Distributed CA-CFAR and OS-CFAR Detectors Mentored by Biogeography Based Optimization Tool

Amel Gouri, Amar Mezache and Houcine Oudira

***Abstract*— In this paper, distributed constant false alarm rate (CFAR) detection in homogeneous and heterogeneous Gaussian clutter using Biogeography Based Optimization (BBO) method is analyzed. For independent and dependent signals with known and unknown power, optimal thresholds of local detectors are computed simultaneously according to a preselected fusion rule. Based on the Neyman-Pearson type test, CFAR detection comparisons obtained by the genetic algorithm (GA) and the BBO tool are conducted. Simulation results show that this new scheme in some cases performs better than the GA method described in the open literature in terms of achieving fixed probabilities of false alarm and higher probabilities of detection.**

Index Terms— **BBO, distributed CFAR detection, CA-CFAR, OS-CFAR, fusion rule.**

I. INTRODUCTION

In an automatic radar detection system, range resolution cells are used to estimate the background level and a threshold is then formed to test for the presence of a target in the cell under test (CUT). Centralized CFAR detectors operating in homogeneous and heterogeneous clutter are initially developed in terms of different test statistics. For instance, the cell averaging CFAR (CA-CFAR), the maximum likelihood CFAR (ML-CFAR), the logt-CFAR and the geometric mean CFAR (GM-CFAR) algorithms are all suited when the clutter is independent and identically distributed (iid) in the reference window [1-4]. In the realistic case when interfering targets and clutter edge situations are present, CFAR procedures based on the censoring of cells resolution contents like the order statistic CFAR (OS-CFAR), censored mean level CFAR (CMLD-CFAR), censored maximum likelihood CFAR (CML-CFAR) and Weber-Hykin CFAR (WH-CFAR) are proposed to maximize the detection probability [1].

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Another way to increase the detection performance of targets is to use multi-static radars (sensors) which are distributed geographically [2-5]. In this system, all CFAR detectors are executed together and local decisions are then made. Form these binary declarations, a fusion rule must be applied at the fusion center to get the global binary decision. Compared to standard CFAR detectors, decentralized CFAR detectors require the optimization of unknown parameters (i.e., thresholds multipliers, t_i and ranked cells orders, K_i) in the expressions of the overall false alarm and detection probabilities. In this context, Blum and Qiao [3] applied OS-CFAR detection techniques to a distributed detection system with dependent observations from sensor to sensor under the assumption of weak signals. The best thresholds were given for schemes employing either an "AND" or "OR" fusion rule for specific cases. In all of the cases, the "OR" fusion rule provided better performance than the "AND" fusion rule for false alarm probabilities larger than some critical value. In [6], the performance of multi-static radar system for both CA-CFAR and OS-CFAR for homogeneous and heterogeneous backgrounds by using the GA is also investigated. For independent signals with known power, the trends of the probability of detection P_d and the optimum rank K in the fusion center are presented. With respect to other parameters like t_i , C_i, and K_i, the trends seem still not very clear because of the sensitive property of the performance. For dependent signals with unknown power, the obtained results show that better results can be found with the GA approach.

In this work, we attempt to improve the detection performance of decentralized CA-CFAR and OS-CFAR detectors in presence of Gaussian clutter presented in [6]. To this effect, the BBO algorithm which is constructed principally by immigration and emigration operators is used to find optimal values of local thresholds. Based on the Neyman-Pearson type test, CFAR detection comparisons obtained by the GA and the BBO tools are presented. Simulation results show that this new scheme in some cases performs better than the GA method described in the literature in terms of achieving lower probabilities of false alarm and higher probabilities of detection.

In the following, the paper is organized as follows. Section 2 reviews the overall expressions of false alarm and detection probabilities in Gaussian background for distributed CA-CFAR and OS-CFAR detectors. Section 3 describes the operation of GA and BBO algorithms for parameters finding of the distributed CA-CFAR and OS-CFAR systems using "AND" and "OR" fusion rules. Section 4 illustrates a series of Swerling 1 target CFAR detection comparisons using GA and BBO tools. Finally, Section 5 reports some concluding remarks.

II. DISTRIBUTED CA-CFAR AND OS-CFAR DETECTORS

Recall that at the output of square law detector, centralized CA-CFAR and OS-CFAR detectors are suited for homogeneous and heterogeneous background respectively (see Fig. 1). The scale factor α controls the desired value of the false alarm probability and a target is declared when the clutter intensity in the cell under test (CUT) exceeds the adaptive detection threshold T. A set of the data in the reference window x_1, x_2, …, x_N are used for real time estimates of the clutter power, Q.

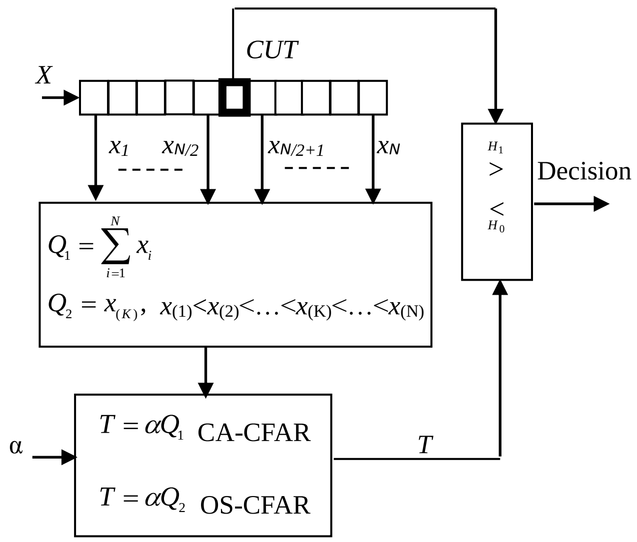


Fig. 1.Centralized CA-CFAR and OS-CFAR detectors in presence of Gaussian clutter

Expression of Q in terms of recorded data is highly dependent on the situation of the clutter background. In Gaussian noise case and according to the two hypotheses H_1 (Target signal plus Gaussian noise) and H_0 (Gaussian noise only), corresponding probability density functions (pdfs) of the CUT are given by

