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ENHANCING MULTIUSER MIMO COOPERATIVE SPECTRUM SENSING OPTIMIZATION IN COGNITIVE RADIO NETWORKS

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Abstract: This research delves into the optimization of cooperative spectrum sensing in multiuser multiple-input–multiple-output (MIMO) systems, where both the primary user (PU) and the cognitive radio (CR) are endowed with multiple antennas. The focal point of optimization lies in determining optimal weights assigned to the received signals of CRs. The objective is to maximize the probability of detection while adhering to a predefined probability of false alarm. Statistical characteristics of parameters in MIMO cooperative spectrum sensing systems have been ascertained for various scenarios, including the PU with a single antenna and the CR with multiple antennas, the PU with multiple antennas and the CR with a single antenna, as well as both the PU and the CR equipped with multiple antennas. Given the non-convex nature of the optimization problem, an alternative approach utilizing a genetic algorithm (GA) is proposed. This deviation from convex methods allows for the exploration of optimal weight vectors without imposing solution domain restrictions or convexity constraints. Additionally, various classical GA crossover operators are examined to assess their impact on sensing performance. Simulation results underscore that the reliability of spectrum sensing in cooperative spectrum sensing systems experiences significant enhancement with the integration of multiple antennas. Moreover, the GA method emerges as a promising approach for addressing the challenges associated with cooperative spectrum sensing.

Index Terms - Cognitive radio, Spectrum sensing, Genetic algorithm, Crossover, MIMO

I. Introduction

The current dilemma of spectrum scarcity has been made even more difficult by the rapid expansion of wireless communications, which has resulted in a significant demand for the deployment of new wireless services in both licensed and unlicensed frequency bands. Cognitive radio, often known as CR, is a mode of communication that has been proposed as a solution to the problem of limited spectrum resources for communication.The purpose of the Carrier Radio (CR) system is to enhance the efficiency of the spectrum by enabling its users to access spectrum holes that are not being utilized by primary users (PUs), provided that they do not interfere with the PUs. The fundamental idea of CR is to improve the adaptability of radio systems by drawing inspiration from intelligent human behavior. CR is capable of sensing, acting, learning, judging, and implementing cognitive actions, and as a result, it overlaps with artificial intelligence [2, 3] to a certain extent. Investigations on the application of artificial intelligence to customer relationship management (CR) have the potential to yield promising outcomes. Spectrum sensing is a highly significant enabling functionality in CR networks since it is required to identify the available spectra and prevent detrimental interference with peripheral units (PUs) in order to improve the usage of the spectrum. Consequently, the precision of spectrum sensing is a factor that is of utmost significance in terms of the sensing performance of a CR network. Recently, a number of different methods have been suggested in order to enhance the accuracy of sensing. These methods include the utilization of energy detectors, feature detectors, covariance-based detection, wavelet-based detection, and cyclisation detectors [4].

