Research Article

An Improved Optimal Linear Weighted Cooperative Spectrum Sensing Algorithm for Cognitive Radio Sensor Networks

Yonghua Wang, Yuehong Li, Jian Yang, Pin Wan, and Qinruo Wang

1 School of Automation, Guangdong University of Technology, Guangzhou 510006, China
2 School of Electronic and Information Engineering, South China University of Technology, Guangzhou 510641, China
3 Shenzhen Key Laboratory of High Performance Data Mining, Shenzhen 518055, China

Correspondence should be addressed to Yonghua Wang; sjzwyh@163.com

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In order to improve the sensing accuracy of the Cognitive Radio Sensor Networks and reduce the interference to the primary user, this paper proposes an improved optimal linear weighted cooperative spectrum sensing scheme on the assumption that the report channel is not ideal. Through mathematical modeling, the spectrum sensing problem is ultimately converted into a constrained nonconvex optimization problem, and the chaotic harmony search (CHS) algorithm is to be used to find the optimal weighting vector value. The simulation results show that the proposed linear cooperative spectrum detection scheme based on the CHS algorithm has better performance than HS, SFLA, EGC, MRC, and MDC algorithm. In addition, the influence of local noise power, report channel noise power, and report channel gain on the performance of the algorithm is analyzed by simulation. The results show that local noise power has greater impact on the sensing performance.

1. Introduction

Currently, the wireless sensor networks (WSNs) use the Industrial, scientific, and medical (ISM) band, for example, the 2.4 GHz band. However, other applications, such as Wi-Fi, Bluetooth, and cordless phones, also work in this band. So the ISM band is becoming more and more engaged. The interference level among these applications has increased and even caused the unavailability of the ISM band in certain regions [1]. And for the large-scale WSNs, when a large number of nodes try to send data simultaneously, the collision probability and packet loss rate increase [2]. One solution of the abovementioned problem is to adopt the cognitive radio (CR) technology by WSN. The CR technology [3] can provide dynamic spectrum access and improve the efficiency of spectrum utilization. The WSNs using the cognitive radio technology is referred to as cognitive radio sensor networks (CRSNs) [4].

Spectrum sensing is one of the significantly important functions of the CRSN [4]. Its goal is to detect the spectrum holes that the CRSN nodes (secondary users) can use. There are three main spectrum-sensing methods: matched filter detection, energy detection, and cyclostationary feature detection [5]. They are noncooperative spectrum sensing schemes. However, there are the shadows, multipath, fading, and other unfavorable factors in the wireless environments, which can significantly degrade the detection performance of the single CRSN node. To improve the accuracy of spectrum sensing, multinode cooperative sensing can be used.

At present, a lot of cooperative spectrum sensing techniques have been proposed. In [6], the “OR”, “AND” rules were used to fuse the SU sensing results for the final judgment. The performances of hard decision based on the likelihood ratio test (LRT) and soft decision based on the “AND” rule are compared in [7], and the results show that the soft decision method has better performance. In [8], D-S evidence theory is applied to soft information fusion in cooperative spectrum sensing and can achieve the suboptimal fusion performance. This method outperforms the traditional “AND” and “OR” rules, but it requires the prior information.

The data fusion method based on the Bayesian was proposed in [9], but its disadvantage is that the prior probability
of the PU signal, such as the false alarm probability and the detection probability of the SU, needs to be known beforehand. This prior information is difficult to be obtained in the actual communications system. In order to save the nodes’ energy, a sensor-based cooperative spectrum sensing scheme for CRSN has been proposed in [10]. And in [2], the authors proposed a Takagi and Sugeno’s (T-S) fuzzy logic based spectrum sensing scheme for CRSNs. In [11], a simplified linear cooperative spectrum sensing model based on energy detection has been proposed. The performance of this method is close to the optimal LRT’s and is simpler. However, the method based on the modified deflection coefficient (MDC) for solving the weight vector is only a suboptimal method and cannot guarantee that the optimal solution in theory can be obtained.