$$\begin{cases} H_0 : p_X(x|H_0) = \dfrac{1}{b}\exp\left(-\dfrac{x}{b}\right) \\ H_1 : p_X(x|H_1) = \dfrac{1}{b+a}\exp\left(-\dfrac{x}{b+a}\right) \end{cases} \tag{1}$$

where b and a are respectively the intensities of the clutter and the target of interest. From [1], calculation of the false alarm probability P_f and the detection probability P_d for CA-CFAR detection is given by

$$\begin{cases} P_f = \int_0^\infty \exp\left(-\dfrac{\alpha q}{b}\right).\dfrac{q^{M-1}}{b^M\Gamma(N)}\exp\left(-\dfrac{q}{b}\right)dq \\ P_d = \int_0^\infty \exp\left(-\dfrac{\alpha q}{b(1+SNR)}\right).\dfrac{q^{M-1}}{b^M\Gamma(N)}\exp\left(-\dfrac{q}{b}\right)dq \end{cases} \tag{2}$$

Integrals of (2) are resolved to yield compact expressions of P_f and P_d as

$$\begin{cases} P_f = (1+\alpha)^{-N} \\ P_d = \left(1+\dfrac{\alpha}{1+SNR}\right)^{-N} \end{cases} \tag{3}$$

Similarly, P_f and P_d of OS-CFAR detector are computed using the following integrals

$$\begin{cases} P_f = \int_0^\infty \exp\left(-\dfrac{\alpha q}{b}\right)\dfrac{k}{b}\begin{pmatrix}N\\K\end{pmatrix}\exp\left(-\dfrac{q}{b}\right)^{M-k+1}\left(1-\exp\left(-\dfrac{q}{b}\right)\right)^{k-1}dq \\ P_d = \int_0^\infty \exp\left(-\dfrac{\alpha q}{b(1+SNR)}\right)\dfrac{K}{b}\begin{pmatrix}N\\K\end{pmatrix}\exp\left(-\dfrac{q}{b}\right)^{M-k+1}\left(1-\exp\left(-\dfrac{q}{b}\right)\right)^{k-1}dq \end{cases} \tag{4}$$

Integrals of (4) are calculated to be

$$\begin{cases} P_f = \dfrac{N!}{(N-K)!}\dfrac{\Gamma(N-K+\alpha+1)}{\Gamma(N+\alpha+1)} \\ P_d = \dfrac{N!}{(N-K)!}\dfrac{\Gamma(N-K+1+\alpha/(1+SNR))}{\Gamma(N+1+\alpha/(1+SNR))} \end{cases} \tag{5}$$

From the past two decades, distributed signal detection schemes have received significant attention, but usually under the assumption of stationary observations which are independent from sensor to sensor [4, 6]. The parallel structure of distributed CFAR detection is highlighted in Fig. 2. Each local CFAR detector provides its binary decision and then transmits it to the fusion center. The n received decisions are then combined to yield a global decision according to "AND", "OR" or "k" out of "n"fusion rule.

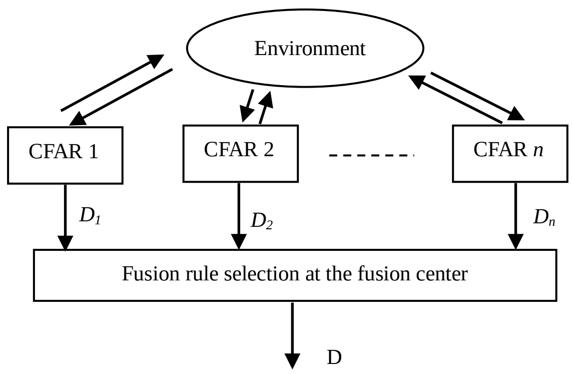


Fig. 2. Distributed CFAR processor system.

In the presence of Gaussian background, two situations can be occurred for decentralized CFAR detection [4, 6]; independent signals with known power and non stationary observations where the signal observations are assumed to be dependent from sensor to sensor. In the following section, we give explicit formulas of the total false alarm and detection probabilities when "AND" and "OR" fusion rules are taken into account in the fusion center.

A. *Independent signals with known power*

Supposing that we have n detectors, the data fusion center determines the presence of a target in the cell under test (CUT) if at least k detectors have made the same decision. For n receivers this represents all the possible cases between the rule "OR" (k =1) and the "AND" rule (k=n). We assume an environmental interference with a Gaussian probability density function (pdf) for the in-phase and quadrature components, and targets having a similar pdf with a slow fluctuation (Swerling I model). The following false alarm rate probability, P_f and detection probability, P_d for distributed CA-CFAR detector in homogeneous background are given in [6].

(i) "AND" fusion rule:
In this case, P_f and P_d hold the following formulas

$$\begin{cases} P_f = \prod_{i=1}^{n} (1+t_i)^{-N_i} \\ P_d = \prod_{i=1}^{n} \left(\frac{1+S_i}{1+S_i+t_i} \right)^{N_i} \end{cases} \tag{6}$$

where N_i, $i=1, \ldots, n$ is the total number of estimation cells of the detector i, $t_i = C_i / N_i$ is the scale factor and S_i is the SNR (signal-to-noise ratio).

