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Research Article

A Two-Step Cooperative Energy Detection Algorithm Robust to Noise Uncertainty

Tingting Yang,[1] **Yucheng Wu**,[1] **Liang Li**,[1] **Weiyang Xu**,[1] **and Weiqiang Tan**[2]

[1]*School of Microelectronics and Communication Engineering, Chongqing University, Chongqing, China*
[2]*School of Computer Science and Network Engineering, Guangzhou University, Guangzhou, China*

Correspondence should be addressed to Yucheng Wu; wuyucheng@cqu.edu.cn

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In order to achieve accurate interference detection in complex electromagnetic environments, a two-step cooperative stochastic resonance energy detection (TCSRED) algorithm is proposed to address the problem, where the traditional energy detection (ED) performance is susceptible to noise uncertainty. By combining two thresholds and two-step cooperation, the generalized stochastic resonance is applied to the energy detection, which effectively reduces the complexity and detection time. In particular, when a certain decision result is obtained in the first step of detection, the decision is finished and the second step of detection is unnecessary. Otherwise, the second step of detection is performed to obtain the final decision result. Simulation results show that the proposed algorithm is robust to the noise uncertainty. Even in the case of a low signal-to-noise ratio (SNR), it also performs better than existing methods without significant increment of the complexity.

1. Introduction

Interference detection has attracted more and more attention in recent years due to its importance to anti-interference processing [1–4]. There are numerous methods to achieve signal detection, such as cyclostationary detection [3], covariance based detection [5], matched-filter detection, and energy detection (ED). Nevertheless, energy detection algorithm has proven to be one of the promising solutions for signal detection by virtue of its simplicity, ease of implementation, and availability. Moreover, energy detection provides key benefits in terms of signal detection, readily achievable in practical application scenario without any priori information [6, 7]. Like any other interference detection algorithms, energy detection is facing challenges due to its sensitivity to noise uncertainty and the increasing demands for better detection performance and shorter detection time. Under the circumstances of weak signal and high-intensity background noise, its reliability and accuracy of detection will significantly deteriorate. Owing to the fact that proper selection of decision threshold to ensure the detection performance is very difficult at low signal-to-noise ratio (SNR), accurate estimate of noise variance is nearly impossible due to the existence of noise uncertainty.

In recent years, some researchers have found that the signal strength can be enhanced significantly in some specific nonlinear systems which include the stochastic resonance noise and signal. This phenomenon has been named as stochastic resonance (SR) in [8]. Therefore, researchers adopted the stochastic resonance technology into energy detection algorithms to avoid the degradation of detection performance in environments with strong background noise in [9, 10]. Since the addition of stochastic resonance noise to a nonlinear system can amplify the output SNR of the noisy signals, compared to the traditional energy detection, the new algorithm based on stochastic resonance can obtain a better detection performance with the premise of same algorithm complexity and detection efficiency [10]. However, these researchers bring the performance of energy detection algorithm at low SNR to a new level, yet still fail to counteract the effects of noise uncertainty. The reliability and accuracy of these algorithms drop sharply when the noise uncertainty exceeds a certain value. Unfortunately, increasing sampling number, the false alarm probability, and the detection time

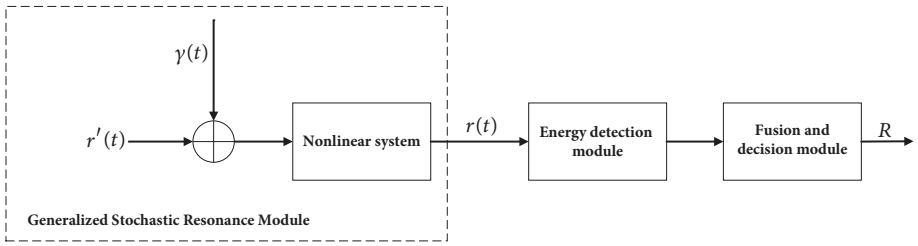

Figure 1: The model of the proposed algorithm.

could not improve the detection probability in a relatively poor channel environment.

To overcome the impact of noise uncertainty on detection performance, many valuable works have been proposed [11–15]. For example, the authors in [11] proposed a dual threshold energy detection method, which aimed to improve the detection performance under an additive white Gaussian noise (AWGN) channel, but the improvement of performance is not well enough in response to a large noise uncertainty. A method to adaptively adjust the decision threshold based on the detection statistic of energy over a period was proposed to maximize the probability of detection and minimize the false alarm probability [12]. But a long-term observation is very necessary for the algorithm, which means that its detection efficiency cannot be guaranteed. A cooperative energy detection algorithm which consists of two-step judgment mechanism and convex sample threshold has been mentioned in [13] to obtain the minimum total error detection probability, but in this case, the algorithm has a high missed detection probability. In addition, the algorithm did not consider the stability of the algorithm under diverse noise uncertainty. In [14], a cooperative energy detection algorithm based on soft decision was presented. This algorithm utilized the noise uncertainty factor to estimate the decision threshold, but it requires a large transmission bandwidth for transmitting the detection statistic of each node. Therefore, it is difficult to be applied to interference detection systems which have some strict requirements for the detection accuracy and transmission overhead.

To avoid the influence of strong background noise and noise uncertainty, a two-step cooperative stochastic resonance energy detection algorithm is proposed in this paper, which efficiently solves the contradiction between detection probability and detection efficiency (The detection efficiency is usually measured by detection time. Increasing the total number of samples increases the detection probability but also detection time. That means detection performance is a tradeoff between detection efficiency and detection probability.). We point out the influence of stochastic resonance noise intensity on the detection probability and design scheme to adaptively modulate the stochastic resonance noise intensity on the basis of the channel environment [16]. Then, according to the characters of interference detection problems and the limitations of previous methods, we present the selection mechanism of double threshold and fusion criterion of the detection information in the case of the noise uncertainty. Furthermore, the expressions of the false alarm probability and detection probability of the proposed algorithm are also derived.