In real-world situations, on the other hand, there is always more than one user sharing a single frequency band. In addition, it is difficult for a CR to discern between two signals in a reliable manner because of shadowing, fading, and the ambiguity with the receiver. Inside the range of a spectrum hole and a primary signal that is faint if it can conduct spectrum sensing on its own. Cooperative spectrum sensing has been presented [5] as a means of mitigating the impact of these difficulties. This method has the potential to effectively increase sensing performance by capitalizing on the spatial variety that may be acquired through collaboration across several CR organizations. The literature has a number of different cooperative techniques that have been developed because to the fact that cooperative spectrum sensing has the potential to produce much higher performance in comparison to single CR sensing. The cooperative spectrum sensing problem was presented as a probabilistic inference problem in [6], and belief propagation was utilized to compute the likelihoods of both the null hypotheses and the alternative hypotheses. Basic approaches for making difficult judgments at the fusion center (FC) were published in [7]. These methods included AND, OR, and k-out-of-N logic. The fusion center (FC) is responsible for making final decisions. As a test statistic at the FC, a weighted sum of power measurements was utilized in [8] in order to achieve the highest possible likelihood of detection. The sensing judgments that were made by individual CR were fused at the FC using a linear quadratic fusion rule. In this rule, the signal-to-noise ratios (SNRs) of each CR were supposed to be the same. [9] describes this process. A soft fusion technique was proposed by Quan et al. [10], which consisted of linearly combining the received signal energies of CRs. This technique made use of the spatial variety that exists among numerous CRs to enhance the sensing reliability. Further discussion and solutions to these improvements have been provided by Quan et al. [11], who used semidefinite programming to solve the problem. In general, the sensing formulations that were discussed earlier are non-convex problems, which means that convex optimization strategies are unable to directly solve them by direct solutions. Therefore, in order to solve these optimization issues, they are always divided into estimated convex subproblems by the process of approximation. For instance, in Quan et al. [10], the lower and upper bounds on the likelihood of detection for a given probability of false alarm were first computed based on the information provided by the authors. The next step was to describe the optimization process that would be used to determine the answer based on the Lagrangian dual theory. This method, on the other hand, could require an excessive amount of effort and has proven to be fundamentally unproductive in terms of addressing the issue. For the purpose of this paper, the multiuser linear cooperative spectrum sensing optimization in the CR system is first investigated. The PU and the CRs both use multiple antennas, and the objective of this investigation is to maximize the probability of detection by optimizing the weights assigned to the received signals of the CRs, given a targeted probability of false alarm. Following this, an efficient solution that is based on a genetic algorithm (GA) is introduced to solve the nonconvex problem that was discussed earlier. This is done in order to avoid approximations or convexity limitations instead of using the convex optimization approaches. The use of genetic algorithms (GA) to cooperative spectrum sensing has been discussed in the past in a few pieces of literature [12–14]. However, this research is primarily distinct from those studies in the following respects. To begin, there is the cooperative spectrum sensing system, which consists of CR and PU with many antennas have been the subject of research. In addition, several different classical GA crossover operators have been supplied, and tests have been conducted to explore the influence that these operators have on the performance of sensing. Furthermore, the findings of the simulation demonstrate that the sensing accuracy may be improved by using numerous antennas, and that GA can achieve superior sensing performance in comparison to other approaches that are currently in use. The following are some of the ways in which this paper contains connections to the scope of this journal. To begin, the cognitive radio, which can be categorized as a subset of the cognitive systems, serves as the foundation for this research. The cognitive process of the human brain serves as a source of inspiration for the development of natural language processing (CR), with the goal of making CR equipment as intelligent as human people. Second, the spectrum sensing problem in CR that was discussed in this research has been resolved by GA, which is widely utilized in the field of artificial intelligence because to its great ability to search across the entire world. Since CR incorporates the benefits of both wireless communication and artificial intelligence, GA could be a viable solution to address problems in CR, hence demonstrating the usefulness of artificial intelligence in CR. It is for this reason that experiments centered on alternative ways of artificial intelligence [15–17] could also be carried out. These approaches include neural networks, evolutionary algorithms, and machine learning. As a result, our study can be considered, to a certain extent, to be an example of the application of artificial intelligence to cognitive radio, which is something that falls within the primary area of the magazine. Furthermore, the spectrum sensing described in this study has a process that is extremely like the fundamental cognitive process. This process includes sensing, communicating, learning, storing, acting, judging, and decision-making. In addition, the findings of the experiments offer knowledge that can be utilized in the future hardware implementations of data recovery. We believe that our work is appropriate for publication in this journal for all these reasons.