(ii) "OR" fusion rule:
In this case, corresponding expressions of P_f and P_d are

$$\begin{cases} P_f = 1 - \prod_{i=1}^{n} \left(1 - (1+t_i)^{-N_i}\right) \\ P_d = 1 - \prod_{i=1}^{n} \left(1 - \left(\frac{1+S_i}{1+S_i+t_i} \right)^{N_i} \right) \end{cases} \tag{7}$$

For distributed OS-CFAR detection, the probabilities of false alarm and detection in heterogeneous background are also given in [6].

(iii) "AND" fusion rule:
For this situation, P_f and P_d are expressed as

$$\begin{cases} P_f = \prod_{i=1}^{n} \prod_{L=0}^{Ki-1} \frac{N_i - L}{N_i - L + t_i} \\ P_d = \prod_{i=1}^{n} \prod_{L=0}^{Ki-1} \frac{N_i - L}{N_i - L + \frac{t_i}{1+S_i}} \end{cases} \tag{8}$$

where K_i is the ranked cell order at the detector i.

(iv) "OR" fusion rule:
Here, P_f and P_d are

$$\begin{cases} P_f = 1 - \prod_{i=1}^{n} \left(1 - \prod_{L=0}^{Ki-1} \frac{N_i - L}{N_i - L + t_i} \right) \\ P_d = 1 - \prod_{i=1}^{n} \left(1 - \prod_{L=0}^{Ki-1} \frac{N_i - L}{N_i - L + \frac{t_i}{1+S_i}} \right) \end{cases} \tag{9}$$

B. Dependent signals with unknown power

In [4], the authors analyzed the case where the signal observations are assumed to be dependent from sensor to sensor and weak narrowband random signal are observed in additive Gaussian noise-plus-clutter of unknown power. Their results are very useful especially when it is difficult to get accurate estimation of the SNRs and in cases where the SNRs are varying. Taking into account the "AND" and "OR" fusion rules, we use the formulations in [4]. In order to obtain the best performance of a given multi-static radar system, we can choose the thresholds $t_1, \ldots, t_n$, to maximize $\sigma^2 P_d''(0)$ subject to the false alarm constraint, $P_f = \alpha_0$

(i) "AND" fusion rule:
For the "AND" rule, the equations of P_f and $P_d''(0)$ are given by

$$\begin{cases} P_f = \prod_{i=1}^{n} \prod_{L=0}^{K_i-1} \frac{(N_i - L)}{N_i - L + t_i} = \alpha_0 \\ P_d''(0) = \frac{2P_f}{\sigma^2} \sum_{i=1}^{n} \sum_{L=0}^{K_i-1} \frac{t_i}{N_i + t_i - L} \\ g(t_1, N_1, K_1) = g(t_j, N_j, K_j), \ j = 2, \ldots, n \end{cases} \tag{10}$$

where $g(t,N,K) = \sum_{l=0}^{K-1} \frac{(N-L)}{(N+t-L)^2} / \sum_{L=0}^{K-1} \frac{1}{(N+t-L)}$.

(ii) "OR" fusion rule:
For the "OR" rule, the equations of P_f and $P_d''(0)$ are given by

$$\begin{cases} P_f = 1 - \prod_{i=1}^{n} \left(1 - \prod_{L=0}^{Ki-1} \frac{(N_i - L)}{N_i - L + t_i} \right) = \alpha_0 \\ P_d''(0) = \frac{(1-P_f)}{\sigma^2} \sum_{i=1}^{n} \left(\frac{\prod_{L=0}^{Ki-1} N_i - L}{\prod_{L=0}^{Ki-1} (N_i + t_i - L) - \prod_{L=0}^{Ki-1} (N_i - L)} \right) \\ \qquad \sum_{L=0}^{Ki-1} \frac{t_i}{N_i + t_i - L} \\ g(t_1, N_1, K_1) = g(t_j, N_j, K_j), \ j = 2, \ldots, n \end{cases} \tag{11}$$

If the number of local detectors is equal to 3, the "MAJORITY" fusion rule can be considered for which the P_f and P_d are given by

$$\begin{cases} P_f = P_{f1}P_{f2} + P_{f2}P_{f3} + P_{f1}P_{f3} - 2P_{f1}P_{f2}P_{f3} \\ P_d = P_{d1}P_{d2} + P_{d2}P_{d3} + P_{d1}P_{d3} - 2P_{d1}P_{d2}P_{d3} \end{cases} \tag{12}$$

III OPTIMIZATION METHODS

To solve the above detection problem, we propose in this work a flexible approach using the BBO to give the global optimal results in different situations. Each chromosome is a vector of the parameters of P_d and P_f at the fusion center. The lengths of the chromosomes for CA-CFAR and OS-CFAR are n and $2n$ respectively, where n is the number of sensors in the defined multi-static radar system. To optimize the system parameters, GA and BBO tools are used to find specifically optimum thresholds multipliers. This involves the maximization of the overall P_d while keeping the overall P_f constant. In the sense of the N-P criterion and in the case of independent signals with known power, the fitness or objective function to be minimized by the BBO algorithm is [6].

$$Fitness(t_i, K_i) = w_1\left|1 - P_d\right| + w_2\left|P_f - \alpha_0\right| \quad (13)$$

In the case of dependent signals with unknown power, a third term given in (5) and (6) is added in (8). Hence [6]

$$Fitness(t_i, K_i) = w_1\left|1 - \sigma^2 P_d^{"}(0)\right| + w_2\left|P_f - \alpha_0\right| + w_3\sum_{i=2}^{n}\left|g(t_1, N_1, K_1) - g(t_i, N_i, K_i)\right| \quad (14)$$

w_1 , w_2 and w_3 are the weights parameters to adjust the convergence of the BBO.

