Optimal Cooperative Spectrum Sensing in Cognitive Radio with Taguchi Method

Yingying Ma and Derong Liu
Department of Electrical and Computer Engineering
University of Illinois at Chicago
Chicago, Illinois 60607, USA
E-mail: yma21@uic.edu, derong@uic.edu

***Abstract*—Spectrum sensing is an essential topic in cognitive radio networks to detect primary users. Cooperative spectrum sensing with linear fusion scheme is studied in multiband channel systems. The problem turns out to be a nonconvex optimization problem in general with thresholds of the energy detectors and the weights of linear fusion scheme as parameters. In this paper, we use the Taguchi method to estimate the gradient of the aggregate throughput function, determine thresholds of the energy detector and linear combination weights of the linear fusion rule. One of the advantages of our approach is to optimize the thresholds and the linear weights simultaneously. In addition, we modify the input parameters of experiments to satisfy the constraints before we calculate the cost and analyze the trends, and it improves the computation and search efficiency. Simulation results show that the proposed method can be used in all classes of CR. Our approach has a very good performance with short computational time and it is also insensitive to initial values of parameters and gives a relatively stable result.**

I. Introduction

Cognitive radio (CR) [1] is a technology that the secondary users (unlicensed users) continuously sense the communication environment and detect the presence of primary users (licensed users) in the frequency bands. It is defined by the Federal Communication Commission (FCC) in 2002 [2]. The reliability of CR networks greatly depends on spectrum sensing algorithm. Hidden primary users, white Gaussian noise and multipath fading acting together degrade sensing accuracy. Cooperative spectrum sensing is developed to tackle this problem. A survey on spectrum sensing, especially cooperative sensing, can be found in [3], [4] and [5].

Linear fusion rule (LFR) [6] works as a linear combination of the secondary users' observations at the fusion center. Three classes of CR, conservative system, aggressive system, hostile system, are defined in [6]. In this work, the signals are transmitted through a single band. Optimal cooperation for conservative system and aggressive system is studied in [6]. The same author proposes another method to maximize the throughput in [7]. Another relative work [8] seeks for the optimal solutions to these three classes with a common approach. PSO is proposed to improve the single band detection performance as well in [9]. [10] describes the LFR used in multiband spectrum sensing where the subband channels are divided from a wideband channel. In [10], the optimal design for only aggressive system is considered, because only for aggressive system, this problem is convex and can be solved with known techniques, such as interior point method. For conservative and hostile system, the problems are both nonconvex. [11] defines another class of CR, insolent system, and genetic algorithm (GA) has been applied to find the maximum throughput in general. However, GA does not have stable performance because of the randomness in its procedure. In addition, GA is easy to fall into local optimum and miss the global optimum.

In this paper, we express the energy detection thresholds properly to make sure that they are not affected by the varying ranges with changing weights. The Taguchi method are applied to search for global maximum of aggregate throughput effectively for all classes of CR, and it helps to improve the search efficiency and accuracy. The best combination of energy detector thresholds and linear weights are obtained in the process.

II. System Model and Problem Statement

In this section, we introduce cooperative spectrum sensing operates in multiband transmission environment. LFR [10] is employed at the fusion center. Primary signals are transmitted through K non-overlapping subbands. For each individual secondary user i, it senses N sampling time intervals. The binary hypotheses of the kth subband at sampling time n are as follows:

$$\begin{aligned}&\mathcal{H}_{0,k}:\ X_k^i(n) = V_k^i(n),\\ &\mathcal{H}_{1,k}:\ X_k^i(n) = H_k^i(n)S_k(n) + V_k^i(n), \quad k = 1, 2, ..., K,\end{aligned} \tag{1}$$

For each sampling time n, $\mathcal{H}_{0,k}$ represents that the kth subband is idle, while $\mathcal{H}_{1,k}$ means that the kth subband is taken by a primary user. $S_k(n)$ denotes the primary signal transmitting at time n. We assume that the channels between the primary user and the secondary users have the same white Gaussian noise, which is denoted as $V_k^i \sim \mathcal{N}(0, \sigma_v^2)$. H_k^i is the kth subband channel gain between the primary user and the secondary user i. X_k^i denotes the signal received at the secondary user i. Because we are lack of prior knowledge of primary users, the energy detector is the best choice to be used in this problem. Let Y_k^i be the energy of X_k^i accumulated up

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to sampling time N, which is given by

$$Y_k^i = \sum_{n=1}^{N} \left| X_k^i(n) \right|^2. \tag{2}$$

The discussion of the cooperative spectrum sensing starts from the fusion center,

$$z_k = \sum_{i=1}^{M} w_{i,k} Y_k^i, \tag{3}$$

where $w_{i,k}$ means the weight for the observations of the ith secondary user on the kth subband. M is the number of secondary users in the network. When $z_k > \gamma_k$, the subband k is taken by the primary user, otherwise it is available.