In this paper, the linear weighted cooperative spectrum sensing model [11] is improved and the nonideal report channel conditions are considered. To improve the robustness and the convergence speed of basic harmony search (HS) algorithm [12], an improved chaos harmony search (CHS) algorithm is proposed. And the CHS algorithm is used to solve the optimal weight vector value in the cooperative linear spectrum sensing. Simulation results show that the proposed method has high detection accuracy.

The rest of this paper is organized as follows. In Section 2, we introduce the improved optimal linear weighted cooperative spectrum sensing structure and mathematical model. In Section 3, we give the CHS algorithm and use it to calculate the optimal weight vector. Section 4 gives the simulation results and analysis. Section 5 concludes this paper.

2. System Model of the Improved Optimal Linear Weighted Cooperative Spectrum Sensing Algorithm

2.1. Framework of Linear Weighted Cooperative Spectrum Sensing. The information fusion framework of the optimal linear weighted cooperative spectrum sensing can be divided into three phases, as shown in Figure 1.

The first phase is the local sensing. The CRSN nodes in cooperative sensing use the energy detection method to detect the PU signal and do the local processing on the sensing signal, thus making the local sensing function complete. The second phase is the information fusion. The FC (fusion center) weights the local sensing information of SU linearly and, through the intelligent optimization, gets the optimal weighted complete information. Thus, the information fusion is completed. The third phase is the global decision. The FC processed information will be compared with the threshold, and a final decision about the existence of the PU signal will be made.

2.2. Mathematical Model of Linear Weighted Cooperative Spectrum Sensing. In [11], the author proposed a simplified linear cooperative spectrum sensing model, but in this model the report channel is assumed to be ideal. However, in practical cases, the report channel is not ideal. Therefore, the linear weighted cooperative spectrum sensing model is improved in this paper and the nonideal report channel conditions are considered.

The system model is shown in Figure 2. We consider that the CRSN is comprised of M cognitive sensors and an FC. The binary hypotheses test model whether the primary user is present (H_1) or not (H_0) of the i (1 ≤ i ≤ M) th-node at the k (0 ≤ k ≤ N)th sense interval is

\[ x_i(k) = \begin{cases} m_i(k) , & i = 1, 2, \ldots, M; \ H_0, \\ h_i s(k) + m_i(k) , & i = 1, 2, \ldots, M; \ H_1, \end{cases} \quad (1) \]

where \( x_i(k) \) is the received composite signal at the i th CRSN node. \( s(k) \) denotes the primary user’s signal. \( h_i \) is the wireless channel gain between the PU and the i th CRSN node, and \( h_i \) is assumed to be a constant in a sensing period. \( m_i(k) \) denotes the Gaussian noise and is assumed to be an i.i.d Gaussian random process with zero mean and variance \( \sigma_i^2 \), that is, \( m_i(k) \sim \mathcal{N}(0, \sigma_i^2) \). The vector \( \{ m_i(k) \} \) is composed of the local noise of the respective i th node, and the vector \( \sigma = [\sigma_1^2, \sigma_2^2, \ldots, \sigma_M^2] \) is composed of the corresponding noise variances. The signal \( s(k) \) and the noise \( m_i(k) \) are assumed independent of each other.

2.2.1. Local Sensing. Suppose the node of CRSN using the energy detection and the summary statistic of i th node \( u_i \) are:

\[ u_i = \sum_{k=0}^{N-1} |x_i(k)|^2 \quad i = 1, 2, \ldots, M, \quad (2) \]

where \( N \) is the number of samples.