A. Genetic algorithm method

Genetic algorithms are gradient free parallel-optimization algorithms that use a performance criterion for the evaluation and a population of possible solutions to search for a global optimum [2] [7-8]. The manipulation is done by the genetic operators that work on the chromosomes in which the parameters of possible solutions are encoded. In each generation of the GA, the new solutions replace the solutions in the population that are selected for deletion. In real-coded GA, the variables appear directly in the chromosome and they are modified by special genetic operators. In the following, $r \in [0,1]$ is a random number (uniformly distributed), $t = 0, 1, ..., T$ is the generation number, s_v and s_w are chromosomes selected for operation of the GA, $k \in \{1,2,..., N\}$ is the position of an element in the chromosome, and v_k^{min} and v_k^{max} are the lower and upper bounds, respectively , on the parameter encoded by element k. For crossover operator, the chromosomes are selected in pairs (s_v, s_w). The Whole arithmetic crossover, is a linear combination, is usually used. For the mutation operator, all elements of a chromosome are mutated by a Gaussian mutation for example. Then, the crossover and the mutation operators can produce solutions that violate the bounds. After these operations, the constraints are forced. The length of a chromosome is n and 2n for distributed CA-CFAR and OS-CFAR detectors respectively. The structure of each chromosome can be expressed as a vector of parameters shown as below.

$$Chromosome_{CA-CFAR} = [t_1, t_2, \ldots, t_n]_n \quad (15)$$

$$Chromosom_{OS-CFAR} = [t_1, t_2, ..., t_n; K_1, K_2, ..., K_n]_{2n} \quad (16)$$

The real-coded GA is given by the steps as follows:

Step 1:
Create the initial population of chromosomes where their values are obtained between the lower and upper bounds.

Step 2:
Calculate initial fitness values using (8) or (9).

Step 3:
Repeat genetic optimisation for t=0, 1, 2… max iteration

- Select a pair of chromosomes and use a crossover operator.
- Use mutation operator of the resulting chromosomes by the crossover operator.
- Operate on chromosomes acknowledging the search space constraints.
- Create new population by substituting the operated chromosomes for those selected for deletion.

Step 4:
Select the best solution from a final population by evaluating the best fitness function.

B. Biogeography based optimization method

The BBO algorithm is a new kind of optimization technique based on biogeography concept. It is an evolutionary algorithm that optimizes a function by stochastically and iteratively improving candidate solutions with regard to a given measure of quality, or fitness function. This population based algorithm uses the idea of the migration strategy of animals or other species for solving optimization problems. This method belongs to the class of meta-heuristics since it includes many variations, and since it does not make any assumptions about the problem and can therefore be applied to a wide class of problems [9-12].
The structure of habitat for OS-CFAR can be expressed as a vector.

$$Habitat_{CA-CFAR} = [t_1, t_2, \ldots, t_n]_n \quad (17)$$

$$Habitat_{OS-CFAR} = [t_1, t_2, ..., t_n; K_1, K_2, ..., K_n]_{2n} \quad (18)$$

The environment of BBO corresponds to an archipelago where every possible solution to the optimization problem is an island, each solution feature is called a suitability index variable (SIV). The goodness of each solution is called its habitat suitability index (HSI) where a high HSI of an island means good performance on the optimization problem and a low HSI means bad performance on the optimization problem. Improving the population is the way to solve problems in heuristic algorithms. The method to generate the next generation in BBO is by immigrating solution features to other islands and receiving solution features by emigration from other islands. The mutation is performed for the whole population in a manner similar to the mutation in GA.

In the BBO algorithm, Fig. 2 illustrates migration models, the immigration rate λ and the emigration rate μ of a solution which are functions of its fitness. The immigration curve shows that the least fit solution has the largest immigration rate and smallest emigration rate. The most fit solution has the smallest immigration rate and the largest emigration rate. S_1 represents a poor solution while S_2 represents a good solution. The process of the BBO involves the following steps [11, 12]:

Step 1: Initialize the BBO parameters: maximum species count S_{max} , the maximum migration rates E and I, the maximum rate m_{max} , an elitism parameters and number of iterations.

Step 2: Initialize a random set of habitats, each habitat corresponding to a potential solution to the given problems.

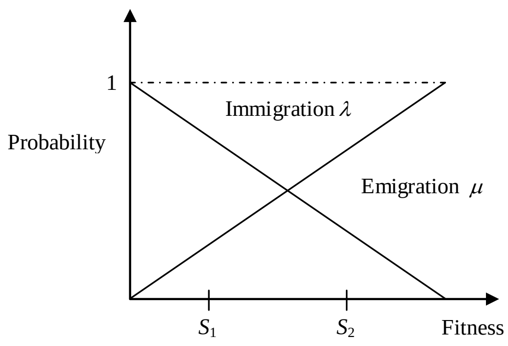


Fig. 3. Illustration of two BBO individuals using linear migration curves where S_1 represents a poor solution and S_2 represents a good solution

Step 3: For each habitat, map the habitat suitability index to the number of species S, the immigration rate λ and the emigration rate, μ .

Step 4: Probabilistically use immigration and emigration to modify each non_elite habitat, then recompute each HSI.

Step 5: For each habitat, update the probability of its species count, then mutate each probability and recomputed each HSI.

Step 6: Is acceptable solution found? If yes then go to step 8.

Step 7: Number of iteration over? If no then go to Step 3 for the next iteration.

Step 8: Stop.

The BBO has the ability to search for total optimal results without fixing any parameters as classical methods.