In subband k, we assume the transmitted signal's power to be 1, i.e., $\mathcal{E}[|S_k|^2] = 1$, where $\mathcal{E}[\cdot]$ denotes the expectation. The probability of false alarm, detection, and missed detection can be written as

$$P_f^k(\gamma_k, \mathbf{w_k}) = P(\mathcal{H}_{1,k}|\mathcal{H}_{0,k}) = \mathcal{Q}\left(\frac{\gamma_k - N\sigma_v^2 \mathbf{w_k^T 1}}{\sigma_v^2 \sqrt{2N\mathbf{w_k^T w_k}}}\right), \tag{4}$$

$$P_d^k(\gamma_k, \mathbf{w_k}) = P(\mathcal{H}_{1,k}|\mathcal{H}_{1,k}) = \mathcal{Q}\left(\frac{\gamma_k - N\mathbf{w_k^T}(\sigma_v^2 \mathbf{1} + \mathbf{G_k})}{\sigma_v \sqrt{2N\mathbf{w_k^T}\Sigma_k \mathbf{w_k}}}\right), \tag{5}$$

$$P_m^k(\gamma_k, \mathbf{w_k}) = 1 - P_d^k(\gamma_k, \mathbf{w_k}), \tag{6}$$

where $\mathcal{Q}(\cdot)$ denotes the Q-function. $\mathbf{G_k}$=$[|H_k(1)|^2,\ |H_k(2)|^2,\ ...,\ |H_k(M)|^2]^T$ and $\Sigma_k = \sigma_v^2 I + 2\text{diag}(\mathbf{G_k})$. $\mathbf{w_k}$ is denoted by $[w_{1,k}\ w_{2,k}\ ...\ w_{M,k}]^T$. $\mathbf{1} = [1\ 1\ ...\ 1]^T$ is a $K \times 1$ vector.

The purpose of designing CR network is to obtain as many opportunities as possible for secondary users with limited aggregate interference and limited interference for each individual subband, as mentioned in [10]. The expression of objective function and the constraints are as follows:

$$\max_{\boldsymbol{\gamma}, \mathbf{W}} R(\boldsymbol{\gamma}, \mathbf{W}) \tag{7}$$

$$s.t. \quad \sum_{k=1}^{K} c_k P_m^k(\gamma_k, \mathbf{w_k}) \leq \epsilon, \tag{8}$$

$$P_m^k(\gamma_k, \mathbf{w_k}) \leq \alpha_k, \quad k = 1, 2..., K, \tag{9}$$

$$P_f^k(\gamma_k, \mathbf{w_k}) \leq \beta_k, \quad k = 1, 2..., K, \tag{10}$$

where the overall weight matrix $\mathbf{W}$ is composed of the vector $\mathbf{w}_k$ for each subband k, and it is denoted by

$$\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, ..., \mathbf{w}_K] \tag{11}$$

and $\boldsymbol{\gamma} = [\gamma_1\ \gamma_2\ ...\ \gamma_K]^T$ denotes the thresholds for K subbands. $R(\boldsymbol{\gamma}, \mathbf{W})$ is defined as

$$R(\boldsymbol{\gamma}, \mathbf{W}) = \mathbf{r}^T[\mathbf{1} - \mathbf{P_f}(\boldsymbol{\gamma}, \mathbf{W})] = \sum_{k=1}^{K} r_k(1 - P_f^k(\gamma_k, \mathbf{w}_k)). \tag{12}$$

where $\mathbf{r} = [r_1\ r_2\ ...\ r_K]^T$ is the vector of throughput achievable coefficients for K subbands. The first constraint (8) limits the aggregate interference. $\mathbf{c} = [c_1\ c_2\ ...\ c_K]^T$ is the vector of cost coefficients of interference of K subbands. α_k and β_k are the limits of probability of interference and spectrum efficiency for kth subband, respectively.