2. System Model

Consider a cognitive radio network with one PU and M CR users, each is equipped with a single antenna. For CR i, the binary hypothesis representing whether the PU is absent or not for spectrum sensing at the k-th time instant is then formulated as:

$$\begin{cases} H_0 : x_i(k) = n_i(k) \\ H_1 : x_i(k) = h_i s(k) + n_i(k) \end{cases} \quad i = 1, \ldots, M \tag{1}$$

where xi(k) is the cognitive received signal of CR i, and s(k) is the signal transmitted by the PU. his(k) 1; 2; . . .;M denotes the channel gain for CR i during the detection interval. ni(k); 1,2; . . .;M is the sensing zero-mean additive white Gaussian noise with variance r2i . Assuming that the energy detector is employed in spectrum sensing,CR I then calculates a summary statistic over a detection interval of N samples as follows:

$$u_i = \sum_{k=1}^{N} |\mathbf{x}_i(k)|^2, \quad i = 1, 2, \ldots, M. \tag{2}$$

Next, the summary statistic is transmitted to the FC, the i-th statistic received by the FC can be denoted as ri = ui þ zi ; i = 1; 2; . . .;M, where zi is the zero-mean Gaussian noise induced by the control channel with variance d2 i . The FC calculates a global test statistic yc from the outputs ri of the individual CR by a linear statistic combination (LSC) manner [10] below:

$$y_c = \sum_{i=1}^{M} w_i r_i = \mathbf{w}^T \mathbf{r} \tag{3}$$

ri and wi are the weight vectors that are assigned to the summary statistics of each CR by the FC. The weight vectors are denoted by the symbols r and w, respectively. A comparison is made between the global test statistic yc and a threshold cc for the FC to arrive at a judgment regarding global detection. If yc > cc, then FC grants permission to the CRs to access the channel; otherwise, they are unable to do so. In order to assess the performance of the sensing system, one can consider the chance of the false alarm as well as the probability of detection. According to (2), we are aware that the test statistic ui of CR i is the sum of the squares of N Gaussian random variables. As a result, ui=r2i adheres to a chi-square v2 distribution with N degrees [10].

$$u_i/\sigma_i^2 = \begin{cases} \chi_N^2, & H_0 \\ \chi_N^2(\eta_i), & H_1 \end{cases} \tag{4}$$

where gi = jhij2Es r2i can be regarded as the local SNR of CR i and Es = PN k=1 jsðkÞj2. According to the central limit theorem, if N is large enough, the test statistic ui is asymptotically normally distributed with mean E(ui) and variance V(ui):

$$E[u_i] = \begin{cases} N\sigma_i^2, & H_0 \\ (N+\eta_i)\sigma_i^2, & H_1 \end{cases}, \tag{5}$$

$$V[u_i] = \begin{cases} 2N\sigma_i^4, & H_0 \\ 2(N+2\eta_i)\sigma_i^4, & H_1 \end{cases} \tag{6}$$

The received statistic ri at the FC is normally distributed with mean E(ri) and variance V(ri):

$$E[r_i] = \begin{cases} N\sigma_i^2, & H_0 \\ (N+\eta_i)\sigma_i^2, & H_1 \end{cases}, \tag{7}$$

$$V[r_i] = \begin{cases} 2N\sigma_i^4 + \delta_i^2, & H_0 \\ 2(N+2\eta_i)\sigma_i^4 + \delta_i^2, & H_1 \end{cases} \tag{8}$$

In order to make the investigation of the statistical properties of yc in the latter section more convenient, we will define the conditional means and covariances of as follows:

$$\begin{cases} \mu_h = E[\mathbf{y}|H_h], \quad h = 0, 1 \\ \mathbf{A} = E[\mathbf{r}\mathbf{r}^{\mathbf{T}}|H_0] - \mu_0\mu_0^T \\ \mathbf{B} = E[\mathbf{r}\mathbf{r}^T|H_1] - \mu_1\mu_1^T \end{cases} \tag{9}$$

for the purpose of calculating the global probability of false alarm and detection, the following formula can be developed:

$$P_{\mathrm{f}} = \Pr(y_{\mathrm{c}} > \gamma_{\mathrm{c}}|H_0) = Q\left(\frac{\gamma_{\mathrm{c}} - \mu_0^T\mathbf{w}}{\sqrt{\mathbf{w}^T\mathbf{A}\mathbf{w}}}\right) \tag{10}$$

$$P_{\mathrm{d}} = \Pr(y_{\mathrm{c}} > \gamma_{\mathrm{c}}|H_1) = Q\left(\frac{\gamma_{\mathrm{c}} - \mu_1^T\mathbf{w}}{\sqrt{\mathbf{w}^T\mathbf{B}\mathbf{w}}}\right) \tag{11}$$