The remainder of the paper is constructed as follows. Section 2 introduces the model of the proposed algorithm. After that, the double threshold and two-step cooperative detection scheme of the introduced algorithm are presented in Section 3. And then, we compare the performance among the traditional energy detection algorithm, energy detection algorithm based on generalized stochastic resonance, and the proposed algorithm and give the corresponding simulation results and theoretical analysis in Section 4. Finally, Section 5 draws the conclusion.

For the sake of the convenience, we present a list of the major symbols that are used in Table 1 with their definitions.

2. System Model and Discussion

2.1. System Model. Since the traditional energy detection algorithm is very sensitive to the strong background noise, stochastic resonance is applied to the discussed algorithm to improve the detection performance and detection efficiency at low SNR. The system model under consideration is given in Figure 1, where $r'(t)$ is the received signal of the detection system, $\gamma(t)$ denotes the DC noise with an intensity of ρ, and R is the inferred decision. Generalized stochastic resonance means that a certain intensity of DC noise is added to the received signal, so that the noise, useful signal, and interference resonate in the nonlinear system, thereby improving the SNR of the received signal. Then we send the amplified signal to the energy detection module and the fusion and decision module in a sequential manner to achieve interference detection and obtain the detection result. The key idea of energy detection is to compare the energy of the signal received during a specific time period with a preset decision threshold and make a decision to obtain a corresponding detection result. The implementation block diagram of the energy detection module is shown in Figure 2. Among them, $r(t)$ is the input signal, N is the total number of samples, and T denotes the test statistic of energy detection.

2.2. Discussion. A central unit or a common receiver and L cooperative detection nodes are considered to join the cooperative interference detection. The central unit manages all detection nodes and combines the overall detection information to make an ultimate decision. Assume that each detection node performs local interference detection

Table 1: List of major symbols.

Symbol	Description
$r'(t)$	Received signal of the detection system
$\gamma(t)$	DC noise
ρ	Intensity of DC noise
R	Inferred decision
$r(t)$	Input signal of energy module
N	Total number of samples
T	Test statistic of energy detection
L	Number of cooperative detection nodes
i	The i-th detection node
$n_i(t)$	Gaussian white noise of i-th detection node
β_i	Mean of Gaussian white noise of i-th detect-ion node
σ_i^2	Variance of Gaussian white noise of i-th detection node
$s_i(t)$	Useful signal of i-th detection node
ω_i	Mean of useful signal of i-th detection node
$\sigma_{s\_i}^2$	Variance of useful signal of i-th detection node
$\gamma_i(t)$	DC noise of i-th detection node
ρ_i	Mean of DC noise of i-th detection node
$j_i(t)$	Interference signal of i-th detection node
μ_i	Mean of interference signal of i-th detection node
$\sigma_{j\_i}^2$	Variance of interference signal of i-th detection node
H_0	Absence of interference signal
H_1	Presence of interference signal
T_i	Detection statistic of energy detection of i-th detection node
λ_i	Decision threshold of i-th detection node
R_i	Decision result of i-th detection node
P_{f_i}	False alarm probability of i-th detection node
P_{d_i}	Detection probability of i-th detection node
ρ_{i_best}	Intensity of best random resonance noise of i-th detection node
$\sigma_{n\_i}^2$	Nominal noise power of i-th detection node
u_c	The quantifies of noise uncertainty
λ_{l_i}	Decision threshold of detection node i calculated by minimum noise variance
λ_{h_i}	Decision threshold of detection node i calculated by maximum noise variance
P_{f_FSC}	False alarm probability of first cooperation step
P_{d_FSC}	Detection probability of first cooperation step
α_i	The weighting factor
T_{SSC}	Detection statistic calculated by weighting factor
R_{SSC}	Decision criterion of second cooperation step
P_{f_SSC}	False alarm probability of second cooperation step
P_{d_SSC}	Detection probability of second cooperation step
P_{f_TCSRED}	False alarm probability of TCSRED algorithm
P_{d_TCSRED}	Detection probability of TCSRED algorithm

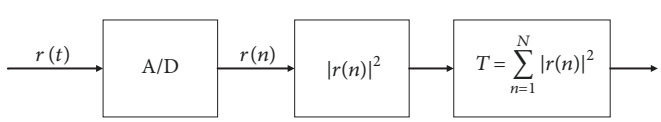

Figure 2: The implementation block diagram of the energy detection module.

independently. First, consider the i-th detection node. According to the Neyman-Pearson criteria, the interference detection problem of the i-th detection node can be modeled as a binary hypothesis test [17]:

$$r_i(t) = \begin{cases} n_i(t) + s_i(t) + \gamma_i(t), & H_0 \\ n_i(t) + s_i(t) + \gamma_i(t) + j_i(t), & H_1 \end{cases}, \quad i = 1, \ldots, L, \tag{1}$$

where $n_i(t)$ denotes the Gaussian white noise with mean β_i and variance σ_i^2. Without loss of generality, $s_i(t)$ is supposed to be the useful signal with mean ω_i and variance $\sigma_{s\_i}^2$, $\gamma_i(t)$ is the DC noise with mean of ρ_i, and $j_i(t)$ is the interference signal with mean μ_i and variance $\sigma_{j\_i}^2$. Meanwhile, $n_i(t)$, $s_i(t)$, and $\gamma_i(t)$ are independent of each other. H_0 and H_1 indicate the absence of interference signal and the presence of interference signal, respectively. To simplify the model, we might as well suppose $\beta_i = 0$, $i = 1, \ldots, L$ and $w_i = 0$, $i = 1, \ldots, L$. In addition, we assume that the useful signal exists throughout the detection processing. When N becomes large enough, according to the central limit theorem, the detection statistic of energy detection for the i-th detection node approximately obeys a normal distribution [18]:

$$T_i \sim \begin{cases} \mathcal{N}(E_{0\_i}, D_{0\_i}), & H_0 \\ \mathcal{N}(E_{1\_i}, D_{1\_i}), & H_1 \end{cases}, \tag{2}$$

where

$$\begin{aligned} E_{0\_i} &= N\left(\sigma_i^2 + \sigma_{s\_i}^2 + \rho_i^2\right), \\ D_{0\_i} &= 2N\sigma_i^2 + \sigma_{s\_i}^2\Big)^2 + 4N\rho_i^2\left(\sigma_i^2 + \sigma_{s\_i}^2\right), \\ E_{1\_i} &= N\left(\sigma_i^2 + \sigma_{s\_i}^2 + \sigma_{j\_i}^2\right) + N\left(\mu_i + \rho_i\right)^2, \\ D_{1\_i} &= 2N\left(\sigma_i^2 + \sigma_{s\_i}^2 + \sigma_{j\_i}^2\right)^2 \\ &\quad + 4N\left(\mu_i + \rho_i\right)^2\left(\sigma_i^2 + \sigma_{s\_i}^2 + \sigma_{j\_i}^2\right). \end{aligned} \tag{3}$$

Proof. The proof is given in Appendix A. □

When the i-th node makes its decision in noncooperative mode, the decision criterion is defined as

$$\begin{aligned} T_i &< \lambda_i, \\ R_i &= H_0 \\ T_i &\geq \lambda_i, \\ R_i &= H_1, \end{aligned} \tag{4}$$

where λ_i and R_i denote the decision threshold and the decision result of the i-th detection node, respectively.

The false alarm probability and detection probability of the i-th detection node can be illustrated from (4) as follows:

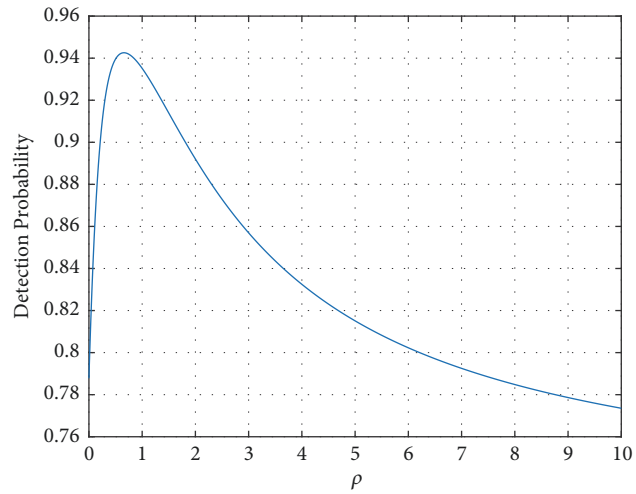

Figure 3: Relationship between the stochastic resonance noise intensity and the detection probability.

$$P_{f\_i} = \text{Prob}\left(T_i \geq \lambda_i \mid H_0\right) = Q\left(\frac{\lambda_i - E_{0\_i}}{\sqrt{D_{0\_i}}}\right), \tag{5}$$

$$P_{d\_i} = \text{Prob}\left(T_i \geq \lambda_i \mid H_1\right) = Q\left(\frac{\lambda_i - E_{1\_i}}{\sqrt{D_{1\_i}}}\right). \tag{6}$$

When P_{f_i} is given, the decision threshold of the i-th detection node can be obtained from (5) as

$$\lambda_i = Q^{-1}\left(P_{f\_i}\right)\sqrt{D_{0\_i}} + E_{0\_i}, \tag{7}$$

where $Q(\cdot)$ is the complementary cumulative distribution function.

Then, by substituting (7) into (6), the final expression for the detection probability is

$$P_{d\_i} = Q\left(\frac{Q^{-1}\left(P_{f\_i}\right)\sqrt{D_{0\_i}} + E_{0\_i} - E_{1\_i}}{\sqrt{D_{1\_i}}}\right). \tag{8}$$

From (8), we observe that adjusting the value of ρ_i adaptively according to various channel conditions can render a maximum detection probability. It can be modeled as an optimization problem that the mathematical expression is

$$\rho_{i\_best} = \arg\max_{-\infty<\rho<\infty} Q\left(\frac{Q^{-1}\left(P_{f\_i}\right)\sqrt{D_{0\_i}} + E_{0\_i} - E_{1\_i}}{\sqrt{D_{1\_i}}}\right), \tag{9}$$

where ρ_{i_best} is the intensity of the best random resonance noise.

However, the expression of the detection probability is quite complicated and it is not easy to describe the effect of ρ_i on the detection probability mathematically. In this case, we use MATLAB® to obtain the relationship between ρ and detection probability as shown in Figure 3. In the simulation, we have $\mu_i = 0.05$, $\sigma_{s\_i}^2 = 0.1$, $\sigma_i^2 = 1$, $P_{f\_i} = 0.05$, and

$N = 2000$. Besides, the interference-to-noise ratio (INR) is -11 dB.

From Figure 3, it is obvious that the stochastic resonance noise intensity will affect the detection probability. Therefore, an optimum intensity of stochastic resonance noise can be found for the best detection performance.