In this optimization problem, there are $(M+1)K$ parameters to be optimized, $\mathbf{W}$ and $\boldsymbol{\gamma}$. Generally speaking, for all possible ranges of $\mathbf{w}_k$ and γ_k (all classes of CR), it is a nonconvex problem. From (4) to (10), we have the upper and lower boundary of γ_k as mentioned in [10]:

$$\gamma_{\min,k} = N\sigma_v^2 \mathbf{1}^T \mathbf{w_k} + \sigma_v \mathcal{Q}^{-1}(\beta_k)\sqrt{2N\mathbf{w_k}^T \mathbf{w_k}} \tag{13}$$

$$\begin{aligned}\gamma_{\max,k} =& \sigma_v \mathcal{Q}^{-1}(1-\alpha_k)\sqrt{2N\mathbf{w_k}^T \Sigma_k \mathbf{w_k}} \\ &+ N(\sigma_v^2 \mathbf{1}^T + \mathbf{G_k}^T)\mathbf{w_k}.\end{aligned} \tag{14}$$

So, (9) and (10) can be combined into one constraint:

$$\gamma_{\min,k} \leq \gamma_k \leq \gamma_{\max,k} \tag{15}$$

Seeking the global maximum of a nonconvex problem with $(M+1)K$ parameters has high computational complexity. In addition, the range for $\boldsymbol{\gamma}_k$ changes with $\mathbf{w}_k$, which causes another barrier.

III. Introduction to the Taguchi Method

In optimization problem, $J(\mathbf{v})$ is the cost function to be maximized that depends on the factors $\mathbf{v}$. We use an example to illustrate how TM works. This example has four factors $\mathbf{v} = [v_1\ v_2\ v_3\ v_4]$ and three levels for each factor. We denote the level l of the kth factor as $v_k^{(l)}$. For example, $v_1^{(2)}$ means level 2 of v_1. Initially, we set the same values for factors of the same level, i.e., $v_k^{(1)} = 0.5$, $v_k^{(2)} = 0.8$, $v_k^{(3)} = 1.2$, $k = 1, 2, 3, 4$. These initial values are adopted in [12] and work very well. We will use these values as three level initial factors in our algorithms and simulations in the following sections. We set up experiments referring to OA $L_9(3^4)$ in Table I. In $L_9(3^4)$, 3 means three levels for each factor and 4 indicates that we have four factors to be optimized. 9 is the total number of experiments in one cycle. With the values of parameters selected according to OA, we can calculate the costs J_i for each experiment (row), $i = 1, 2, ..., 9$, and save the maximum one $\max J_i$. The contribution of the level l for the individual factor k can be expressed as: $C_k^{(l)} = \sum_{i \in L_k^{(l)}} J_i$, where $L_k^{(l)}$ is the set whose elements are the indices of tests with level l of v_k, e.g., $C_2^{(1)} = J_1 + J_4 + J_7$. The comparison of $C_k^{(1)}$, $C_k^{(2)}$, and $C_k^{(3)}$ reveals the trends of the factors v_k. Totally, we face five cases for specific k:

Case 1. If $C_k^{(1)} > C_k^{(2)} > C_k^{(3)}$, $v_{\text{new},k}^{(l)} = v_k^{(l)} - \lambda$, $l = 1, 2, 3$.

Case 2. If $C_k^{(1)} < C_k^{(2)} < C_k^{(3)}$, $v_{\text{new},k}^{(l)} = v_k^{(l)} + \lambda$, $l = 1, 2, 3$.

Case 3. If $C_k^{(2)} < C_k^{(1)} < C_k^{(3)}$, $v_{\text{new},k}^{(l)} = v_k^{(l)} + \lambda$, $l = 1, 2, 3$.

TABLE I
ORTHOGONAL ARRAY $L_9(3^4)$

Test index	p_1	p_2	p_3	p_4	Cost
1	1	1	1	1	J_1
2	1	2	2	2	J_2
3	1	3	3	3	J_3
4	2	1	2	3	J_4
5	2	2	3	1	J_5
6	2	3	1	2	J_6
7	3	1	3	2	J_7
8	3	2	1	3	J_8
9	3	3	2	1	J_9
Contributions of level 1	$C_1^{(1)}$	$C_2^{(1)}$	$C_3^{(1)}$	$C_4^{(1)}$	
Contributions of level 2	$C_1^{(2)}$	$C_2^{(2)}$	$C_3^{(2)}$	$C_4^{(2)}$	
Contributions of level 3	$C_1^{(3)}$	$C_2^{(3)}$	$C_3^{(3)}$	$C_4^{(3)}$	

Case 4. If $C_k^{(2)} < C_k^{(3)} < C_k^{(1)}$, $v_{\text{new},k}^{(l)} = v_k^{(l)} - \lambda$, $l = 1, 2, 3$.