With these expressions, the threshold γc can be obtained by:

$$\gamma_{\mathrm{c}} = \begin{cases} Q^{-1}(P_{\mathrm{f}})\sqrt{\mathbf{w}^T\mathbf{A}\ \mathbf{w}} + NL\sigma^T\mathbf{w} \\ Q^{-1}(P_{\mathrm{d}})\sqrt{\mathbf{w}^T\mathbf{B}\ \mathbf{w}} + (NL\sigma + E_{\mathrm{s}}\mathbf{g})^T\mathbf{w} \end{cases} \tag{12}$$

When a targeted probability of false alarm, denoted by Pf, is considered, the probability of detection, denoted by Pd, can be estimated as follows:

$$P_{\mathrm{d}} = Q\left(\frac{Q^{-1}(P_{\mathrm{f}})\sqrt{\mathbf{w}^T\mathbf{A}\ \mathbf{w}} - E_{\mathrm{s}}\mathbf{g}^T\mathbf{w}}{\sqrt{\mathbf{w}^T\mathbf{B}\ \mathbf{w}}}\right) \tag{13}$$

By adjusting the weight vector w, we believe that we will be able to achieve the highest possible probability of detection (13). Because of this, the problem of optimizing cooperative spectrum sensing becomes the problem of determining the ideal value of w in order to maximize Pd while staying within a fixed Pf. Due to the fact that the Q-function is a non-increasing function, maximizing Pd is equivalent to minimizing the function f (w):

$$f(\mathbf{w}) = \frac{Q^{-1}(P_{\mathrm{f}})\sqrt{\mathbf{w}^T\mathbf{A}\ \mathbf{w}} - E_{\mathrm{s}}\mathbf{g}^T\mathbf{w}}{\sqrt{\mathbf{w}^T\mathbf{B}\ \mathbf{w}}} \tag{14}$$

Therefore, the optimization issue for a multiuser cooperative spectrum sensing system can be phrased. It is important to mention that the constraint that was established in (15) is more advantageous in terms of limiting the search space and improving the search. Efficiency in comparison to the case where there were no constraints.

3. Multiuser Cooperative Spectrum Sensing Optimization Analysis

The statistical features of are an important issue to consider when it comes to the cooperative spectrum sensing. When this information is taken into consideration, the statistical properties of the global test statistic yc can be determined using the linear combination of the random variables ri. It is therefore possible to establish the best threshold cc as well as the weight vector w through the process of optimization. The fundamental optimization structure of cooperative spectrum sensing is presented in chapter [10].An outline was provided for a system in which both the PU and the CR are fitted with a single antenna, in other words, an SPSC. Since multiple-input–multiple-output (MIMO) has been considered an effective method that has the potential to significantly boost spectrum efficiency, the purpose of this paper is to investigate the effect of MIMO applied in cooperative spectrum sensing optimization in order to determine whether or not it can further improve the sensing accuracy of spectrum sensing. The optimization of the basic MIMO cooperative spectrum sensing systems, i.e, the PU with a single antenna and the CR with multiple antennas (SPMC), the PU with multiple antennas and the CR with a single antenna (MPSC) as well as both the PU and the CR with multiple antennas (MPMC) are investigated in this section.

4. Cooperative Spectrum Sensing Method

Two of the more traditional approaches to optimizing cooperative spectrum sensing are detailed in this section. These approaches were proposed in [10]. The optimization of the probability distribution function of the global test statistic yc is the source of inspiration for the modified deflection coefficient (MDC) algorithm, which is based on the optimization of the optimal linear (OPT-LIN) algorithm, which is based on the inherent structures of the cooperative spectrum sensing optimization problem.