Assuming each node is independent of each other, let \( y_i \) be the local signal-to-noise ratio of PU signal that the i th node received. The summary statistics \( \{ u_i \} \) of the i th node can be expressed as quadratic sum of \( N \) Gaussian random variables. Then, the \( u_i/\sigma_i^2 \) obeys the following distribution:

\[ \frac{u_i}{\sigma_i^2} \sim \begin{cases} \chi^2_N, & \ H_0, \\ \chi^2_N(y_i), & \ H_1. \end{cases} \quad (3) \]

According to the central limit theory, when the sampling number \( N \) is large enough (e.g., \( N \geq 10 \)), the summary statistics \( \{ u_i \} \) approximately obeys the normal distribution \( \mathcal{N}(E[u_i], \text{Var}[u_i]) \), where \( E[\cdot] \) and \( \text{Var}[\cdot] \) represent the mean and variance of the \( u_i \), respectively:

\[ u_i \sim \begin{cases} \mathcal{N}(Na_i^2, 2N\sigma_i^4), & \ H_0, \\ \mathcal{N}((N + y_i)\sigma_i^2, 2(N + 2y_i)\sigma_i^4), & \ H_1. \end{cases} \quad (4) \]

Let the \( \lambda_i \) be the decision threshold of i th node’s energy detection; the local decision rules are as follows:

\[ u_i > \lambda_i, \quad H_1, \]
\[ u_i < \lambda_i, \quad H_0, \quad i = 1, 2, \ldots, M. \quad (5) \]
Then, the local false alarm probability $P_f^i$ and detection probability $P_d^i$ of the $i$th node can be obtained:

$$
P_f^i = Q \left( \frac{\lambda_i - E[U_i/H_0]}{\sqrt{\text{Var}[U_i/H_0]}} \right) = Q \left( \frac{\lambda_i - N\sigma_i^2}{\sqrt{2N\sigma_i^4}} \right),
$$

$$
P_d^i = Q \left( \frac{\lambda_i - E[U_i/H_1]}{\sqrt{\text{Var}[U_i/H_1]}} \right) = Q \left( \frac{\lambda_i - (N + y_i)\sigma_i^2}{\sqrt{2(N + 2y_i)\sigma_i^4}} \right),
$$

where $Q(\cdot)$ is complementary cumulative distribution function, which calculates the tail probability of a zero mean unit variance Gaussian variable [11]; that is, $Q(x) = \int_x^{+\infty} \exp(-t^2/2)dt / \sqrt{2\pi}$.

2.2.2. Global Decision. The summary statistics $\{u_i\}$ will be transmitted to the FC through the control channel for final decision. There are noise and channel gain in the control channel. Assuming that the channel noise $\{\eta_i\}$ in the control channel obeys the $\mathcal{N}(0,\delta^2_i)$ Gaussian distribution, let $\{g_i\}$ denote the gain of control channel. The summary statistics $\{y_i\}$ of SU that the FC received is

$$
y_i = g_i u_i + \eta_i, \quad i = 1, 2, \ldots, M.
$$

From the above, we can see that the $\{y_i\}$ obeys normal distribution $\mathcal{N}(\mathbb{E}[y_i], \text{Var}[y_i])$:

$$
y_i \sim \begin{cases}
\mathcal{N}(Ng_i\sigma_i^2, 2Ng_i^2\sigma_i^4 + \delta_i^2) , & H_0, \\
\mathcal{N}((N + y_i)g_i\sigma_i^2, 2(N + 2y_i)g_i^2\sigma_i^4 + \delta_i^2) , & H_1.
\end{cases}
$$

After the FC receives $\{y_i\}$, then the global decision statistics can be calculated linearly as follows:

$$
y_{fc} = \sum_{i=1}^{M} w_i y_i = w^T y,
$$

where weight vector $w = [w_1, w_2, \ldots, w_M]^T$, and it satisfies the condition $\sum_{i=1}^{M} w_i = 1, w_i \geq 1$. 

### Figures

**Figure 1:** The information fusion framework of optimal linear weighted cooperative spectrum sensing.

**Figure 2:** System model of linear weighted cooperative spectrum sensing.
Weight \( w_i \) of each node is used to reflect the contribution degree to the global decision. If the received signal of the node is with high SNR, it indicates that the detection results of this node can reflect the actual situation, then this node will be assigned a greater weight. On the contrary, this node will be assigned a smaller weight to reduce its influence on the global decision.