Case 5. If $C_k^{(2)}$ is the largest among three levels, the trend of C_k is a parabola. With the known three pairs of points on the parabola, $v_k^{(1)}$ and $C_k^{(1)}$, $v_k^{(2)}$ and $C_k^{(2)}$, $v_k^{(3)}$ and $C_k^{(3)}$, we can decide the parameters a, b, and c of the parabola $C = ax^2 + bx + c$. Then $v_{\text{new},k}$ of each level is updated as follows:

$$v_{\text{new},k}^{(2)} = -\frac{b}{2a}, \tag{16}$$

and

$$v_{\text{new},k}^{(1)} = v_{\text{new},k}^{(2)} - \frac{1}{2}\lambda'(v_k^{(3)} - v_k^{(1)}), \tag{17}$$

$$v_{\text{new},k}^{(3)} = v_{\text{new},k}^{(2)} + \frac{1}{2}\lambda'(v_k^{(3)} - v_k^{(1)}), \tag{18}$$

where λ is the step size and $\lambda' < 1$ is called a shrinking coefficient.

$v_{\text{new},k}^{(l)}$ then becomes the new factor in the next cycle of tests. The cycles of tests stop when the number of cycles reaches the maximum number we set in advance.

IV. OPTIMIZATION OF THRESHOLDS AND LINEAR WEIGHTS USING THE TAGUCHI METHOD

In this section, the optimal thresholds of the energy detector and the weights of LFR will be searched by the Taguchi method. We apply Taguchi method with 3-level factors in our optimization problem. Even though two levels are also acceptable, three-level factors have better performance than two levels. The number of subbands K is the number of factors in the Taguchi method. There are T rows in an orthogonal array which means the total number of tests in one cycle is T.

A. Joint Optimization of Thresholds and Weights for Cooperative Spectrum Sensing

For the problem (7)–(10), $\boldsymbol{\gamma}$ and $\mathbf{W}$ are the two groups of parameters to be optimized. In this subsection, we develop a method that can optimize $\boldsymbol{\gamma}$ and $\mathbf{W}$ simultaneously. First, we have to solve the problem that the range of γ_k changes with the value of $\mathbf{w}_k$. We introduce a new vector $\mathbf{v}$ with the size of $1 \times (M+1)K$ as the factors in TM. The last MK elements of $\mathbf{v}$ are rearranged from $\mathbf{W}$. Since the range of γ_k varies with the value of $\mathbf{w}_k$, it is impossible to use $\boldsymbol{\gamma}$ as factors directly. We use the first K elements of the new factors, $[v_1\ v_2\ ...\ v_K]$, instead of using $\boldsymbol{\gamma}$ directly. v_k is the ratio between $\gamma_{\min,k}$ and $\gamma_{\max,k}$, $0 \le v_k \le 2$. The formula to evaluate γ_k is as follows:

$$\gamma_k = \gamma_{\min,k} + \frac{1}{2}v_k(\gamma_{\max,k} - \gamma_{\min,k}). \tag{19}$$

with the limits $\gamma_{\min,k}$ and $\gamma_{\max,k}$ in (13) and (14).

The following steps are the summary of the search algorithm for optimal thresholds and linear weights using the Taguchi method:

Step 1: Initialize the factors with three levels. Set the maximum number of cycles as G.

Step 2: For $g = 1, 2, ..., G$, do 2.1–2.3.

2.1) According to the factor assignments in OA, the value of the factor v_k can be designed for each experiment.

2.2) For $t = 1, 2, ..., T$, do 2.2.1–2.2.3.

  2.2.1) The last KM elements in $\mathbf{v}$ are rewritten to the weight matrix $\mathbf{W}$. With (13) and (14), the range of γ_k is calculated. The first K elements of $\mathbf{v}$ are used to obtain γ_k with (19).

  2.2.2) Check the constraint (8). If the constraint (8) is not satisfied, use the γ_k modification algorithm (see below) to update $\boldsymbol{\gamma}$.