5. Optimal Linear Algorithm (OPT-LIN)

In order to solve the problem, a divide-and-conquer technique is used. This is for the reason that directly solving (15) for general circumstances is a tough task. First, the CR system can be broken down into three distinct categories: the aggressive system (Pd[1]2; Pf[1]2), the conservative system (Pd[1]2; Pf[1]2), and the hostile system (Pd (1)2; Pf (1)2). In the case of hostile systems, it is challenging to locate the most effective approach. Additionally, in practice, setting a low Pd to boost spectrum efficiency is rarely allowed for CR because it will cause unacceptable interference to the PU. As a result, the optimal solution can be obtained by combining the solution to the aggressive case with that of the conservative case. This is because the combination of these two solutions ensures that the optimal solution is obtained.

6. Modified Deflection Coefficient (MDC) Algorithm

The MDC algorithm is inspired by the impact that the weight vector has on the probability distribution functions of the global test statistic yc when seen through the lens of two distinct hypotheses. Because the weight vector w plays a significant role in the formation of the probability density function (PDF) of yc, a novel method for determining the variance normalized distance between the centers of two conditional probability distribution functions can be defined as follows:

$$d_{\mathrm{m}}^2(\mathbf{w}) = \frac{[E(y_{\mathrm{c}}|H_1) - E(y_{\mathrm{c}}|H_0)]^2}{\mathrm{var}(y_{\mathrm{c}}|H_1)} = \frac{E_{\mathrm{s}}^2 \mathbf{w}^T \mathbf{g}\mathbf{g}^T \mathbf{w}}{\mathbf{w}^T \mathbf{B}\ \mathbf{w}} \tag{15}$$

7. GA-Based Cooperative Spectrum Sensing Method

Additionally, a novel alternative GA-based strategy is proposed in this part in order to overcome the optimization problem that was presented in (15). To begin, the fundamental ideas of GA are presented to the audience. Following that, the specifics of the galactic algorithm that was used to solve the MIMO cooperative spectrum sensing problem are provided.

8. Basic Concepts of GA

The genetic algorithm (GA) is a search and optimization technique that is founded on the concepts of genetics and natural selection. It employs processes that are comparable to genetic recombination and mutation to facilitate the process of organism evolution [18–20]. In genetic algorithms, the first step is to define a population of individuals, which are referred to as chromosomes, and which are comprised of a collection of potential solutions to the optimization issue. Everyone is then analyzed using the fitness function, and the individuals that are deemed to be of higher quality are selected for the selective breeding process and crossover operator to create a greater number of offspring than those that are of lower quality. For increasing the population's level of diversity, a subsequent mutation operator is utilized. Following the completion of all of these actions, a new population is created in order to carry out the process once more during the subsequent iteration of the algorithm. In most cases, the algorithm will stop working either when the maximum number of generations has been reached or when a suitable level of fitness has been achieved. To make things easier to understand, the most important GA processes in a single iteration are depicted in Figure 1, and additional information may be found in [18].