In most communication systems, noise can be regarded as a collection of multiple independent noise sources. As time and position change, neither the noise at the receiver nor the noise in the environment, the variance of them, is constantly changing, that is, the noise uncertainty. Receivers often use a large number of samples to estimate the noise variance, but it is still difficult to completely eliminate the effects of noise uncertainty. Assume that the noise estimated by a large number of samples obeys a uniform distribution within a certain range, which can be denoted as $\sigma_i^2 \sim U(\sigma_{n\_i}^2/u_c, u_c\sigma_{n\_i}^2)$, where $\sigma_{n\_i}^2$ is the nominal noise power of the i-th detection node and $u_c > 1$ indicates the quantities of uncertainty [16]. According to (5) and (6), we can obtain the expression of the false alarm probability and the detection probability with the worst influence of the noise uncertainty as given in (10) and (11).

$$P_{f\_worse\_i} = Q\left(\frac{\lambda - N\sigma_{s\_i}^2 - Nu_c\sigma_{n\_i}^2 - N\rho_i^2}{\sqrt{2N\left(\sigma_{s\_i}^2 + u_c\sigma_{n\_i}^2\right)^2 + 4N\sigma_{s\_i}^2\rho_i^2 + 4Nu_c\sigma_{n\_i}^2\rho_i^2}}\right). \tag{10}$$

$$P_{d\_worse} = Q\left(\frac{\lambda - N\sigma_{s\_i}^2 - N\sigma_{n\_i}^2/u_c - N\sigma_{j\_i}^2 - N\left(\mu_i + \rho_i\right)^2}{\sqrt{2N\left(\sigma_{s\_i}^2 + \sigma_{n\_i}^2/u_c + \sigma_{j\_i}^2\right)^2 + 4N\left(\sigma_{s\_i}^2 + \sigma_{n\_i}^2/u_c + \sigma_{j\_i}^2\right)\left(\mu_i + \rho_i\right)^2}}\right). \tag{11}$$

3. The Two-Step Cooperative Stochastic Resonance Energy Detection Algorithm

For the purpose of overcoming the influence of noise uncertainty on detection performance, we introduce a two-step cooperative stochastic resonance energy detection algorithm. The first step algorithm is to use the hard decision as the fusion criterion, in which case each node needs to send the local decision result to the fusion center for information fusion. Conversely, the second step of the algorithm is to use the soft decision as the fusion criterion. At this time, the detection statistic of each node is sent to the fusion center rather than the decision result.

3.1. The First Step of Cooperative Algorithm. The double threshold has been applied to improve the detection performance [18]. In this paper, two thresholds λ_{l_i} and λ_{h_i} of the i-th detection node are calculated by (7) with minimum noise variance and maximum noise variance respectively

$$\lambda_{l\_i} = AQ^{-1}\left(P_{f\_i}\right) + N\left(\sigma_{s\_i}^2 + \frac{\sigma_{n\_i}^2}{u_c} + \rho_i^2\right), \tag{12}$$

$$\lambda_{h\_i} = BQ^{-1}\left(P_{f\_i}\right) + N\left(u_c\sigma_{n\_i}^2 + \sigma_{s\_i}^2 + \rho_i^2\right), \tag{13}$$

where

$$A = \sqrt{2N\left(\frac{\sigma_{n\_i}^2}{u_c} + \sigma_{s\_i}^2\right)^2 + 4N\rho_i^2\left(\frac{\sigma_{n\_i}^2}{u_c} + \sigma_{s\_i}^2\right)},$$
$$B = \sqrt{2N\left(u_c\sigma_{n\_i}^2 + \sigma_{s\_i}^2\right)^2 + 4N\rho_i^2\left(u_c\sigma_{n\_i}^2 + \sigma_{s\_i}^2\right)}. \tag{14}$$

Based on the energy-based detection statistic obtained from L cooperative detection nodes, the detection result of all detection nodes can be divided into three cases, and their fusion and cooperative strategies are explained separately as below.

Case 1 ($\forall T_i < \lambda_{h\_i}, \exists T_i < \lambda_{l\_i}, i = 1, 2, \ldots, L$). Each node takes λ_{l_i} as the decision threshold and makes decision independently, and the fusion criterion is defined by (15). If the decision result is H_0, it is considered to be the final decision result; that is, there is no interference signal. Otherwise, the second cooperative step will be performed.

$$R_{NAND} = \begin{cases} H_0, & \forall R_i = H_0,\ i = 1, 2, \ldots, L \\ uncertain, & else \end{cases} \tag{15}$$

Different from traditional and decision criterion [19], the decision criterion (NAND criterion) shown in (15) has two different decision results: H_0 or *uncertain*. The latter means that it is impossible to determine whether or not the interference signal exists. In this situation, the decision results of all the detection nodes are H_0; it can be considered there is no interference signal. The advantage of this criterion is to minimize the missed detection probability, avoiding the situation that the interference signal exists to be detected as nonexistential.

Case 2 ($\forall \lambda_{l\_i} \le T_i < \lambda_{h\_i}, i = 1, 2, \ldots, L$). In order to minimize the detection time and reduce the system overhead as much as possible, the first cooperation step would be ignored, and the second cooperation step would be directly performed to obtain the final decision result.

Case 3 ($\exists T_i \ge \lambda_{h\_i}, i = 1, 2, \ldots, L$). Each node takes λ_{h_i} as the decision threshold and makes independent decision, and the fusion criterion is defined by (16). If the decision result is

H_1, it is considered to be the final detection result; otherwise, the second step will be performed.

$$R_{NOR} = \begin{cases} uncertain, & else \\ H_1, & \exists R_i = H_1,\ i = 1, 2, \ldots, L \end{cases} \tag{16}$$

Different from traditional OR decision criterion [20], the decision criterion (NOR criterion) shown in (16) has two decision results: H_1 or *uncertain*. According to this decision criterion, if the decision result of any detection node is H_0, we consider there is no interference signal. In the case when the noise uncertainty exists and the judgment threshold is set to λ_{h_i}, the detection probability can be maximized by using (16) as its fusion criterion.

