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

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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].

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.
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 \(x_1, x_2, \ldots, x_N\) 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](image)

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

\[
\begin{align*}
H_0 : p_x(x|H_0) &= \frac{1}{b} \exp \left( -\frac{x}{b} \right) \\
H_1 : p_x(x|H_1) &= \frac{1}{b+a} \exp \left( -\frac{x}{b+a} \right)
\end{align*}
\]

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

\[
\begin{align*}
P_f &= \int_{0}^{\infty} \exp \left( -\frac{aq}{b} - \frac{q}{b} \right) \frac{q^{n-1}}{b^n \Gamma(N)} \left(1 - \exp \left( -\frac{q}{b} \right) \right)^{\frac{N}{b}+1} dq \\
P_d &= \int_{0}^{\infty} \frac{aq}{b} \frac{q^{n-1}}{b^n \Gamma(N)} \left(1 - \exp \left( -\frac{q}{b} \right) \right)^{\frac{N}{b}+1} dq
\end{align*}
\]

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

\[
\begin{align*}
P_f &= (1 + \alpha)^n \\
P_d &= \left(1 + \frac{\alpha}{1 + SNR} \right)^n
\end{align*}
\]

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

\[
\begin{align*}
P_f &= \int_{0}^{\infty} \exp \left( -\frac{aq}{b(1+SNR)} - \frac{q}{b} \right) \frac{q^{n-1}}{b^n \Gamma(N)} \left(1 - \exp \left( -\frac{q}{b} \right) \right)^{\frac{N}{b}+1} dq \\
P_d &= \int_{0}^{\infty} \frac{aq}{b(1+SNR)} \frac{q^{n-1}}{b^n \Gamma(N)} \left(1 - \exp \left( -\frac{q}{b} \right) \right)^{\frac{N}{b}+1} dq
\end{align*}
\]

Integrals of (4) are calculated to be

\[
\begin{align*}
P_f &= \frac{N!}{(N-K)!} \frac{\Gamma(N-K+\alpha+1)}{\Gamma(N)} \\
P_d &= \frac{N!}{(N-K)!} \frac{\Gamma(N-K+1+\alpha/(1+SNR))}{\Gamma(N+\alpha/(1+SNR))}
\end{align*}
\]

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](image)

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 homogenous background are given in [6].

(i) “AND” fusion rule:
In this case, \(P_f\) and \(P_d\) hold the following formulas
\[
\begin{align*}
P_f &= \prod_{i=1}^{n} (1 + t_i)^{-N_i} \\
P_d &= \prod_{i=1}^{n} \left( \frac{1 + S_i}{1 + S_i + t_i} \right)^{N_i}
\end{align*}
\] (6)
where \(N_i, i=1, ..., n\) 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
\[
\begin{align*}
P_f &= 1 - \prod_{i=1}^{n} (1 - (1 + t_i)^{-N_i}) \\
P_d &= 1 - \prod_{i=1}^{n} \left( 1 - \left( \frac{1 + S_i}{1 + S_i + t_i} \right)^{N_i} \right)
\end{align*}
\] (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
\[
\begin{align*}
P_f &= \prod_{i=1}^{n} \prod_{j=0}^{N_i-1} \frac{N_i - L}{N_i - L + t_i} \\
P_d &= \prod_{i=1}^{n} \prod_{j=0}^{N_i-1} \frac{N_i - L}{N_i - L + \frac{t_i}{1 + S_i}}
\end{align*}
\] (8)
where \(K_i\) is the ranked order at the detector \(i\).