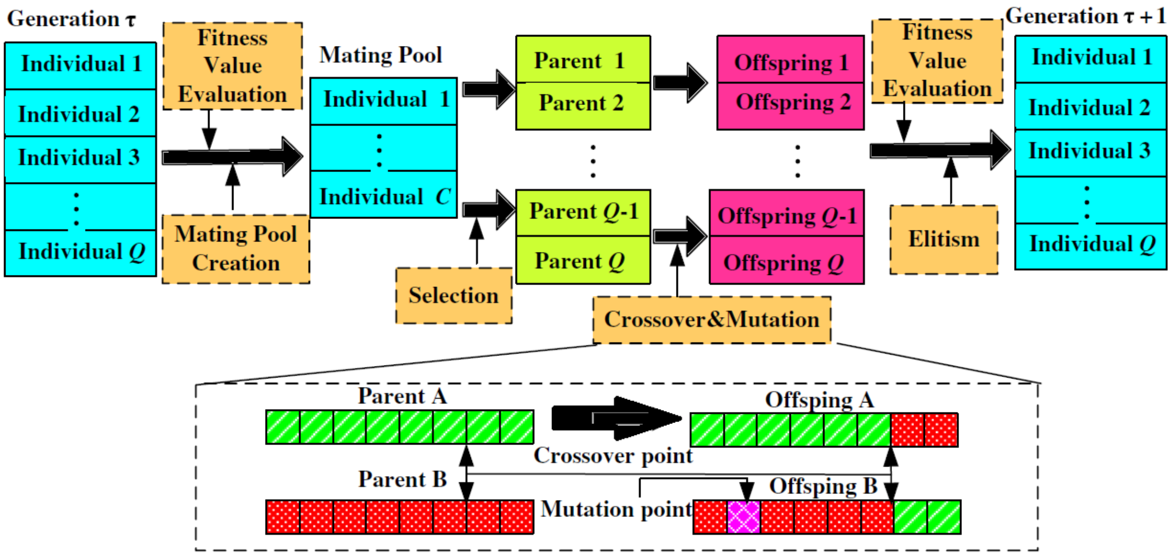

Fig. 1 General block diagram of Genetic Algorithm

A Genetic Algorithm is a search heuristic inspired by the process of natural selection. Here's a simplified block diagram representing the main components and flow of a Genetic Algorithm:

1. Initialization:
Generate an initial population of individuals (potential solutions to the problem).

2.Evaluation:
Evaluate the fitness of each individual in the population. Fitness is a measure of how well an individual solves the given problem.

3. Selection:
Select individuals to be parents based on their fitness. Individuals with higher fitness have a higher chance of being selected.

4. Crossover (Recombination):
Combine the genetic information of selected parents to create new individuals (offspring). This is typically done by exchanging genetic material between parents.

5. Mutation:
Introduce random changes in the genetic information of some individuals to maintain genetic diversity.

6. Replacement:
Replace the old population with the new population, which includes parents and offspring.

7. Termination:
Check if the termination criteria are met (e.g., a solution with sufficient fitness is found or a maximum number of generations is reached).

8. Solution Extraction:
Extract the best individual or one of the top individuals as the final solution to the problem.

This block diagram captures the main steps involved in a basic Genetic Algorithm. It's worth noting that the details may vary depending on the specific implementation and problem domain. Additionally, parameters such as mutation rate, crossover probability, and population size can be adjusted to influence the algorithm's performance.

Genetic Algorithms (GAs) use various crossover (also known as recombination) operators to combine genetic information from parent individuals and create offspring individuals. Here are some commonly used crossover operators in GA:

1. Single-Point Crossover:
   A single crossover point is chosen, and the genetic material beyond that point is swapped between two parents to create two offspring.
2. Two-Point Crossover:
   Two crossover points are chosen, and the genetic material between these two points is swapped between two parents to create two offspring.
3. Uniform Crossover:
   Each bit in the offspring is independently chosen from either parent with equal probability. This allows for a more diverse combination of genetic material.
4. Arithmetic Crossover (Blending Crossover):
   This operator works for continuous representations of individuals. The average of the corresponding genes from two parents is taken to create an offspring.
5. Simulated Binary Crossover (SBX):
   Like arithmetic crossover, SBX is used for real-valued representations. It simulates the behavior of two-point crossover in binary-coded GAs and adjusts the offspring values based on a probability distribution.
6. Whole Arithmetic Crossover:
   This operator is similar to arithmetic crossover but operates on the entire solution vectors, not individual genes.
7. Partially Mapped Crossover (PMX):
   This is used for permutation-based representations. A portion of one parent's genes is mapped onto the corresponding portion of the other parent, and the remaining genes are then filled in by exchanging non-conflicting genes.
8. Order Crossover (OX):
   Another crossover operator for permutation-based representations. It selects a random subset of genes from one parent and fills in the remaining genes in the order they appear in the other parent, avoiding duplication.
9. Edge Recombination Crossover (ERX):
   Specifically designed for permutation-based representations in TSP (Traveling Salesman Problem). It constructs offspring by considering the edges shared by the parents.
10. Blend Crossover:
    Similar to arithmetic crossover, but instead of taking a weighted average, the offspring's genes are randomly selected from within a range defined by the parents' genes.