Similarly, the FC global decision statistic \( y_{fc} \) is normally distributed \( \mathcal{N}(E[y_{fc}], \text{Var}[y_{fc}]) \):

\[
y_{fc} \sim \begin{cases} 
\mathcal{N} \left( \sum_{i=1}^{M} N w_i g_i \sigma_i^2, \sum_{i=1}^{M} (2 N g_i^2 \sigma_i^4 u_i^2 + \delta_i^2 w_i^2) \right), & H_0, \\
\mathcal{N} \left( \sum_{i=1}^{M} (N + \gamma_i) w_i g_i \sigma_i^2, \sum_{i=1}^{M} (2 (N + 2 \gamma_i) g_i^2 \sigma_i^4 u_i^2 + \delta_i^2 w_i^2) \right), & H_1.
\end{cases}
\]

(10)

Let the FC fusion center decision threshold be \( \lambda_{fc} \); then according to the following global decision rule:

\[
y_{fc} \geq \lambda_{fc}, \quad H_1, \\
y_{fc} < \lambda_{fc}, \quad H_0.
\]

(11)

At last, the global false alarm probability \( P_f \) and detection probability \( P_d \) can be obtained:

\[
P_f = Q \left( \frac{\lambda_{fc} - E[y_{fc}/H_0]}{\sqrt{\text{Var}[y_{fc}/H_0]}} \right)
\]

\[
= Q \left( \frac{\lambda_{fc} - \sum_{i=1}^{M} N w_i g_i \sigma_i^2}{\sqrt{\sum_{i=1}^{M} (2 N g_i^2 \sigma_i^4 u_i^2 + \delta_i^2 w_i^2)}} \right),
\]

(12)

\[
P_d = Q \left( \frac{\lambda_{fc} - E[y_{fc}/H_1]}{\sqrt{\text{Var}[y_{fc}/H_1]}} \right)
\]

\[
= Q \left( \frac{\lambda_{fc} - \sum_{i=1}^{M} (N + \gamma_i) w_i g_i \sigma_i^2}{\sqrt{\sum_{i=1}^{M} (2 (N + 2 \gamma_i) g_i^2 \sigma_i^4 u_i^2 + \delta_i^2 w_i^2)}} \right).
\]

Let the control (report) channel gain vector be \( g = [g_1, g_2, \ldots, g_M]^T \), local (sensing channel) SNR vector be \( \gamma = [\gamma_1, \gamma_2, \ldots, \gamma_M]^T \), local noise variance vector be \( \sigma = [\sigma_1^2, \sigma_2^2, \ldots, \sigma_M^2]^T \), and the control channel variance vector be \( \delta = [\delta_1^2, \delta_2^2, \ldots, \delta_M^2]^T \), and let \( 2 N \text{diag}^2(g) \text{diag}^2(\sigma) + 4 \text{diag}(\gamma) \text{diag}^2(g) \text{diag}^2(\sigma) + \text{diag}(\delta) = \sum_{H_0} 2 N \text{diag}^2(g) \text{diag}^2(\sigma) + \text{diag}(\delta) = \sum_{H_0}, \) where \( T \) represents the transpose vector matrix and \( M \) is the number of nodes that participate in cooperative sensing. Let \( \text{diag}(\cdot) \) represents the diagonal matrix. Then, formula (12) can be converted to,

\[
P_f = Q \left( \frac{\lambda_{fc} - \sum_{i=1}^{M} N w_i g_i \sigma_i^2}{\sqrt{\text{Var}[y_{fc}/H_0]}} \right)
\]

\[
P_d = Q \left( \frac{\lambda_{fc} - \sum_{i=1}^{M} (N + \gamma_i) w_i g_i \sigma_i^2}{\sqrt{\text{Var}[y_{fc}/H_1]}} \right).
\]