IV. DISTRIBUTED CFAR DETECTION COMPARISONS

In this section, we will employ the GA and BBO algorithms presented in the previous section for the optimization of local thresholds of distributed CA-CFAR and OS-CFAR detectors. First, the search interval is set to $t_i \in [0,100]$ and the ranked order is fixed in the interval $K_i \in [1, N_i]$. The initial population of about 30 random islands is generated for the BBO method and equations (13) and (14) are used as the objective measure functions (fitness functions) in the sense of the Neyman-Pearson criterion. After giving the desired value of $P_f = \alpha_0$, the weighting parameters in (13) and (14) are fixed in all simulations to $w_1 = 1$, $w_2 = 1/\alpha_0$ and $w_3 = 1$ in all simulations. Two cases of distributed CFAR detection are assessed in this section; distributed CA-CFAR and OS-CFAR detectors with known power and distributed OS-CFAR detectors with unknown power.

A. Distributed CFAR detection with known power

In this situation, we start by using the BBO method for the optimization of single, two and three identical CA-CFAR and OS-CFAR detectors given in equations (7) and (9) with the “OR” fusion rule, N_i=32 (i.e., N_1=N_2=N_3=32) and S_i=20 (S_1=S_2=S_3=20). As ploted in Figs. 4 and 5, the increase of the number of sensors provides better detection performances. When the desired value of P_f is used as a parameter, P_d values versus S (*SNR*) are depicted for the case of non-identical CA-CAR sensors using GA method and “AND” fusion rule. Moreover, Figures. 6. a and 6. b show that the best detection performances are achieved for high values of P_f. Taking the same conditions as before, the BBO is executed and high values of P_d results are obtained for large values of P_f as illustrated in Figs. 7. a and 7. b. Now, we apply the two optimization tools (i.e., GA and BBO methods) to the distributed OS-CFAR detectors with “OR” fusion and N_i=32 (see Figs. 8 and 9). In terms of the optimization method, similar P_d results are given and the P_d values will be better if P_f takes high level. Fig. 10. b depicts the detection performances of non-identical CA-CFAR detectors using GA tool and “OR” fusion rule. It is noticed that the finale fitness function has a full dependent on the desired value of P_f. Also, the fitness function evolution versus the number of iterations is illustrated in Fig. 10.a. As expected, the maximization of the P_d is related to the desired values of P_f.

To compare optimized values of local thresholds, t_i we consider identical CA-CFAR with N_i=40 and S_i=20. These variables which have similar values are optimized by the GA and the BBO tools. It is observed in TABLE I that the GA and the BBO tools give the same detection results, because we have only one variable to be optimized i.e., t_i. Our second experiment is the determination of unknown thresholds by means of GA and BBO methods when non identical sensors with N_1=16, N_2=24 and N_3=32 are used. Compared to the GA results in the case of “AND” fusion rule, the BBO algorithm provides the best P_d values as shown in TABLE II. If the “OR” fusion rule is used, the BBO and the GA tools give almost the equivalent P_d values with slight superiority to BBO algorithm as shown in TABLE III.

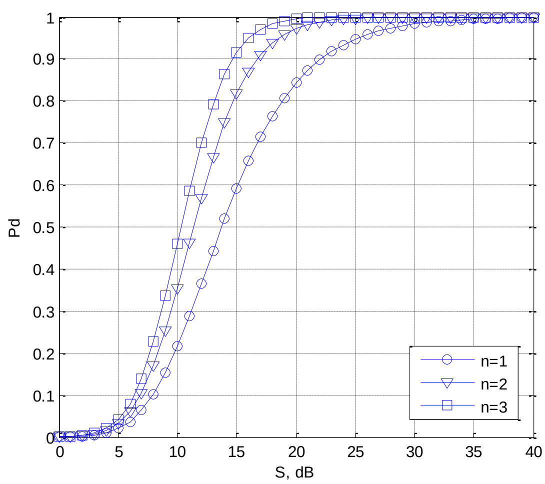


Fig. 4. Detection probability of identical CA-CFAR detectors using BBO method for “OR” rule, P_f=1e-6, N_i=32 and K_i=3N_i/4.

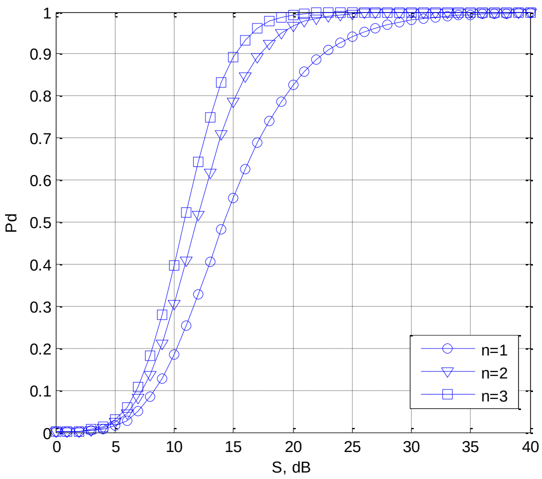
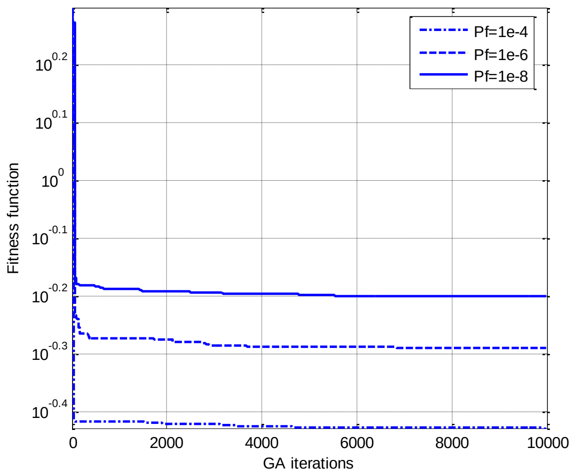


Fig. 5. Detection probability of identical OS-CFAR detectors using BBO method for "OR" rule, P_f=1e-6, N_i=32 and K_i=3N_i/4.