  2.2.3) Use $\boldsymbol{\gamma}$ found in 2.2.2) to determine the cost for this experiment. Go to 2.2) for the next test t.

2.3) Save the maximum value of the costs and corresponding $\boldsymbol{\gamma}$ and $\mathbf{W}$ in the experiments of this cycle g. Determine the trends of the cost function in (12) and update each level of factors $\mathbf{v}$ to make the cost in the next iteration closer to the optimal value J_{opt} with the method discussed in Section III. Go to Step 2 for next cycle g.

Step 3: Select the maximum cost value among the best cost in each cycle. Corresponding $\boldsymbol{\gamma}$ is the optimal thresholds and $\mathbf{W}$ is the optimal linear weight matrix. This maximum value is the maximum aggregate throughput in (7).

We modify γ_k as follows:

a) Denote the value of the left hand side of (8) as I. Here we discuss the case $I > \epsilon$, which means $\boldsymbol{\gamma}$ needs to be modified.

b) $\eta = \epsilon / I$.

c) $\sum_{i=1}^{K} c_i P_m^i(\gamma_{\text{new},i}, \mathbf{w}_i) = \epsilon$, where $P_m^i(\gamma_{\text{new},i}, \mathbf{w}_i) = \eta P_m^i(\gamma_i, \mathbf{w}_i)$. With (5) and (6), $\gamma_{\text{new},k}$ can be formulated as follows:

$$\begin{aligned}\gamma_{\text{new},k} =& \mathcal{Q}^{-1}(1 - \eta P_m^k(\gamma_k, \mathbf{w}_k))\sigma_v \sqrt{2N\mathbf{w}_k^T \Sigma_k \mathbf{w}_k} \\ &+ N\mathbf{w}_k^T(\sigma_v^2 \mathbf{1} + |G_k|).\end{aligned} \tag{20}$$

d) If $\gamma_{\min,i'} \le \gamma_{\text{new},i'} \le \gamma_{\max,i'}$, $\gamma_{i'} = \gamma_{\text{new},i'}$. Let $\mathcal{I}'$ be the set of index i'.

e) A set $\mathcal{I}$ is used to collect the index of $\boldsymbol{\gamma}_{\text{new}}$ that beyond the range or exactly on the boundaries. If $\gamma_{\text{new},i} \ge \gamma_{\max,i}$, let $\gamma_i = \gamma_{\max,i}$. Similarly, if $\gamma_{\text{new},i} \le \gamma_{\min,i}$, let $\gamma_i = \gamma_{\min,i}$. Let $\mathcal{I}$ be the set of index i.

f)

$$\eta' = \frac{\epsilon - \sum_{i\in\mathcal{I}} c_i P_m^i(\gamma_i, \mathbf{w}_i)}{\sum_{i\in\mathcal{I}'} c_i P_m^i(\gamma_i, \mathbf{w}_i)}. \quad (21)$$

g)

$$\gamma_{\text{new},k} = \mathcal{Q}^{-1}(1 - \eta' P_m^k(\gamma_k, \mathbf{w}_k))\sigma_v \sqrt{2N\mathbf{w}_k^T \Sigma_k \mathbf{w}_k + N\mathbf{w}_k^T(\sigma_v^2 \mathbf{1} + |G_k|)}, \quad k \in \mathcal{I}'. \quad (22)$$

h) Check $\gamma_{\text{new},k}$, $k \in \mathcal{I}'$. If all the $\gamma_{\text{new},k}$, $k \in \mathcal{I}'$, are in their ranges, $\gamma_k = \gamma_{\text{new},k}$. If not, force $R(\boldsymbol{\gamma}) = 0$, which means this factor combination gives a very small cost that it can never be chosen as the best factor combination.

B. Sequential Optimization of Thresholds and Weights for Cooperative Spectrum Sensing

In [10], a suboptimal approach called sequential optimization is discussed to optimize aggregate throughput. In sequential optimization, the optimal linear weight matrix $\mathbf{W}_{\text{opt}}$ is first worked out with modified deflection coefficient method. The optimal linear weight vector $\mathbf{w}_k^o$ is given by

$$\mathbf{w}_k^o = \frac{\Sigma_k^{-1}\mathbf{G}_k}{\|\Sigma_k^{-1}\mathbf{G}_k\|_2}. \quad (23)$$

Then, (13) and (14) are used to find the range of γ_k. The joint optimization problem of $\boldsymbol{\gamma}$ and $\mathbf{W}$ is eventually simplified to the optimization problem with only $\boldsymbol{\gamma}$ as parameters.

