisfy $p_d \ge \beta$, then this $\omega_c$ is the sensor set we will choose and the method terminates.

### *B. The confidence based trustless sensor detecting method*

When there are some trustless sensors in CRN, the sensor set selecting method described above may have some limitations. For example, some sensors that receive "fake signals" coming from the spectrum leakage interference of an unknown wireless device (energy detector can not distinguish between interference and primary signals) may easily be chosen into the chosen sensor set $\omega_c$ and make the probability of false alarm extremely high. As illustrated in Fig. 2, a sensor whose "fake SNR" is 0.9 will make the probability of false alarm higher than 0.99.

Luo and Lin, in their pioneering effort, have proposed "confidence distance measures" as a criterion for the purpose of sensor errors detection [17]. In this paper, we use these measures, denoted as $d_{ij}$ and $d_{ji}$, to evaluate the difference between $y_i$ and $y_j$, where

$$\begin{aligned} d_{ij} &= 2\left|\int_{y_i}^{y_j} p_i(y \mid y_i) p_i(y_i) dy\right| \\ d_{ji} &= 2\left|\int_{y_j}^{y_i} p_j(y \mid y_j) p_j(y_j) dy\right| \end{aligned} \tag{18}$$

As $y_i$ and $y_j$ are normally distributed, $d_{ij}$ and $d_{ji}$ can be computed by the use of an error function which can be defined as

$$\mathrm{erf}(\theta) = \frac{2}{\sqrt{\pi}} \int_0^{\theta} e^{-z^2} dz$$

Then $d_{ij}$ and $d_{ji}$ can be respectively given by

$$\begin{aligned} d_{ij} &= \frac{1}{\sqrt{2\pi \mathrm{Var}(y_i)}} \mathrm{erf}\left(\frac{\left|y_j - y_i\right|}{\sqrt{2\mathrm{Var}(y_i)}}\right) \\ d_{ji} &= \frac{1}{\sqrt{2\pi \mathrm{Var}(y_j)}} \mathrm{erf}\left(\frac{\left|y_j - y_i\right|}{\sqrt{2\mathrm{Var}(y_j)}}\right) \end{aligned} \tag{19}$$

It can be seen from (19) that usually $d_{ij} \ne d_{ji}$ (unless $\eta_i = \eta_j$). For ease of exposition, we use a concise way for computing $d_{ij}$ and $d_{ji}$, which can be shown as follows,

$$d_{ij} = d_{ji} = \mathrm{erf}(\left|y_j - y_i\right|) \tag{20}$$

Let us denote by $r_{ij} = 1 - d_{ij}$ the mutual support degree between $y_j$ and $y_i$. From (20) we can see that the bigger $r_{ij}$ is, the higher the mutual support degree between $y_j$ and $y_i$ will be. As there are $M$ secondary users in CRN, the general "mutual support degrees" of CRN can be described by a symmetric matrix defined as $\mathbf{R} = \left(r_{ij}\right)_{M \times M}$.

Let $\rho_i$ denote the synthetic support degree of $y_i$ by other test statistics. The bigger $\rho_i$ is, the higher the synthetic support degree of $y_i$ by other test statistics is and the truer $y_i$ is. So $\rho_i$ is the weight value of $y_i$ in $\mathbf{y}$ which is defined as confidence degree and satisfy

$$\begin{aligned} &\sum_{i=1}^{M} \rho_i = 1 \\ &\rho_i \ge 0 \qquad i \in [1, 2, \cdots, M] \end{aligned} \tag{21}$$

As $\rho_i$ should be the total information of $r_{i1}, r_{i2}, \cdots, r_{iM}$, a group of positive values denoted by $\alpha_1, \alpha_2, \cdots, \alpha_M$ should exist, which would satisfy

$$\rho_i = \alpha_1 r_{i1} + \alpha_2 r_{i2} + \cdots + \alpha_M r_{iM} \tag{22}$$

Then we can get

$$\boldsymbol{\rho} = \mathbf{R}\boldsymbol{\alpha} \tag{23}$$

with $\boldsymbol{\alpha} = [\alpha_1, \alpha_2, \cdots, \alpha_M]^T_{M\times 1}$ and $\boldsymbol{\rho} = [\rho_1, \rho_2, \cdots, \rho_M]^T_{M\times 1}$.