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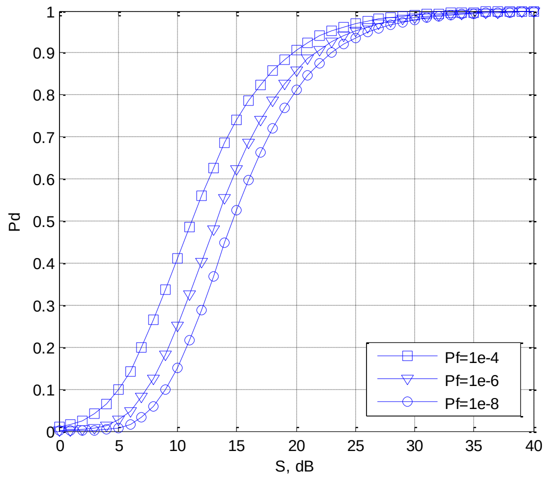
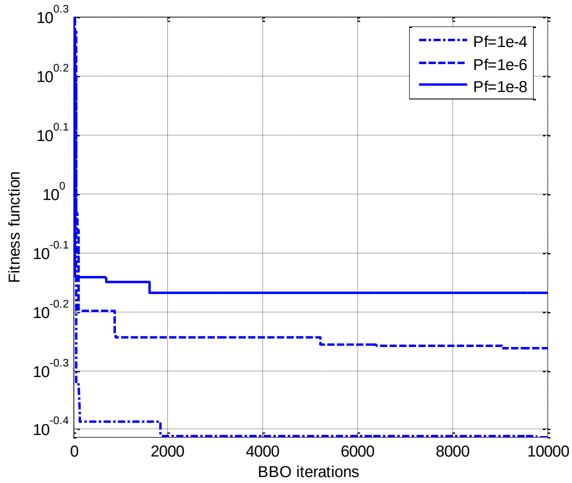


(b)

Fig. 6. Detection performances of non identical CA-CFAR detectors using GA method for N_1=16, N_2=24, N_3=32 and "AND" fusion rule.
(a) Fitness function versus the number of generations.
(b) P_d versus S (SNR).



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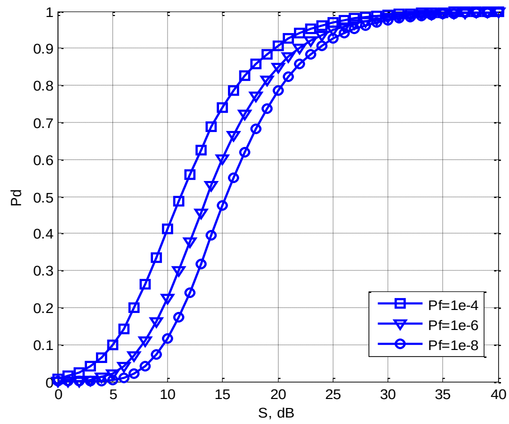
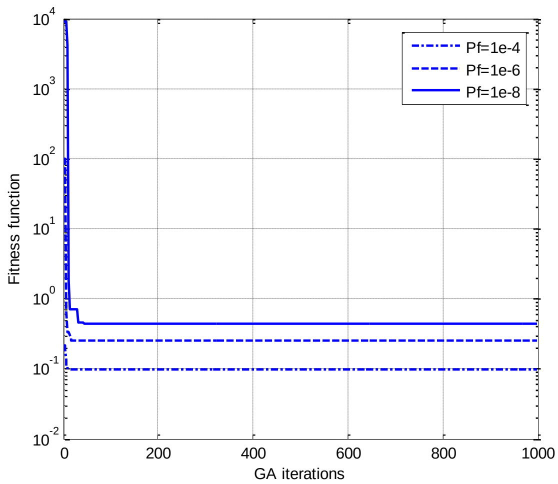


(b)

Fig. 7. Detection performances of non identical CA-CFAR detectors using BBO method for N_1=16, N_2=24, N_3=32 and "AND" fusion rule
(a) Fitness function versus the number of generations.
(b) P_d versus S (SNR).



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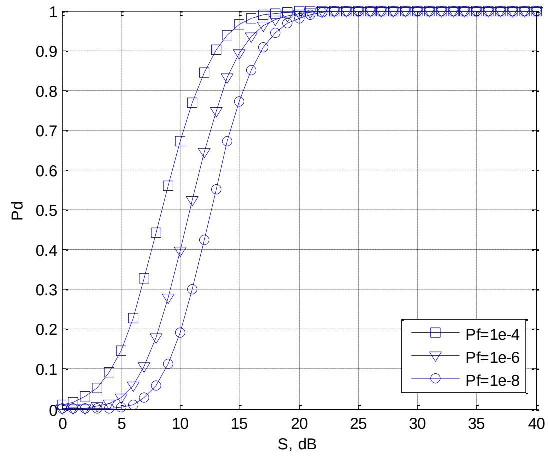
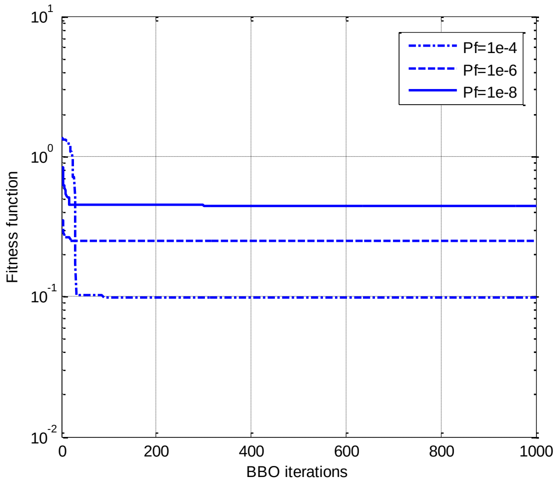
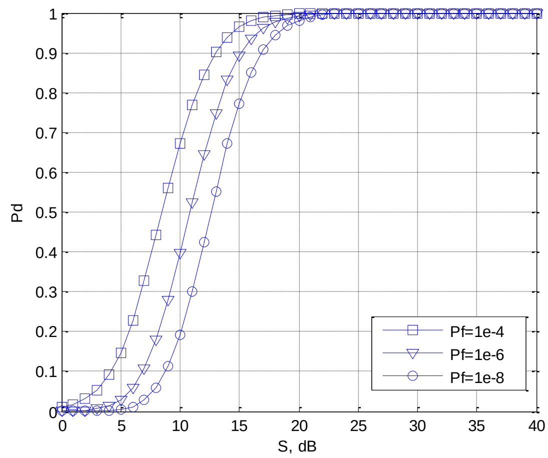