In order to reduce the computational complexity and system overhead, the decision result H_0 or H_1 of the first cooperation can be directly used as the final decision result, which means the second step of cooperative would not be triggered until the decision result is uncertain. In this case, the false alarm probability and detection probability of first cooperation step are described by (17) and (18), respectively.

$$P_{f\_FSC} = 1 - \prod_{i=1}^{L} \left(1 - Q\left(\frac{\lambda_h - N\left(u_c\sigma_{n\_i}^2 + \sigma_{s\_i}^2 + \rho_i^2\right)}{\sqrt{2N\left(u_c\sigma_{n\_i}^2 + \sigma_{s\_i}^2\right)^2 + 4N\rho_i^2\left(u_c\sigma_{n\_i}^2 + \sigma_{s\_i}^2\right)}} \right) \right), \tag{17}$$

$$P_{d\_FSC} = 1 - \prod_{i=1}^{L} \left(1 - Q\left(\frac{\lambda_h - N\left(\sigma_{n\_i}^2/u_c + \sigma_{s\_i}^2 + \sigma_{j\_i}^2\right) - N\left(\mu_i + \rho_i\right)^2}{\sqrt{2N\left(\sigma_{n\_i}^2/u_c + \sigma_{s\_i}^2 + \sigma_{j\_i}^2\right)^2 + 4N\left(\mu_i + \rho_i\right)^2\left(\sigma_{n\_i}^2/u_c + \sigma_{s\_i}^2 + \sigma_{j\_i}^2\right)}} \right) \right). \tag{18}$$

3.2. The Second Step of Cooperative Algorithm. Maximum ratio combining (MRC) is used as the fusion criterion in the second step of cooperation. Meanwhile, the power of the interference signal received by each node is used as the setting basis of the weighting factor. The definition of the weighting factor is

$$\alpha_i = \frac{\mu_i^2 + \sigma_{ji}^2}{\mu_1^2 + \sigma_{j1}^2 + \cdots + \mu_L^2 + \sigma_{jL}^2}, \quad i = 1, \ldots, L. \tag{19}$$

Due to the influence of the noise uncertainty, the variance of the noise is time-varying. Therefore, our proposed algorithm mainly considers the worst effects of noise uncertainty, so that the false alarm probability can be minimized without increasing the detection probability. Therefore, the workflow of the second cooperation is as follows. First, set the decision threshold to λ_{h_i}. Then, each node makes a decision without cooperation and sends the detection statistic to the central unit, separately. Next, the central unit uses the MRC as a fusion strategy to get an energy statistic T_{SSC}. Finally, compare with λ_h to get the decision result. The fusion and decision criteria are described as follows:

$$T_{SSC} = \sum_{i=1}^{L} \alpha_i T_i, \tag{20}$$

$$R_{SSC} = \begin{cases} H_0, & T_{SSC} < \lambda_h \\ H_1, & T_{SSC} \geq \lambda_h \end{cases}, \tag{21}$$

where $\lambda_h = \max(\lambda_{h\_i})$.

Similar to (2), when N is large enough, T_{SSC} can be approximated as a normal distribution

$$T_{SSC} \sim \begin{cases} \mathcal{N}\left(E_0, D_0\right), & H_0 \\ \mathcal{N}\left(E_1, D_1\right), & H_1 \end{cases}, \tag{22}$$

where

$$\begin{aligned} E_0 &= \sum_{i=1}^{L} \alpha_i N\left(u_c\sigma_{n\_i}^2 + \sigma_{s\_i}^2 + \rho_i^2\right), \\ D_0 &= \sum_{i=1}^{L} \alpha_i^2 \left(2N\left(u_c\sigma_{n\_i}^2 + \sigma_{s\_i}^2\right)^2 + 4N\rho_i^2\left(u_c\sigma_{n\_i}^2 + \sigma_{s\_i}^2\right)\right), \\ E_1 &= \sum_{i=1}^{L} \alpha_i N\left(\frac{\sigma_{n\_i}^2}{u_c} + \sigma_{s\_i}^2 + \sigma_{j\_i}^2 + \left(\mu_i + \rho_i\right)^2\right), \\ D_1 &= \sum_{i=1}^{L} \alpha_i^2 \left(2N\left(\frac{\sigma_{n\_i}^2}{u_c} + \sigma_{s\_i}^2 + \sigma_{j\_i}^2\right)^2 \right. \\ &\quad \left. + 4N\left(\frac{\sigma_{n\_i}^2}{u_c} + \sigma_{s\_i}^2 + \sigma_{j\_i}^2\right)\left(\mu_i + \rho_i\right)^2\right). \end{aligned} \tag{23}$$

Proof. The proof is given in Appendix B. □

From (22), the false alarm probability and detection probability in the second step cooperation are

$$P_{f\_SSC} = \text{Prob}\left\{T_{SSC} \geq \lambda_h \mid H_0\right\} = Q\left(\frac{\lambda_h - E_0}{\sqrt{D_0}}\right), \tag{24}$$

$$P_{d\_SSC} = \text{Prob}\left\{T_{SSC} \geq \lambda_h \mid H_1\right\} = Q\left(\frac{\lambda_h - E_1}{\sqrt{E_1}}\right). \tag{25}$$

In summary, the TCSRED algorithm will perform the first step cooperation and the second step cooperation in sequence, and the detection will not stop until the decision result is finally obtained. The implementation block diagram of the TCSRED algorithm is shown in Figure 4.