As $\alpha_j$ is the weight value of $r_{ij}$ in $r_{i1}, r_{i2}, \cdots, r_{iM}$, the bigger $\rho_j$ is, the bigger $\alpha_j$ should be. Thus $\boldsymbol{\rho}$ and $\boldsymbol{\alpha}$ should have the same weight value distribution and we can get

$$\boldsymbol{\rho} = \delta\boldsymbol{\alpha} \tag{24}$$

with $\delta = 1\Big/\sum_{i=1}^{M}\alpha_i$.

By substituting (24) into (23), we can get

$$\delta\boldsymbol{\alpha} = \mathbf{R}\boldsymbol{\alpha} \tag{25}$$

Let $\delta'$ ( $\delta' > 0$ ) denote the biggest eigenvalue of $\mathbf{R}$. According to the matrix theory, only the eigenvector corresponding to $\delta'$, denoted by $\boldsymbol{\alpha}'$, is positive and satisfy the needs of $\boldsymbol{\rho}$, so we can firstly compute $\delta'$ and $\boldsymbol{\alpha}'$ of $\mathbf{R}$, and then $\boldsymbol{\rho}$ can be achieved by

$$\boldsymbol{\rho} = \boldsymbol{\alpha}'\Big/\sum_{i=1}^{M}\alpha'_i \tag{26}$$

After achieving $\boldsymbol{\rho}$, we can delete the trustless sensors from the CRN using a uniform threshold $\varepsilon$ when $\rho_i \le \varepsilon$.

### C. The confidence based sensor set selecting algorithm

Based on the two methods above, a confidence based sensor set selecting algorithm is proposed in this section. The algorithm firstly deletes the trustless sensors from CRN using the confidence based trustless sensor detecting method and gets a confidence sensor set, denoted by $\Phi$, containing all of the trustful sensors in CRN. Then it chooses a sensor set $\omega$ from $\Phi$ using the sensor set selecting method. The algorithm can be specified as follows,

- Step 1: Firstly, fusion center receives $\mathbf{y}$ from $M$ secondary users; then it uses the confidence based trustless sensor detecting method to delete the trustless sensors from CRN (as the fusion center do not know whether the primary user is absent or not, using this method can delete the trustless sensors and mitigate the negative effect these trustless sensors will cause when primary user is absent); finally it makes decision whether primary user is absent or not based on the sensor set $\Phi'$ containing all of the remaining sensors in CRN. If primary user is present, perform step 2, else, perform step 3.
- Step 2: When primary user is present, the confidence based trustless sensor detecting method may not always detect the trustless sensors in CRN, so, there may be some trustless sensors in $\Phi'$. Store the detecting vector $\mathbf{y}_{\Phi'}$ of $\Phi'$ and choose the sensor set $\omega'$ (may contain trustless sensors) from $\Phi'$ using the sensor set selecting method. Use $\omega'$ as the sensor set until the fusion decision (always use the confidence based trustless sensor detecting method to delete the trustless test statistics of $\omega'$) shows that the primary user is absent, and then perform step 4.
- Step 3: When primary user is absent, the confidence based trustless sensor detecting method can detect the trustless sensors in CRN, thus no trustless sensors exist in $\Phi'$. As the sensor set selecting method needs primary user's signal as a reference, we use $\Phi'$ as the sensor set until the fusion decision (always using the confidence based trustless sensor detecting method to delete the trustless test statistics of $\Phi'$) shows that the primary user is present, and then store the detecting vector $\mathbf{y}_{\Phi'}$ of $\Phi'$ and perform step 4.
- Step 4: Using the confidence based trustless sensor detecting method to delete the trustless sensors from $\Phi'$, the confidence sensor set $\Phi$ can be get and the final sensor set $\omega$ can be chosen from $\Phi$ using the sensor set selecting method based on $\mathbf{y}_{\Phi'}$.
- Step 5: When the global ARSNR $\Gamma$ and the number of cooperative sensors of current $\omega$ don't satisfy $p_d \ge \beta$, use the current confidence sensor set $\Phi$ to make decision whether the primary user is present or not. If it present, choose a new sensor set from $\Phi$ using the sensor set selecting method; if it absent, maintain current sensor set $\omega$ unchangeably.