(b)

Fig. 8. Detection performances of identical OS-CFAR detectors using GA method for N_i=32 and “OR” fusion rule
(a) Fitness function versus the number of generations
(b) P_d versus S

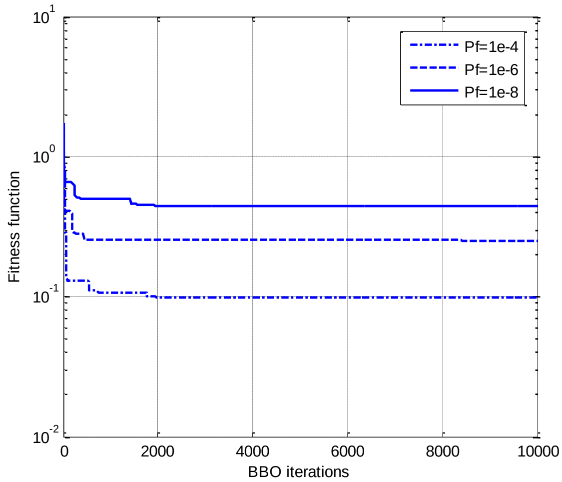


(a)

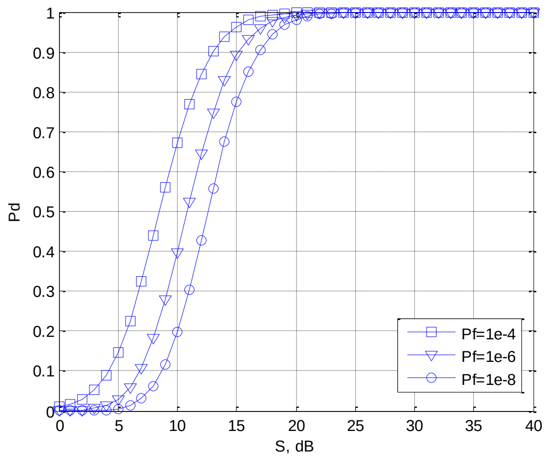


(b)

Fig. 9. Detection performances of identical OS-CFAR detectors using BBO method for N_i=32 and “OR” fusion rule
(a) Fitness function versus the number of generations
(b) P_d versus S



(a)



(b)

Fig. 10. Detection performances of distributed CA-CFAR using GA algorithm for N_1=16, N_2=24, N_3=32 and “OR” fusion rule
(a) Fitness function with S_i=20.
(b) P_d versus S *(SNR)*.

TABLE I

BEST THRESHOLDS FOR IDENTICAL CA-CFAR DETECTORS USING GA AND BBO ALGORITHMS WITH N=40, S=20 AND "OR" FUSION RULE

Optimization tool	P_f	n=2	n=3	n=5	n=7
GA method [6]	10^{-4}	t_i=0.2809 P_d=0.8300	t_i= 0.2940 P_d= 0.9224	t_i= 0.3106 P_d=0.9827	t_i= 0.3217 P_d=0.9959
	10^{-6}	t_i =0.4372 P_d=0.6848	t_i = 0.4519 P_d=0.8116	t_i= 0.4705 P_d=0.9298	t_i= 0.4830 P_d=0.9729
	10^{-8}	t_i= 0.6126 P_d=0.5329	t_i = 0.6290 P_d=0.6673	t_i = 0.6500 P_d=0.8264	t_i = 0.6639 P_d=0.6072
BBO method	10^{-4}	t_i =0.2809 P_d=0.8300	t_i = 0.2940 P_d= 0.9224	t_i = 0.3106 P_d=0.9827	t_i = 0.3217 P_d=0.9959
	10^{-6}	t_i =0.4372 P_d=0.6848	t_i = 0.4519 P_d=0.8116	t_i = 0.4705 P_d=0.9298	t_i = 0.4830 P_d=0.9729
	10^{-8}	t_i = 0.6126 P_d=0.5329	t_i = 0.6290 P_d=0.6673	t_i = 0.6500 P_d=0.8264	t_i = 0.6639 P_d=0.6072

TABLE II

OPTIMAL THRESHOLDS FOR NON IDENTICAL CA-CFAR DETECTORS USING GA AND BBO ALGORITHMS WITH N_1=16, N_2=24, N_3=32, S=20 AND "AND" FUSION RULE

Optimization Tool	P_f	t_1	t_2	t_3
GA method [6]	10^{-4}	0.1531	0.1150	0.1445
			P_d=0.6271	
	10^{-5}	0.0988	0.5049	0.0062
			P_d=0.5196	
	10^{-6}	0.1770	0.2150	0.2266
			P_d=0.4857	
	10^{-7}	0.5362	0.1999	0.1646
			P_d=0.4145	
	10^{-8}	0.3045	0.3804	0.2226
			P_d=0.3684	
BBO method	10^{-4}	0.1289	0.1255	0.1486
			P_d=0.6272	
	10^{-5}	0.1566	0.0991	0.2413
			P_d=0.5502	
	10^{-6}	0.2065	0.2150	0.2115
			P_d=0.4860	
	10^{-7}	0.4086	0.3477	0.1147
			P_d= 0.4161	
	10^{-8}	0.2830	0.2497	0.3282
			P_d=0.3700	