(13)

2.2.3. The Optimal Detection under the Conditions of Constant False Alarm Probability. The missed detection probability \( P_m = 1 - P_d \) reflects the interference degree of SU on the PU signal. \( P_d \) reflects the spectrum utilization rate. When \( P_d \) is too small, it means that the PU will be severely interfered. When \( P_f \) is too large, the spectrum utilization will be reduced. Therefore, according to the Neyman-Pearson criterion, the constant false alarm probability \( P_f \) can be given smaller, to maximize the probability of detection \( P_d \). To improve the detection performance of the system, setting \( P_d \) a reasonable value can maximize the spectrum utilization while avoiding the interference to PU.

According to the given \( P_f \), the final decision threshold at the FC can be obtained by formula (13):

\[
\lambda_{fc} = Q^{-1} \left( \frac{P_f}{\sqrt{\text{Var}[y_{fc}/H_0]}} \right) - \sum_{i=1}^{M} N w_i g_i \sigma_i^2,
\]

(14)

Combined with formulae (14) and (13), the \( P_d \) can be obtained:

\[
P_d = Q \left( \frac{Q^{-1} \left( \frac{P_f}{\sqrt{\text{Var}[y_{fc}/H_1]}} \right) - \sum_{i=1}^{M} (N + \gamma_i) w_i g_i \sigma_i^2}{\sqrt{\text{Var}[y_{fc}/H_1]}} \right).
\]

(15)

Formula (15) shows that, for a given \( P_f \), the maximization of \( P_d \) depends on the optimization of the weight vector \( w = [w_1, w_2, \ldots, w_M]^T \). Since the \( Q(.) \) is a monotonically decreasing function, then the problem of maximizing \( P_d \) is equivalent to minimizing the objective function \( f(w) \). Therefore, we formulate the following optimization model:

\[
\min_w f(w) = \frac{Q^{-1} \left( \frac{P_f}{\sqrt{\text{Var}[y_{fc}/H_1]}} \right) - \sum_{i=1}^{M} (N + \gamma_i) w_i g_i \sigma_i^2}{\sqrt{\text{Var}[y_{fc}/H_1]}} \sqrt{\text{Var}[y_{fc}/H_1]}
\]

s.t. \( \sum_{i=1}^{M} w_i = 1, \quad w_i \geq 0, \quad \forall i \in \{1, 2, \ldots, M\} \)

(16)

Through mathematical modeling, the spectrum sensing problem is ultimately converted into a constrained nonconvex optimization problem in formula (16), and the optimal \( P_d \) cannot be directly obtained. The determination of \( P_d \) is equivalent to determining the weight vector \( w \). The EGC, MRC, and
MDC methods can be used for solving the $w$. However, these methods cannot get the ideal solution. Therefore, the CHS algorithm is proposed to directly optimize the search of formula (16) to find the optimal weight vector $w_{op}$.

3. Chaotic Harmony Search Algorithm

The basic harmony search (HS) algorithm can be found in [6]. The proposed chaotic harmony search (CHS) algorithm for calculating the optimal weight vector $w_{op}$ in the linear optimization weighted cooperative spectrum sensing is summarized as follows.

Step 1. The parameter initialization.

Determine the harmony memory size (HMS) of harmony memory (HM), the feasible solution space dimension $D$, the range of feasible solution $[w_{min}, w_{max}]$, harmony memory considering rate (HMCR), pitch adjusting rate (PAR), the maximum number of iterations $N_{max}$, the number of subharmonic memory $S$, and the size of each subharmonic memory $G$.

Step 2. Initialize the harmony memory by chaos.

(1) Randomly generate a $D$-dimensional vector $z_0 = (z_{01}, z_{02}, \ldots, z_{0D})$; the value of $z_{0i}$ is between 0 and 1. Based on logistic iterative equation $z_{n+1} = 4z_n(1 - z_n)$, $n = 0, 1, 2, \ldots$, the $N$ chaotic sequence $\{z_1, z_2, \ldots, z_N\}$ is obtained.