## IV. Simulation and Analysis

In this section, the performance of the proposed confidence based sensor set selecting algorithm is evaluated numerically. The parameters used in the following simulations are as follows: $L = 20\text{km}$, $\beta = 0.99$, $\gamma = 0.01$ and $p_T = 100\text{W}$. According to the path-loss model, the received primary signal power at the $i$th sensor which is $d$ meters away from $\mathrm{P_T}$ is given as $P_i = p_T d^{-\alpha}$ where $\alpha$ is the path loss exponent which is set to be 3. The simulation results that shown in Fig. 3 to Fig. 9 are all averaged over 1000 realizations of the CRN, with secondary users being uniformly distributed. In simulation, we assume that a trustless sensor exists in the CRN, the received "fake primary signal power" at which is -127 dBm.

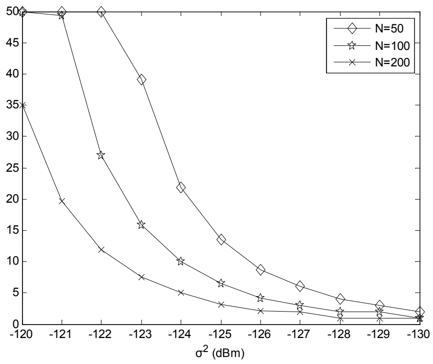


Fig. 3 The number of cooperative sensors $n$ of the selected sensor set $\omega$ versus noise variance $\sigma^2$ for various $N$.

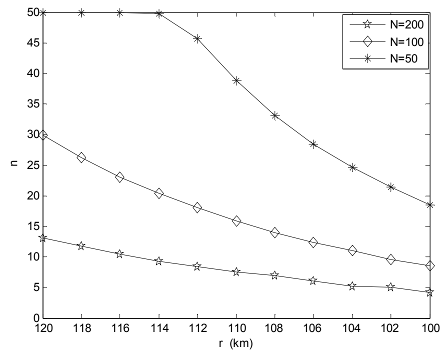


Fig. 4 The number of cooperative sensors $n$ of the selected sensor set $\omega$ versus $r$ (the distance between $P_T$ and the center of the coverage area) for various $N$ .

Fig. 3 shows the number of cooperative sensors $n$ of the sensor set $\omega$ selected by the proposed confidence based sensor set selecting algorithm versus noise power $\sigma^2$, with $M = 50$, $r = 100\text{km}$ and $N = 50$, 100 and 200. From Fig. 3, we can see that $n$ decreases as $\sigma^2$ decreases, as expected, as the local ARSNR of each sensor increases as $\sigma^2$ decreases and one can achieve the same sensing performance requirements using fewer sensors at larger values of local ARSNR. From Fig. 3, we can also see that $n$ decreases as the number of samples $N$ increases, as expected, as the received transmitted signal energy $E_s$ of $P_T$ during each detection interval increases as $N$ increases and one can use fewer sensors to achieve the same sensing performance requirements at larger $E_s$ .

Fig. 4 shows the number of cooperative sensors $n$ of the sensor set $\omega$ selected by the proposed confidence based sensor set selecting algorithm versus the distance $r$ between $P_T$ and the center of the coverage area, with $M = 50$, $\sigma^2 = -123\text{dBm}$ and $N = 50$, 100 and 200. From Fig. 4, we can see that $n$ decreases as $r$ decreases, as expected, as the local ARSNR of each sensor increases as $r$ decreases and one can achieve the same sensing performance requirements using fewer sensors at larger values of local ARSNR. From Fig. 4, we can also see that $n$ decreases as the number of samples $N$ increases, the reason for which is the same as Fig. 3.