We summarize the procedure of the Taguchi method applied to sequential optimization as follows:

Step 1: Use (23) to calculate optimal linear weight vector $\mathbf{w}_k^o$ for subband k.

Step 2: Figure out the range of $\boldsymbol{\gamma}$ with (13) and (14) after $\mathbf{W}$ is determined.

Step 3: Initialize the factors with three levels. Set the maximum number of cycles as G.

Step 4: For $g = 1, 2, ..., G$, do 4.1–4.3.

4.1) According to the factor assignments in OA, the value of the factor v_k can be used to calculate γ_k with (19) for each test.

4.2) For $t = 1, 2, ..., T$, do 4.2.1–4.2.2.

4.2.1) Check the constraint (8). If the constraint (8) is not satisfied, use the γ_k modification algorithm in the last subsection to update $\boldsymbol{\gamma}$.

4.2.2) Use $\boldsymbol{\gamma}$ found in 4.2.1) to determine the cost by using (12). Go to 4.2) for the next t.

4.3) Save the maximum value of the cost and corresponding $\boldsymbol{\gamma}$ in the experiments of this cycle g. Determine the trends of the cost function in (12) and update each level of factors $\mathbf{v}$ to make the cost $R(\boldsymbol{\gamma})$ closer to the optimal cost J_{opt} in the next cycle with the method discussed in Section III. Go to Step 4 for next cycle g.

Step 5: Select the maximum value among the best cost in each cycle. It is known as the maximum throughput $R(\boldsymbol{\gamma})$ we can reach.

TABLE II
PARAMETERS IN THE CR NETWORK WITH TWO SENSORS

$G(1)$	0.38	0.29	0.23	0.26	0.35	0.39	0.33	0.27
$G(2)$	0.51	0.40	0.31	0.19	0.21	0.27	0.43	0.50
r(kbps)	806	755	356	327	68	720	15	972
c	5.95	3.91	0.71	4.21	0.44	2.03	0.58	2.85

From Section IV-A and IV-B, we can see that the nonconvexity does not affect the proposed algorithms. Therefore, the proposed algorithms are valid for all classes of CR.

V. SIMULATION RESULTS

First, we apply the proposed method to cooperative spectrum sensing scheme with joint optimization as described in [10]. In our CR network, the number of subbands is $K = 8$. Each sensor senses $N = 100$ sampling intervals. The variance for the white Gaussian noise is $\sigma_v^2 = 1$. There are two sensors operating together ($M = 2$) and the channel gain of both sensors, the throughput achievable coefficients $\mathbf{r}$, and the cost coefficients $\mathbf{c}$ can be found in Table II. The optimization problem is nonconvex in general. We choose two pairs of α and β to represent two cases which can be found in [11] (please note: in [11], $1 - P_f \geq \beta$, however, in our work, $P_f \leq \beta$). Each pair of α and β is one example. To simplify the design problem, in all examples we illustrate here, $\alpha = \alpha_1 = \alpha_2 = \cdots = \alpha_K$, while $\beta = \beta_1 = \beta_2 = \cdots = \beta_K$. In TM, the initial factors for three levels are 0.5, 0.8 and 1.2. The maximum number of iteration cycles is 20. We choose the step size and shrinking coefficient as $\lambda = 0.1$ and $\lambda' = 0.5$. The values of α and β in the two examples are $\alpha = 0.2$, $\beta = 0.5$ (aggressive) and $\alpha = 0.2$, $\beta = 0.7$ (conservative). We compare the optimization performance with the work in [11] by using GA. In Fig. 1, TM has much stronger performance than GA. In these two examples, for the given aggregate interference, TM can reach much higher aggregate throughput $R(\boldsymbol{\gamma}, W)$ than GA. At the same time, TM can be used when aggregate interference limit is low, when GA cannot even give any results.

The proposed method is also employed to sequential optimization of cooperative spectrum sensing. The performance comparison of two single sensor spectrum sensing, respectively, joint optimization of cooperative spectrum sensing and sequential optimization by using proposed algorithms of the two cases are shown in Fig. 2 to 3. We can see that the cooperative spectrum sensing has much better performance than the single sensor spectrum sensing. The performance of sequential optimization and joint optimization are pretty close to each other and only have minor difference.