The choice of crossover operator depends on the problem domain and the characteristics of the representation used for individuals in the GA. Different operators have different effects on the exploration and exploitation capabilities of the algorithm. Experimentation and tuning are often required to determine the most effective combination of operators for a specific problem.

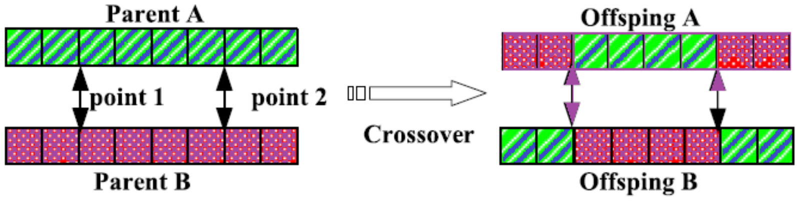

Fig. 2 Two-point crossover operator

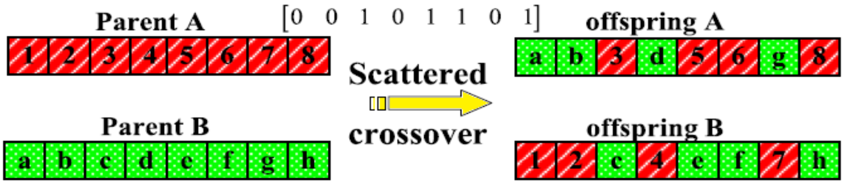

Fig. 3 Scattered crossover operator

9. Simulation Results

A CR network with one PU and M CRs is what we are going to look at. The power unit (PU) is equipped with J antennas, while each CR utilizes L antennas. In the SPSC system, J = 1 and L = 1 are used, while in the SPMC system, J = 1 and L = 2 are utilized. In the MPSC system, J = 2 and L = 1 are utilized, and in the MPMC system, J = 2 and L = 2 are utilized. The assumption that we make is that the channel gain hi of CR i follows a normal distribution, that the number of samples is N, that the sensing noise of CR i is r2i, and that the channel noise is d2 i; i = 1... M. To evaluate the GA-based spectrum sensing method, the single CR spectrum sensing scheme, the selection combing (SC) method, the OPT-LIN algorithm, and the OPT-MDC method described in [10] are also simulated for the purpose of comparison. Table 1 provides a concise summary of the parameters that GA uses for the purpose of referring easier.Take note that the final parameter value was selected by taking into consideration both the typical values found in the literature and our own findings. simulation results. Furthermore, all GA simulation results were statistical averages of a number of runs.

Table 1. Simulation Parameters

S. No	Parameter Description	Value
1	Population number Num	50
2	Maximum iteration number Tmax	20
3	The prob. of crossover Pc	0.8
4	The prob. of mutation Pm	0.1