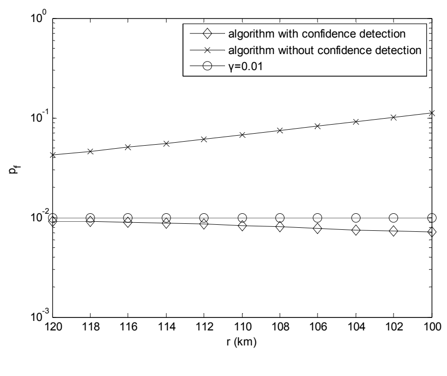


Fig. 5 Sensing performance comparison of the algorithm with and without confidence detection with $\sigma^2 = -123\,\text{dBm}$ and $N = 100$ .

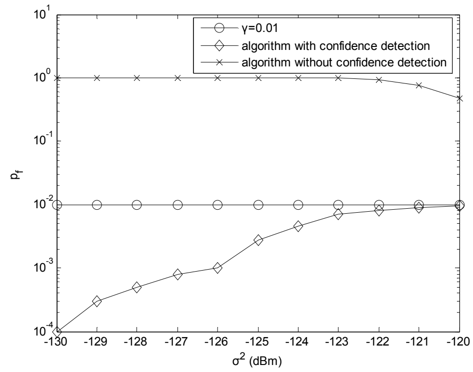


Fig. 6 Sensing performance comparison of the algorithm with and without confidence detection with $r = 100\text{km}$ and $N = 100$ .

Fig. 5 shows the probability of false alarm of the sensor set selecting algorithm with and without confidence detection versus the distance $r$ between $P_T$ and the center of the coverage area, with $M = 50$, $\sigma^2 = -123\text{dBm}$ and $N = 100$. From Fig. 5, we can see that the confidence based sensor set selecting algorithm can always satisfy the sensing performance requirements, as expected, as the confidence based trustless sensor detecting method can effectively delete the trustless sensor from CRN. From Fig. 5, we can also see that the probability of false alarm of the sensor set selecting algorithm without confidence detection is very high, as expected, as the trustless sensor may be easily chosen into the selected sensor set and produces a high probability of false alarm.

Fig. 6 shows the probability of false alarm of the sensor set selecting algorithm with and without confidence detection versus noise power $\sigma^2$, with $M = 50$, $r = 100\text{km}$ and $N = 100$. From Fig. 6, we can see that the confidence based sensor set selecting algorithm can always satisfy the sensing performance requirements and the probability of false alarm of the sensor set selecting algorithm without confidence detection is very high, the reasons for which are the same as Fig. 5.

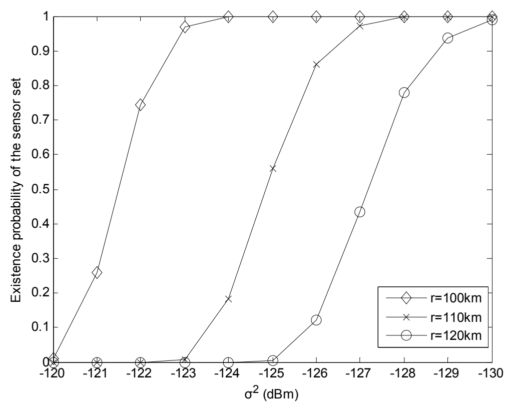


Fig. 7 Existence probability of the sensor set versus noise variance $\sigma^2$ for various $r$

From Figs. 3 and 4, we can note that the entire CRN may not meet the sensing performance requirements when $\sigma^2$ or $r$ is large. That is to say, the needed sensor set may not exist in a CRN when $\sigma^2$ or $r$ is large. The existence probability of the needed sensor set is characterized as a function of $\sigma^2$ and $r$ . The relationships among them are shown in Fig. 7, with $M = 50$ and $N = 100$. From Fig. 7, we can see that the existence probability of the sensor set increases as $\sigma^2$ and $r$ decreases, as expected, since the smaller the value of $\sigma^2$ and $r$ is, the higher the SNR will be.