The Taguchi method is a time efficient method. The computational time is about 3 seconds in cooperative spectrum sensing. The optimum values are reached in about 15 iterations. An advantage of the Taguchi method is that it can be operated in parallel, which further reduces the computational time. Another advantage of the Taguchi method is that it is

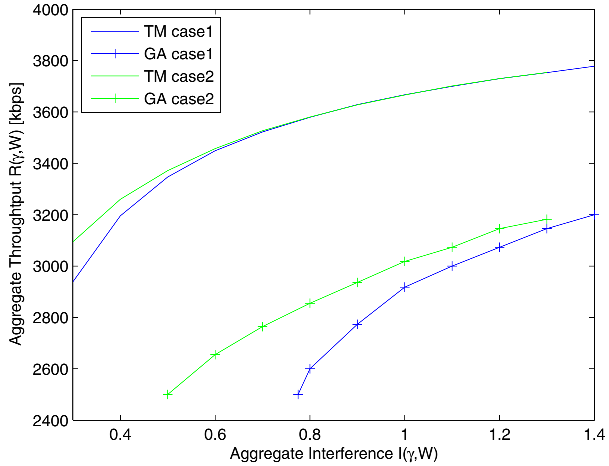

Fig. 1. The comparison of the optimization performance of cooperative spectrum sensing with TM and GA in the case (1) $\alpha = 0.2$ and $\beta = 0.5$; (2) $\alpha = 0.2$ and $\beta = 0.7$

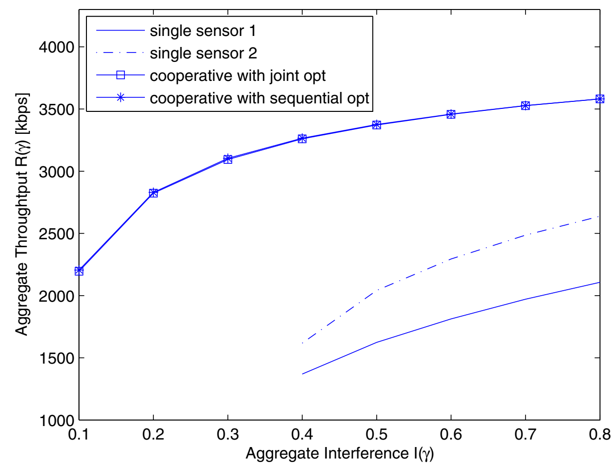

Fig. 3. The comparison for two single senors separately, cooperative sensing with joint optimization and sequential optimization in the case $\alpha = 0.2$ and $\beta = 0.7$

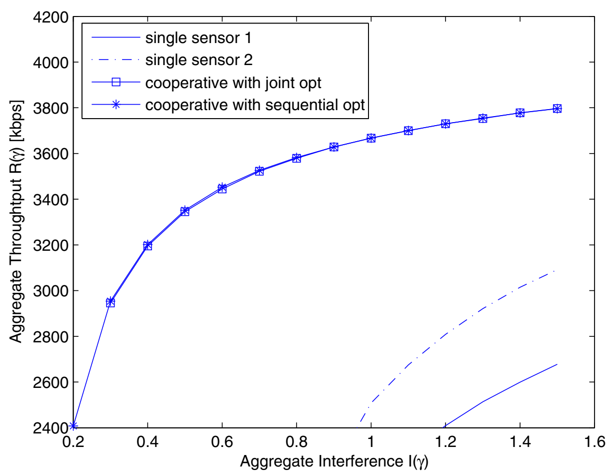

Fig. 2. The comparison for two single senors separately, cooperative sensing with joint optimization and sequential optimization in the case $\alpha = 0.2$ and $\beta = 0.5$

insensitive to initial values of the factors and gives relatively stable results.

VI. Conclusion

In this paper, the Taguchi method is employed to solve the throughput maximization problem in the multiband spectrum sensing. We aim to obtain the optimal thresholds of the energy detector and linear weights of LFR. Our approach can solve this nonconvex optimization problem in general. At the same time it improves the aggregate throughput of secondary users. In addition, we employed a group of new parameters to express thresholds $\boldsymbol{\gamma}$ properly to avoid the influence of the changing ranges of γ_k brought by varying the values of linear weights $\mathbf{w}_k$. Numerical simulation results reveal that the Taguchi method has an outstanding performance of optimization with satisfactory computational complexity. Furthermore, the Taguchi method is less sensitive to initial values of factors which makes the solution relatively robust and stable.

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