TABLE III

OPTIMAL THRESHOLDS OF NON IDENTICAL CA-CFAR DETECTORS USING GA AND BBO ALGORITHMS FOR N_1=16, N_2=24, N_3=32, S=20 AND "OR" FUSION RULE

Optimization Tool	P_f	t_1	t_2	t_3
GA method [6]	10^{-4}	0.9114	0.5405	0.3754
			P_d=0.9025	
	10^{-5}	1.2059	0.6664	0.5055
			P_d=0.8339	
	10^{-6}	1.5352	0.8599	0.5964
			P_d=0.7524	
	10^{-7}	1.9749	1.0673	0.6949
			Pd= 0.6566	

	10^{-8}	2.3957	1.2512	0.8407
		P_d=0.5584		
BBO method	10^{-4}	0.8762	0.5293	0.4018
		P_d=0.9018		
	10^{-5}	1.1964	0.6918	0.4838
		P_d= 0.8355		
	10^{-6}	1.5268	0.8646	0.5962
		P_d=0.7524		
	10^{-7}	1.8740	1.0736	0.7205
		Pd= 0.6567		
	10^{-8}	2.3798	1.2541	0.8432
		P_d=0.5584		

B.Distributed CFAR Detection with unknown power

In the case of dependent signals with unknown power, we compare the detection performance of distributed OS-CFAR detectors using GA and BBO methods. In this study, two sensors are considered with different values of sample sizes, N_1=6 and N_2=20. Optimal parameters are found in TABLES IV and V for “AND” and “OR” fusion rules respectively. A closed look at these tables turns out that the BBO method provides the best P_d values in almost cases.

By investigating the illustrated results, it is observed that the efficiency of the BBO algorithm will be useful when the optimization complexity of the distributed non identical CFAR detection for several parameters increases.

TABLE IV

CFAR DETECTION COMPARISONS BETWEEN THE GA AND BBO ALGORITHMS IN THE CASE NON IDENTICAL OS-CFAR DETECTORS WITH UNKNOWN POWER, N_1=16, N_2=20 AND “AND” FUSION RULE

P_f	BBO method	GA method [6]
10^{-1}	T_1=0.8204, T_2=0.6457 K_1=12, K_2=18 $\sigma^2 P_d''(0)$ = 0.4390	T_1=0.726, T_2 =1.129 K_1=13, K_2=14 $\sigma^2 P_d''(0)$ = 0.4389
10^{-3}	T_1=2.6286, T_2=2.1864 K_1=12, K_2=18 $\sigma^2 P_d''(0)$ = 1.21e-2	T_1=1.556, T_2 =3.281 K_1=15, K_2=15 $\sigma^2 P_d''(0)$ = 1.205e-2
10^{-4}	T_1=3.6178, T_2=3.0954 K_1=12, K_2=18 $\sigma^2 P_d''(0)$ =1.500e-3	T_1= 3.156, T_2=3.539 K_1=13, K_2=17 $\sigma^2 P_d''(0)$ =1.552e-3
10^{-5}	T_1= 4.6611, T_2=4.1103 K_1=12, K_2=18 $\sigma^2 P_d''(0)$ =1.860e-4	T_1= 2.878, T_2=5.162 K_1=15, K_2=16 $\sigma^2 P_d''(0)$ =1.863e-4
10^{-6}	T_1= 5.7803, T_2=5.2269 K_1=12, K_2=18 $\sigma^2 P_d''(0)$ =2.1506e-5	T_1= 5.937, T_2=6.073 K_1=12, K_2=17 $\sigma^2 P_d''(0)$ =2.148e-5

TABLE V

OPTIMIZATION BY GA AND BBO ALGORITHMS OF NON IDENTICAL OS-CFAR DETECTORS WITH UNKNOWN POWER, N_1=16, N_2=20 AND “OR” RULE

P_f	BBO method	GA method [5]
10^{-3}	T_1= 6.1382, T_1= 6.9298 K_1=13, K_2=18 $\sigma^2 P_d''(0)$ = 2.53e-2	T_1= 7.272, T_2=4.655 K_1=13, K_2=18 $\sigma^2 P_d''(0)$ =1.162e-2
10^{-4}	T_1=5.9420, T_2=7.6778 K_1=15, K_2=18 $\sigma^2 P_d''(0)$ =2.900e-3	T_1= 5.3610, T_2=7.703 K_1=16, K_2=17 $\sigma^2 P_d''(0)$ =1.418e-3
10^{-5}	T_1= 8.2147, T_2=10.6284 K_1=15, K_2=18 $\sigma^2 P_d''(0)$ =3.3683e-4	T_1=9.7140,T_2=8.6910 K_1=15, K_2=18 $\sigma^2 P_d''(0)$ =1.662e-4
10^{-6}	T_1= 10.895,T_2=14.0889 K_1=15, K_2=18 $\sigma^2 P_d''(0)$ =3.7978e-5	T_1= 10.12, T_2=9.179 K_1=16, K_2=19 $\sigma^2 P_d''(0)$ =1.873e-5

V. CONCLUSIONS

In this work, the optimization of distributed CFAR detection in Gaussian clutter was carried out using GA and BBO tools. Two CFAR procedures were considered; the CA-CFAR and the OS-CFAR. The detection performances were assessed as a function of the number of sensors, the desired value of the false alarm probability and the preselected “AND” or “OR” fusion rule at the fusion center. The obtained results showed the improvements of the global detection probability using the BBO algorithm in almost cases rather than the GA algorithm.

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