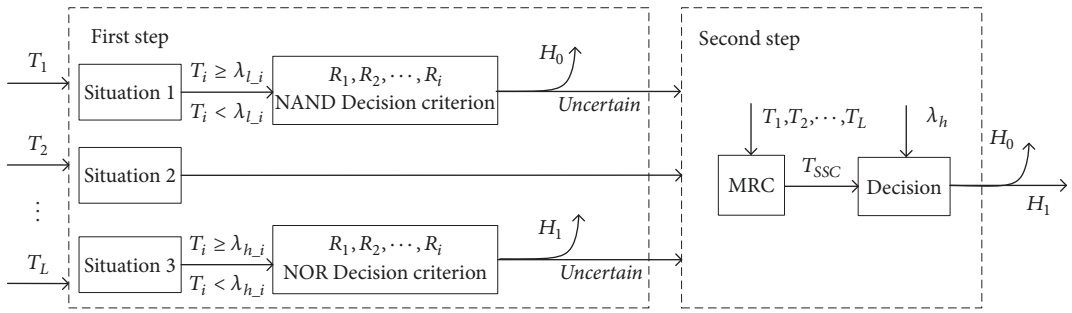

Figure 4: The implementation block diagram of the TCSRED algorithm.

We can easily get the formula of the false alarm probability and detection probability of the TCSRED algorithm under the worst influence of the noise uncertainty, as follows:

$$P_{f\_TCSRED} = P_{f\_FSC} + P_{ts} P_{f\_SSC}, \tag{26}$$

$$P_{d\_TCSRED} = P_{d\_FSC} + P_{ts} P_{d\_SSC}, \tag{27}$$

where P_{ts} indicates the probability of performing the second step of cooperative algorithm, $P_{ts} = \prod_{i=1}^{L} P\{T_i < \lambda_h\} - \prod_{i=1}^{L} P\{T_i < \lambda_l\}$, and $\lambda_l = \min(\lambda_{l\_i}),\ i = 1, \ldots, L$.

4. Simulation Results and Analysis

In this section, we provide numerical results to verify the superiority of the TCSRED algorithm. In the simulations, we assume that the signal is transmitted on an ideal channel with no burst errors, and the basic parameters are set as follows. The number of cooperative detection nodes is $L = 4$. For each detection node, we have $\mu_i = 0.08$, $\sigma_{s\_i}^2 = 0.1$, and $\sigma_{n\_i}^2 = 1$. The simulation results are derived from 3000 Monte-Carlo experiments.

In the following pictures, ED denotes the traditional energy detection algorithm and GSRED denotes the energy detection algorithm based on generalized stochastic resonance. With $P_f = 0.05$ and $N = 2000$, the comparative performance of the three algorithms in terms of detection probability vs. INR (in dB) is shown in Figure 5, and the noise uncertainty is 2 dB, 4 dB, 6 dB, and 8 dB, respectively. For comparison, we provided other algorithms [6, 10], and we observe from Figure 5 that the TCSRED algorithm has a significant improvement compared with other algorithms under the same INR and noise uncertainty. Although the performance increment of the TCSRED algorithm decreases slightly as the noise uncertainty increases, the performance is still better than the other two.

Furthermore, Figure 6 shows the receiver operator characteristic (ROC) curves of the proposed algorithm with different noise uncertainty under INR= −10 dB. It can be found that the detection probability increases with the increase of the false alarm probability, but the increase of the noise uncertainty can reduce the detection probability. This is consistent with the theoretical result. Therefore, in practice, when there is a large noise uncertainty, the method of increasing the preset false alarm probability can be adopted to increase the detection probability.

With the noise uncertainty being 6 dB, the curves of the detection probability versus INR with different number of samples (e.g., 1000, 2000, 4000, 8000, and 10000) are shown in Figure 7. It is not hard to conclude that the detection probability increases with the increase of the INR and sample number, which is consistent with the theoretical result. However, when sampling number increases from 8000 to 10000, the gain of the algorithm performance is not obvious, especially when the INR is relatively high, the performance of the two is very close to each other. This is because the number of samples is no longer a factor limiting the improvement in detection performance. Therefore, increasing the number of sampling points under certain conditions can improve the detection performance until the number of sampling points reaches a certain value.

5. Conclusion

To satisfy the requirements for the detection accuracy and detection time in interference detection field, a TCSRED algorithm has been proposed in this paper, which effectively overcomes the influence of noise uncertainty. We described the algorithm model, analyzed the detection performance of a single node, and verified that there is an optimal random noise to optimize the detection performance. And the fusion criterion and decision criterion were described in detail according to the detection statistic of each node. In addition, the analysis of the simulation results proved the effectiveness of TCSRED algorithm, especially under noise uncertainty or at low SNR. This method can definitely be used to address other similar detection problems, such as underwater weak signal detection and weak radar target detection.