(2) Each component of chaotic sequence $\{z_1, z_2, \ldots, z_N\}$ will be transformed into the variable range $[w_{min}, w_{max}]$ according to the $w_i = w_{min} + (w_{max} - w_{min}) \cdot z_{ji}$; then the feasible solution $w = (w_1, w_2, \ldots, w_D)$ will be obtained, where $j = 1, 2, \ldots, N$, $i = 1, 2, \ldots, D$.

(3) The $N$ feasible solutions $w$ are normalized by $\tilde{w}_i = w_i / \sum_{j=1}^{D} w_j$. Objective function values $f(w)$ are calculated, respectively, and in accordance with the order. HMS preferential values will be selected and be put in the HM. Let $f = 1$, $t = 1$.

Step 3. Harmony search and chaotic disturbance.

(1) Divide the HM into $S$ subharmonic memory and each subharmonic memory contains $G$ harmony. Assign the HMS feasible solutions into the $S$ subharmonic memory according to the quality.

(2) Determine the worst solution $w_{worst}$ and the best solution $w_{best}$ of the $f$th subharmonic memory. Generate a new solution $w_{new} = (w_{1new}, w_{2new}, \ldots, w_{Dnew})$ according to

$$
\begin{align*}
    x_{dnew} &\leftarrow \begin{cases} 
        x_{dnew}^1, \ldots, x_{dnew}^S & \text{if } \text{rand}() \text{ is HMCR}, \\
        x_{dnew}^1, \ldots, x_{dnew}^\text{HMS} & \text{if } \text{rand}() \text{ is HMC}, \\
        x_{dnew}^{\text{HM}}, b_{dU} & \text{if } \text{rand}() \geq \text{HMC},
    \end{cases}
\end{align*}
$$

and generate a random perturbation with probability PAR to each component $w_{inew}$ of $w_{new}$ based on the following:

$$
\begin{align*}
    x_{dnew}^i &\leftarrow \begin{cases} 
        x_{dnew}^i + (2 \text{rand}(\cdot) - 1) \cdot U, & \text{if } \text{rand}() < \text{PAR}, \\
        x_{dnew}^i, & \text{if } \text{rand}() \geq \text{PAR}.
    \end{cases}
\end{align*}
$$

If $f(w_{new}) < f(w_{worst})$, then the $w_{worst}$ is replaced with $w_{new}$, where PAR is perturbation probability, HMCR is retention probability, and rand() indicates generating a random number in the interval of $[0, 1]$.

(3) If $f(w_{new}) > f(w_{best})$, then making a chaos disturbance to the best solution $w_{best}$ of the $f$th subharmonic memory according to the following method.

Randomly generate a vector $u_0 = (u_{01}, u_{02}, \ldots, u_{0D})$, the value $u_{0i}$ is between $[0, 1]$. Based on logistic iterative equation $u_{1j} = 4 \cdot u_{0j} - u_{0j}$, we can get $u_i = (u_{i1}, u_{i2}, \ldots, u_{iD})$, and transform the components of $u_i$ into the chaotic perturbation range $[-\beta, \beta]$. Let the perturbation vector $\Delta x = (\Delta x_1, \Delta x_2, \ldots, \Delta x_D)$, where $\Delta x_i = -\beta + 2\beta u_{i1}$. Let $x_{inew} = x_{i} + \Delta x_i$; then the new $w_{new}$ will be get. If $f(w_{new}) < f(w_{best})$, then replace the $w_{best}$ with $w_{new}$. If $f(w_{new}) > f(w_{best})$, then go to Step 4; otherwise let $f = f + 1$; go to Step 2.

Step 4. Update the harmony memory.

Merge the $S$ subharmonic memories into an HM. Sort all solutions according to $f(w)$ and save the global optimal solution $w_{best}$. If $f > N_{max}$, go to Step 5; otherwise let $t = t + 1$, go to Step 3.