(iv) “OR” fusion rule:
Here, \(P_f\) and \(P_d\) are
\[
\begin{align*}
P_f &= 1 - \prod_{i=1}^{n} \left( 1 - \prod_{j=0}^{N_i-1} \frac{N_i - L}{N_i - L + t_i} \right) \\
P_d &= 1 - \prod_{i=1}^{n} \left( 1 - \prod_{j=0}^{N_i-1} \frac{N_i - L}{N_i - L + \frac{t_i}{1 + S_i}} \right)
\end{align*}
\] (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 \(t_1, ..., t_n\) to maximize \(\sigma^2 P_f(0)\) 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
\[
\begin{align*}
P_f &= \prod_{i=1}^{n} \prod_{j=0}^{N_i-1} \frac{(N_i - L)}{N_i - L + t_i} = \alpha_0 \\
P'_d(0) &= \frac{2P_f}{\sigma^2} \sum_{j=0}^{N_i-1} \frac{t_i}{(N_i - L)} - L \\
g(t_i, N_i, K_i) &= g(t_j, N_j, K_j), j = 2, ..., n
\end{align*}
\] (10)
where \(g(t, N, K) = \sum_{j=0}^{N-1} \frac{(N - L)}{N + t - L} \sum_{j=0}^{N-1} \frac{1}{N + t - L}\).

(ii) “OR” fusion rule:
For the “OR” rule, the equations of \(P_f\) and \(P'_d(0)\) are given by
\[
\begin{align*}
P_f &= 1 - \prod_{i=1}^{n} \left( 1 - \prod_{j=0}^{N_i-1} \frac{(N_i - L)}{N_i - L + t_i} \right) = \alpha_0 \\
P'_d(0) &= \frac{(1 - P_f)}{\sigma^2} \sum_{j=0}^{N_i-1} \frac{t_i}{(N_i - L)} - L \\
g(t_i, N_i, K_i) &= g(t_j, N_j, K_j), j = 2, ..., n
\end{align*}
\] (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
\[
\begin{align*}
P_f &= P_{f1}P_{f2}P_{f3} + P_{f1}P_{f2}P_{f3} + P_{f1}P_{f3}P_{f3} - 2P_{f1}P_{f2}P_{f3} \\
P_d &= P_{d1}P_{d2}P_{d3} + P_{d2}P_{d3}P_{d3} + P_{d2}P_{d3} - 2P_{d1}P_{d2}P_{d3}
\end{align*}
\] (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],

\[
\text{Fitness}(t, K) = w_1[P_t - P_s] + w_2|P_t - \alpha_s| \tag{13}
\]

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

\[
\text{Fitness}(t, K) = w_1[l - \sigma^2P_s(0)] + w_2|P_t - \alpha_s| + w_3\sum_{i=1}^{v}g(t_i, N_i, K_i) \tag{14}
\]

\(w_1, w_2,\) 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, \(s_i\) and \(s_t\) are chromosomes selected for operation of the GA, \(k \in \{1,2,...,N\}\) is the position of an element in the chromosome, and \(v_i^{\text{low}}\) and \(v_i^{\text{high}}\) are the lower and upper bounds, respectively, on the parameter encoded by element \(k\). For crossover operator, the chromosomes are selected in pairs \((s_i, s_t)\). 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.

\[
\text{Chromosome}_{\text{ca-cfar}} = [t_1, t_2, ..., t_n]_n \tag{15}
\]

\[
\text{Chromosome}_{\text{os-cfar}} = [t_1, t_2, ..., t_n; K_1, K_2, ..., K_n]_2n \tag{16}
\]

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.

\[
\text{Habitat}_{\text{ca-cfar}} = [t_1, t_2, ..., t_n]_n \tag{17}
\]

\[
\text{Habitat}_{\text{os-cfar}} = [t_1, t_2, ..., t_n; K_1, K_2, ..., K_n]_2n \tag{18}
\]

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 \(\lambda\) and the emigration rate \(\mu\) 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 \(S_{\text{max}}\), the maximum migration rates \(E\) and \(I\), the maximum rate \(m_{\text{max}}\), 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.

Step 3: For each habitat, map the habitat suitability index to the number of species $S$, the immigration rate $\lambda$ and the emigration rate, $\mu$.