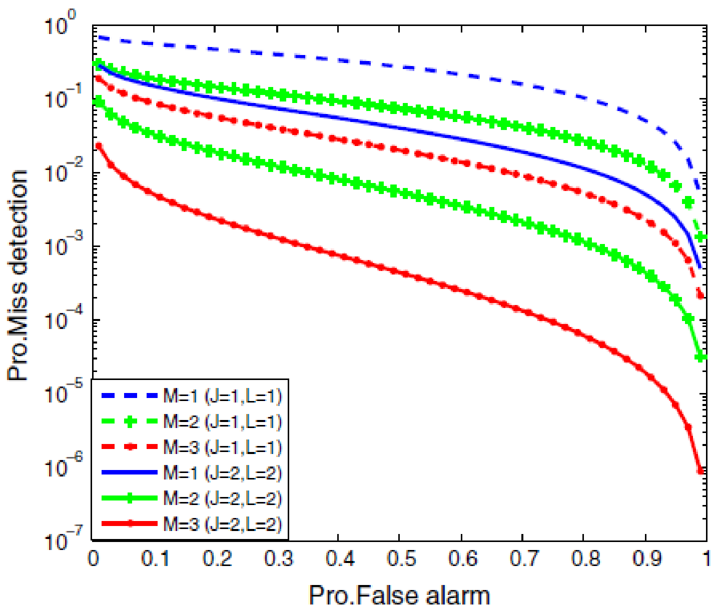

Figure 4

Figure 4 illustrates the likelihood of miss detection (1-Pd) in comparison to the chance of false alarm Pf using GA for a variety of various numbers of complete reports (CRs). It has been shown that when compared to other things,

With the noncooperative spectrum sensing system (M = 1), the likelihood of miss detection decreases in proportion to the number of CRs. This means that the improvement in spectrum sensing becomes more apparent with the increase in the number of CRs, which is an indication of the benefit of cooperative spectrum sensing. It is also possible to greatly improve the detection capability of the cooperative spectrum sensing system by increasing the number of antennas that are installed on the CRs.

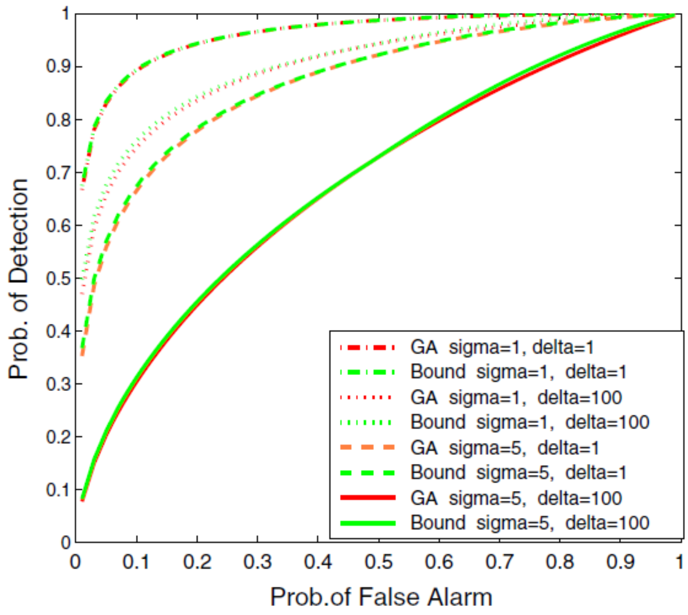

Figure 6

Figure 6 illustrates the relationship between the probability of detection (Pd) and the chance of false alarm (Pf) under a variety of noise situations. As the noise condition continues to deteriorate, the Pd value decreases, while the Pf value remains the same. Furthermore, the detection accuracy is more sensitive to the noise of the sensing channel than it is to the noise of the control channel, which is a fair explanation for why multi-CR should work together to improve the reliability of spectrum sensing.

10. Conclusion

An investigation into multiuser MIMO cooperative spectrum sensing optimization was carried out in this current study. Optimizing the various weights that were assigned to the received signals of CRs to achieve a targeted likelihood of false alarm was the method that was utilized to maximize the probability of detection. Cases of MIMO cooperative spectrum sensing optimization for the PU and the CR with single or multiple antennas were discussed. These cases included both single and multiple antennas. A broad GA-based cooperative spectrum sensing method was proposed as an alternative to convex approaches to be able to meet the non-convex difficulty that was described earlier. Investigations have been conducted on traditional GA crossover operators to demonstrate the impact that they have on sensing performance. The findings of the simulation indicate that the sensing performance can be considerably enhanced by utilizing numerous antennas. Additionally, the GA-based method is found to be both efficient and stable, demonstrating potential sensing properties.

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