Appendix

A. Proof of Equation (2)

Proof. For the i-th detection node, when there is no interference signal, the received signal can be denoted as

$$\begin{aligned} r_i(n) &= n_i(n) + s_i(n) + \gamma_i(n) \\ &= \sum_{k=1}^{N} \left(n_i(k) + s_i(k) + \rho_i\right), \end{aligned} \tag{A.1}$$

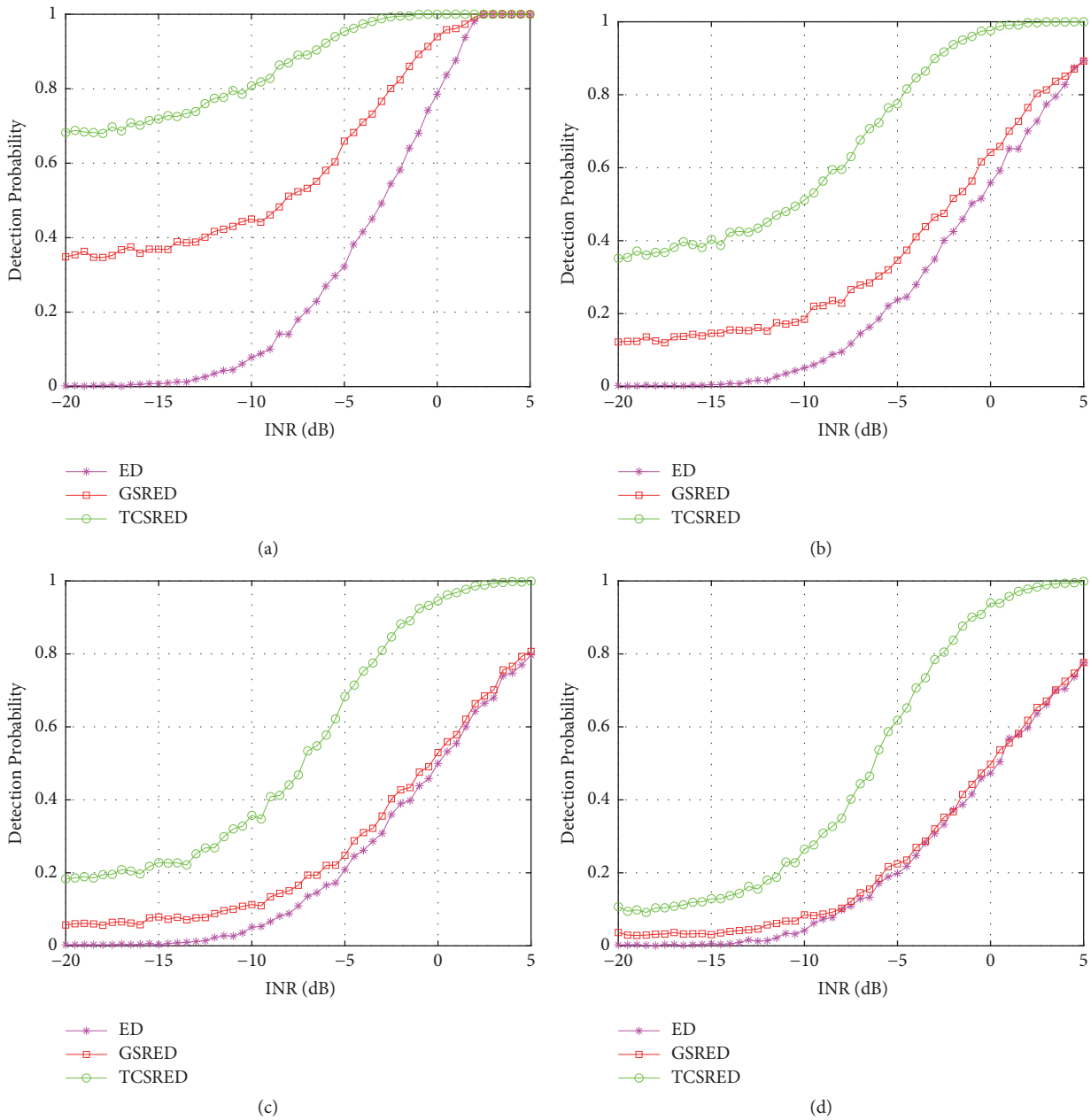

Figure 5: The detection probability versus INR under different noise uncertainty. (a) Noise uncertainty is 2 dB. (b) Noise uncertainty is 4 dB. (c) Noise uncertainty is 6 dB. (d) Noise uncertainty is 8 dB.

where $n_i(k)$ and $s_i(k)$ denote the k-th sample point of noise and useful signal, respectively. As we know, $n_i(k) \sim \mathcal{N}(0, \sigma_i^2)$ and $s_i(k) \sim \mathcal{N}(0, \sigma_{s\_i}^2)$. Therefore, according to the theorem of large numbers, when N is large enough, we can derive the equations as follows:

$$r_i(k) = n_i(k) + s_i(k) + \rho_i \sim \mathcal{N}\left(\rho_i, \sigma_i^2 + \sigma_{s\_i}^2\right), \tag{A.2}$$

$$T_i = \sum_{n=1}^{N} \left|r_i(k)\right|^2 = \sum_{n=1}^{N} \left|n_i(k) + s_i(k) + \rho_i\right|^2. \tag{A.3}$$

Obviously, $r_i(1), r_i(2), \ldots, r_i(N)$ are sequences of independent and identically distributed random variables. According to the relevant properties of noncentral chi-square distribution, the mean and variance of can be derived out as follows:

$$E(T_i) = N\left(\sigma_i^2 + \sigma_{s\_i}^2\right) + N{\rho_i}^2, \tag{A.4}$$

$$D(T_i) = 2N\left(\sigma_i^2 + \sigma_{s\_i}^2\right)^2 + 4N{\rho_i}^2\left(\sigma_i^2 + \sigma_{s\_i}^2\right). \tag{A.5}$$

When interference signal exists, we have

$$\begin{aligned} r_i(n) &= n_i(n) + s_i(n) + \gamma_i(n) + j_i(n) \\ &= \sum_{k=1}^{N} \left(n_i(k) + s_i(k) + \rho_i + j_i(k)\right), \end{aligned} \tag{A.6}$$