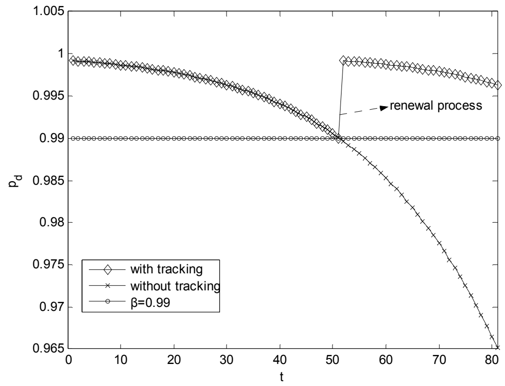


Fig.8 The tracking performance curves of the proposed sensor set selecting algorithm

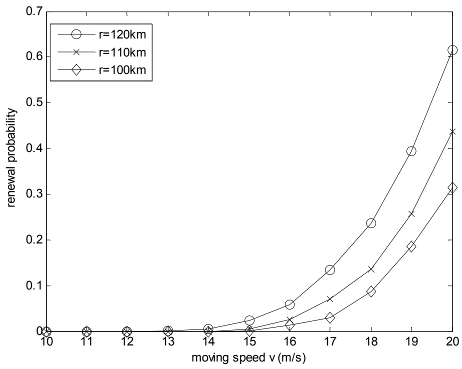


Fig. 9 Ineffective probability $p_{ineff}$ of the proposed adaptive sensor set selecting algorithm versus the moving speed $v$ of sensors for various $r$ .

According to the proposed confidence based adaptive sensor set selecting algorithm, when the global ARSNR $\Gamma$ of the current selected sensor set doesn't satisfy $p_d \geq \beta$ , the fusion center of the CRN will start the renewal process to select a new sensor set.

The tracking performance of the proposed confidence based adaptive sensor set selecting algorithm is evaluated in Figure 8. We assume that the initial value of the average SNR of the selected sensor set when $t = 0$ is $\Gamma = 0.28$ which decreases by $0.001/s$ with $t$ increasing. The parameters used in this simulations are as follows: $N$=100 , $n = 10$ and $\varepsilon$=0.23 . From Figure 8, we can see that the proposed algorithm with tracking function can always make $p_d \geq 0.99$ by the renewal process which starts at $t$=50$s$ in the graph, while the sensing performance of the algorithm without tracking function deteriorating with time increasing.

In this paper, we use the ineffective probability $p_{ineff}$ to evaluate the renewal frequency of the proposed confidence based adaptive sensor set selecting algorithm, which can be defined as

$$p_{ineff} = \frac{\text{total ineffective time}}{\text{total simulation time}}$$

In this paper, we adopt the random walk with reflection mobility model (RWRMM) widely used for simulating sensor movements [17]. The simulation results are shown in Fig. 9, with $M = 50$ . In simulation, we assume the RWRMM assigns each sensor a random moving direction which is changed every one second. For each simulation result, sensors move with a same speed $v$ and the total simulation time is 1000s. From Fig. 9, we can see that the ineffective probability $p_{ineff}$ increases as moving speed increases, as expected, since the higher the moving speed $v$ is, the global ARSNR $\Gamma$ may decreases faster. We can also note from Fig. 9 that the ineffective probability $p_{ineff}$ decreases as $r$ decreases, as expected, since the smaller the value of $r$ is, the higher the SNR of the sensors will be.

## V. Conclusion

This paper attempts to makes a good trade-off between having a high reliability of the sensing and having a low consumption of system resources by using fewest cooperative sensors to satisfy the sensing performance requirements. Firstly, the sensing performance of cooperative spectrum sensing is investigated and the relationship among the sensing performance, the number of cooperative sensors and the global average receiving signal to noise ratio is derived, based on which, a sensor set selecting method is proposed; then a confidence based trustless sensor detecting method is presented to delete the trustless sensors from CRN which would add negative effect on the sensor set selecting method; lastly, based on the two methods above, a confidence based sensor set selecting algorithm is proposed, which not only effectively delete the trustless sensors from CRN but also use fewest cooperative sensors to minimize the consumption of system resources, while still having enough for the sensing performance requirements. Analysis and numerical results illustrate the effectiveness and reliability of the proposed algorithm.

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