Step 5. Terminate algorithm.

Terminate the algorithm. Output the global optimal solution in the HM, which corresponds to the wanted optimal weight vector $w_{op} = w_{best}$.

4. Simulation Results and Analysis

To evaluate the performance of the proposed CHS algorithm which is to solve the linear cooperative spectrum sensing problem in the CRSN, the simulations are implemented in MATLAB7.1. The sensing performance of the proposed scheme is compared with the scheme that is based on the OR, AND, MDC, ISFLA [14], EGC, and MRC [6]. In the simulation, the signal to be sensed is assumed to be the BPSK modulation signal, and the sampling value $N = 20$.

In order to make the simulation results comparable, after a lot of experiments, the parameters of HS and CHS algorithm in the simulation are set as follows: the harmony memory size HMS = 50, the retention probability HMCR = 0.85, the perturbation probability PAR = 0.35, and the bandwidth value $U = 0.005$. The subharmonic memory number of CHS is $S = 10$, size of each subharmonic memory $G = 5$. The parameters of ISFLA algorithm are the same as those in [12]:
The population size (number of frogs) $P = 50$, the number of memplexes $F = 10$, and the number of frogs in memplex $G = 5$. Maximum moving step $d_{\text{max}} = 0.5$. The number of iterations in each memplex is 1, and the max number of shuffling iterations of the HS, CHS and ISFLA $N_{\text{max}} = 200$. In order to ensure the reliability of the experimental data, the optimal solution $w_{\text{op}}$ of each experiment is the average value of 50 times of simulation.

**Experiment 1.** The Optimize Performance of HS, CHS, and ISFLA.

Let the global probability of false alarm $P_f = 0.1$, the number of collaborative spectrum sensing CRSN nodes $M = 9$, the local noise variance and report channel noise variance $\sigma = \delta = 1$, the gain of report channel $g = 1$, and the local SNR of each CRSN node $\gamma = \{-4.5, -6, -7.9, -9.1, -5.5, -10.2, -8.2, -4.3, -9.6\} \text{ dB}$. The average convergence curves of the algorithms in the evaluation index of objective function $f(w)$ and detection probability are shown in Figures 3 and 4. The optimal values of the algorithms in the figure are the optimum values of the objective function that the memplexes can obtain during each iteration. The mean value represents the average value of the memplex objective function.

**Experiment 2.** The effect of the system parameters change on the performance of CHS algorithm.

The Monte Carlo simulation runs with 10,000 samples under the following conditions: $\sigma = 1, \delta = 1, g = 1, N = 20, M = 6$; the SNR of all CRSN nodes is $-7.5$ dB. Figure 5 gives the performance of the ROC curves on condition that different sampling points $N$, the different number $M$ of CRSN nodes, and the different average local SNR of the CHS algorithm. Figure 6 shows the impact of local noise variance $\sigma$, the report channel noise variance $\delta$, and reporting channel gain $g$ to the ROC curves.

**Simulation Results Analysis.** From Figures 5 and 6, we can see that when we increase the sampling points $N$, the CRSN node number $M$ and the local average SNR, the detection
performance of CHS algorithm is significantly improved. When we increase the local noise and reporting channel noise intensity, the performance of CHS will decrease, and the local noise has relatively large impact on the CHS. Further, when the channel attenuation occurs in the report channel, the spectrum detection performance will decrease.

Assuming that the CRSN node number $M = 6$, the local noise variance $\sigma_0 = [2.3, 1.5, 2.0, 0.8, 1.6, 1.2]$, the report channel noise variance $\delta_0 = [0.8, 1.1, 2.1, 2.5, 1.8, 2.3]$ dB. The ROC curves of different algorithms when $\sigma = \sigma_0, \delta = \delta_0$ are shown in Figure 7. The ROC curves of different algorithms when $\sigma = 10\sigma_0, \delta = \delta_0$ are shown in Figure 8. The ROC curves of different algorithms when $\sigma = \sigma_0, \delta = 10\delta_0$ are shown in Figure 9. The ROC curves of different algorithms on condition that report channel attenuation $g = 0.5g_0$ are shown in Figure 10.