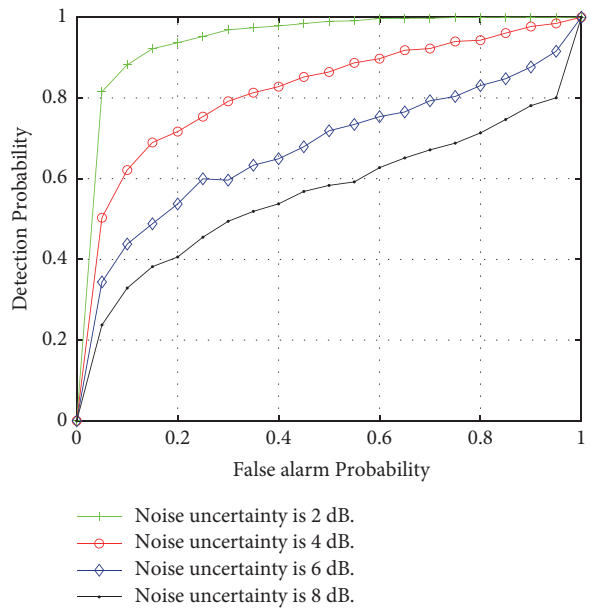

Figure 6: ROC curves of TCSRED algorithm with different noise uncertainty, and INR=-10 dB.

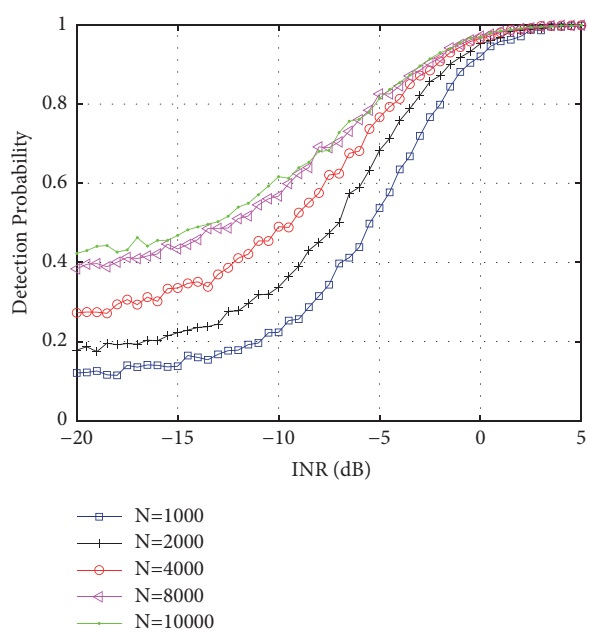

Figure 7: The detection probability versus INR with different sampling number, and the noise uncertainty is 6 dB.

where $j_i(k)$ is the k-th sample point of interference signal and $j_i(k) \sim \mathcal{N}(\mu_i, \sigma_{j\_i}^2)$. Similar to the above analysis, we can derive out

$$\begin{aligned} r_i(k) &= n_i(k) + s_i(k) + \rho_i + j_i(k) \\ &\sim \mathcal{N}\left(\mu_i + \rho_i, \sigma_i^2 + \sigma_{s\_i}^2 + \sigma_{j\_i}^2\right). \end{aligned} \tag{A.7}$$

In addition, we have the following equations:

$$\begin{aligned} T_i &= \sum_{n=1}^{N} \left|r_i(k)\right|^2 \\ &= \sum_{n=1}^{N} \left|n_i(k) + s_i(k) + \rho_i + j_i(k)\right|^2, \end{aligned} \tag{A.8}$$

$$E(T_i) = N\left(\sigma_i^2 + \sigma_{s\_i}^2 + \sigma_{j\_i}^2\right) + N\left(\mu_i + \rho_i\right)^2, \tag{A.9}$$

$$\begin{aligned} D(T_i) &= 2N\left(\sigma_i^2 + \sigma_{s\_i}^2 + \sigma_{j\_i}^2\right)^2 \\ &\quad + 4N\left(\mu_i + \rho_i\right)^2\left(\sigma_i^2 + \sigma_{s\_i}^2 + \sigma_{j\_i}^2\right). \end{aligned} \tag{A.10}$$

Therefore, aided by (A.4), (A.5), (A.9), and (A.10), the T_i can be given as (2), which completes this proof. □

B. Proof of Equation (22)

According to the results in (2) and (20), without considering the noise uncertainty, similar to the proof of (2), we have

$$T_{SSC} \sim \begin{cases} \mathcal{N}\left(\sum_{i=1}^{L}\alpha_i E_{0\_i}, \sum_{i=1}^{L}\alpha_i D_{0\_i}\right), & H_0 \\ \mathcal{N}\left(\sum_{i=1}^{L}\alpha_i E_{1\_i}, \sum_{i=1}^{L}\alpha_i D_{1\_i}\right), & H_1 \end{cases}, \quad i = 1, \ldots, L. \tag{B.1}$$

Considering the worst influence of the noise uncertainty, we compute the false alarm probability by using the maximum value of the noise variation interval as the noise variance to obtain a maximum false alarm probability. Therefore, under the condition of H_0, the noise is maximum, which holds

$$\sigma_i^2 = u_c \sigma_{n\_i}^2. \tag{B.2}$$

At the same time, we compute the detection probability by using the minimum value of the noise variation interval as the noise variance to obtain a minimum detection probability. Under the condition of H_1, we hold that the noise is minimum, that is

$$\sigma_i^2 = \frac{u_c}{\sigma_{n\_i}^2}. \tag{B.3}$$

By substituting (B.2) and (B.3) into (B.1), the T_{SSC} can be given as (22), which completes the proof.

Data Availability

I derived the writing material from different journals as provided in the references. A MATLAB tool has been utilized to simulate our concept.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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