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 $P_f = \alpha_o$, the weighting parameters in (13) and (14) are fixed in all simulations to $w_i = 1$, $w_c = 1/\alpha_o$ and $w_e = 1$ 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., $N_i=N_2=N_3=32$) and $S_i=20$ ($S_1=S_2=S_3=20$). As plotted 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 tools and “OR” fusion rule. It is noticed that the final 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 1 that the GA and the BBO tools give almost the equivalent 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 $N_i=16$, $N_i=24$ and $N_i=32$ 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. 3. Illustration of two BBO individuals using linear migration curves where $S_1$ represents a poor solution and $S_2$ represents a good solution.](image)

![Fig. 4. Detection probability of identical CA-CFAR detectors using BBO method for “OR” rule, $P_f=1e-6, N_i=32$ and $K_i=3N_i/4$.](image)
Fig. 5. Detection probability of identical OS-CFAR detectors using BBO method for “OR” rule, \( P_f = 1e^{-6} \), \( N_i = 32 \) and \( K_i = 3N_i/4 \).

(a) Fitness function versus the number of generations.

(b) \( P_d \) versus \( S \) (SNR).

Fig. 6. Detection performances of non identical CA-CFAR detectors using GA method for \( N_i = 16 \), \( N_2 = 24 \), \( N_3 = 32 \) and “AND” fusion rule.

(a) Fitness function versus the number of generations.

(b) \( P_d \) versus \( S \) (SNR).

Fig. 7. Detection performances of non identical CA-CFAR detectors using BBO method for \( N_i = 16 \), \( N_2 = 24 \), \( N_3 = 32 \) and “AND” fusion rule.

(a) Fitness function versus the number of generations.

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

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

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

<table>
<thead>
<tr>
<th>Optimization tool</th>
<th>$P_f$</th>
<th>$n=2$</th>
<th>$n=3$</th>
<th>$n=5$</th>
<th>$n=7$</th>
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</thead>
<tbody>
<tr>
<td><strong>GA method [6]</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10$^{-4}$</td>
<td>$t_1$ = 0.2809</td>
<td>$t_2$ = 0.2940</td>
<td>$t_3$ = 0.3106</td>
<td>$t_4$ = 0.3217</td>
<td>$t_5$ = 0.3217</td>
</tr>
<tr>
<td></td>
<td>$P_{fa}=0.8300$</td>
<td>$P_{fa}=0.9224$</td>
<td>$P_{fa}=0.9827$</td>
<td>$P_{fa}=0.9959$</td>
<td></td>
</tr>
<tr>
<td>10$^{-5}$</td>
<td>$t_1$ = 0.4372</td>
<td>$t_2$ = 0.4519</td>
<td>$t_3$ = 0.4705</td>
<td>$t_4$ = 0.4830</td>
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<tr>
<td></td>
<td>$P_{fa}=0.6848$</td>
<td>$P_{fa}=0.8116$</td>
<td>$P_{fa}=0.9298$</td>
<td>$P_{fa}=0.9729$</td>
<td></td>
</tr>
<tr>
<td>10$^{-6}$</td>
<td>$t_1$ = 0.6126</td>
<td>$t_2$ = 0.6290</td>
<td>$t_3$ = 0.6500</td>
<td>$t_4$ = 0.6639</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$P_{fa}=0.5329$</td>
<td>$P_{fa}=0.6673$</td>
<td>$P_{fa}=0.8264$</td>
<td>$P_{fa}=0.6072$</td>
<td></td>
</tr>
</tbody>
</table>

| **BBO method**    |       |       |       |       |       |
| 10$^{-4}$         | $t_1$ = 0.2809 | $t_2$ = 0.2940 | $t_3$ = 0.3106 | $t_4$ = 0.3217 |       |
|                   | $P_{fa}=0.8300$ | $P_{fa}=0.9224$ | $P_{fa}=0.9827$ | $P_{fa}=0.9959$ |       |
| 10$^{-5}$         | $t_1$ = 0.4372 | $t_2$ = 0.4519 | $t_3$ = 0.4705 | $t_4$ = 0.4830 |       |
|                   | $P_{fa}=0.6848$ | $P_{fa}=0.8116$ | $P_{fa}=0.9298$ | $P_{fa}=0.9729$ |       |
| 10$^{-6}$         | $t_1$ = 0.6126 | $t_2$ = 0.6290 | $t_3$ = 0.6500 | $t_4$ = 0.6639 |       |
|                   | $P_{fa}=0.5329$ | $P_{fa}=0.6673$ | $P_{fa}=0.8264$ | $P_{fa}=0.6072$ |       |