Figure 11 shows the CHS performance on condition that the local noise variance $\sigma$, the report channel noise variance $\delta$, and the report channel gain $g$ are changed.

Table 1 shows the probability of missed detection ($P_m$) of the CHS, EGC, MDC, and MRC algorithms in different noise environments and channel conditions when the false alarm probabilities are 0.01, 0.05, and 0.1, respectively.

Simulation Results Analysis. From Figures 5–11 and Table 1 we can see that the four algorithms are subject to noise and channel gain influence. The missed detection will increase when the local noise and report channel noise are increasing and the report channel is not ideal, and then the detection
Table 1: The probability of missed detection ($P_m$) of the algorithms in different environments.

| Algorithm | Parameters | $P_f$ | $P_m$  | $P_m$  | $P_m$  | $P_m$  |
|-----------|------------|-------|--------|--------|--------|--------|
|           | $\sigma = \sigma_0, \delta = \delta_0$ |       |        |        |        |        |
| CHS       | $\sigma = \sigma_0, \delta = \delta_0$ | 0.01  | 0.6696 | 0.8745 | 0.7266 | 0.6922 |
|           | $\sigma = \sigma_0, \delta = \delta_0$ | 0.05  | 0.4620 | 0.7096 | 0.5205 | 0.4845 |
|           | $\sigma = \sigma_0, \delta = \delta_0$ | 0.1   | 0.3489 | 0.5892 | 0.4009 | 0.3686 |
|           | $\sigma = \sigma_0, \delta = \delta_0$ | 0.01  | 0.7242 | 0.9028 | 0.7644 | 0.7390 |
| EGC       | $\sigma = \sigma_0, \delta = \delta_0$ | 0.05  | 0.5180 | 0.7527 | 0.5624 | 0.5339 |
|           | $\sigma = \sigma_0, \delta = \delta_0$ | 0.1   | 0.3986 | 0.6353 | 0.4396 | 0.4131 |
|           | $\sigma = \sigma_0, \delta = \delta_0$ | 0.01  | 0.7226 | 0.8753 | 0.7501 | 0.7324 |
| MDC       | $\sigma = \sigma_0, \delta = \delta_0$ | 0.05  | 0.5225 | 0.7114 | 0.5520 | 0.5328 |
|           | $\sigma = \sigma_0, \delta = \delta_0$ | 0.1   | 0.4065 | 0.5915 | 0.4334 | 0.4158 |
|           | $\sigma = \sigma_0, \delta = \delta_0$ | 0.01  | 0.6814 | 0.8893 | 0.7274 | 0.6982 |
| MRC       | $\sigma = \sigma_0, \delta = \delta_0$ | 0.05  | 0.4754 | 0.7308 | 0.5226 | 0.4992 |
|           | $\sigma = \sigma_0, \delta = \delta_0$ | 0.1   | 0.3616 | 0.6111 | 0.4035 | 0.3764 |

5. Conclusions

This paper proposed an improved optimal linear weighted cooperative spectrum sensing scheme. By using chaotic harmony search (CHS) algorithm for solving the optimal weighted coefficient, the overall perception of system performance can be improved. And the validity of the algorithm is verified through simulation. The simulation results show that, compared with MDC, EGC, and MRC and other methods, CHS achieves better detection performance. When the wireless environment becomes more severe, if local noise increases, the report channel noise increases or the report channel in nonideal case, the detection performance of the system will be reduced, and the effect of local noise strength on the final sensing performance of the system is the biggest.
Therefore, while choosing the cooperative secondary users, the influence of the local noise power of secondary users on the final performance of the detection system needs to be given more consideration.

**Conflict of Interests**

The authors declare that there is no conflict of interests regarding the publication of this paper.

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