**Table II**

Optimal thresholds for non identical CA-CFAR detectors using GA and BBO algorithms with N=16, N=24, N=32, S=20 and “AND” fusion rule

<table>
<thead>
<tr>
<th>Optimization Tool</th>
<th>$P_f$</th>
<th>$t_1$</th>
<th>$t_2$</th>
<th>$t_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>GA method [6]</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10$^{-4}$</td>
<td>0.1531</td>
<td>0.1150</td>
<td>0.1445</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$P_{fa}=0.6271$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10$^{-5}$</td>
<td>0.0988</td>
<td>0.5049</td>
<td>0.0062</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$P_{fa}=0.5196$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10$^{-6}$</td>
<td>0.1770</td>
<td>0.2150</td>
<td>0.2266</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$P_{fa}=0.4857$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10$^{-7}$</td>
<td>0.5362</td>
<td>0.1999</td>
<td>0.1646</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$P_{fa}=0.4145$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10$^{-8}$</td>
<td>0.3045</td>
<td>0.3804</td>
<td>0.2226</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$P_{fa}=0.3684$</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| **BBO method**    |       |       |       |       |
| 10$^{-4}$         | 0.1289 | 0.1255 | 0.1486 |
|                   | $P_{fa}=0.6272$ |       |       |       |
| 10$^{-5}$         | 0.1566 | 0.0991 | 0.2413 |
|                   | $P_{fa}=0.5502$ |       |       |       |
| 10$^{-6}$         | 0.2065 | 0.2150 | 0.2115 |
|                   | $P_{fa}=0.4860$ |       |       |       |
| 10$^{-7}$         | 0.4086 | 0.3477 | 0.1147 |
|                   | $P_{fa}=0.4161$ |       |       |       |
| 10$^{-8}$         | 0.2830 | 0.2497 | 0.3282 |
|                   | $P_{fa}=0.3700$ |       |       |       |

**Table III**

Optimal thresholds of non identical CA-CFAR detectors using GA and BBO algorithms for N=16, N=24, N=32, S=20 and “OR” fusion rule

<table>
<thead>
<tr>
<th>Optimization Tool</th>
<th>$P_f$</th>
<th>$t_1$</th>
<th>$t_2$</th>
<th>$t_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>GA method [6]</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10$^{-4}$</td>
<td>0.9114</td>
<td>0.5405</td>
<td>0.3754</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$P_{fa}=0.9025$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10$^{-5}$</td>
<td>1.2059</td>
<td>0.6664</td>
<td>0.5055</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$P_{fa}=0.8339$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10$^{-6}$</td>
<td>1.5352</td>
<td>0.8599</td>
<td>0.5964</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$P_{fa}=0.7524$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10$^{-7}$</td>
<td>1.9749</td>
<td>1.0673</td>
<td>0.6949</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$P_{fa}=0.6566$</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### 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

<table>
<thead>
<tr>
<th>( P_{f} )</th>
<th>BBO method</th>
<th>GA method [6]</th>
</tr>
</thead>
<tbody>
<tr>
<td>( 10^{-4} )</td>
<td>( T_{1} = 0.8204, T_{2} = 0.6457 )</td>
<td>( K_{1} = 12, K_{2} = 18 )</td>
</tr>
<tr>
<td></td>
<td>( \sigma^{2} P_{f} (0) = 0.4390 )</td>
<td></td>
</tr>
<tr>
<td>( 10^{-3} )</td>
<td>( T_{1} = 2.6286, T_{2} = 2.1864 )</td>
<td>( K_{1} = 12, K_{2} = 18 )</td>
</tr>
<tr>
<td></td>
<td>( \sigma^{2} P_{f} (0) = 1.21e-2 )</td>
<td></td>
</tr>
<tr>
<td>( 10^{-2} )</td>
<td>( T_{1} = 3.6178, T_{2} = 3.0954 )</td>
<td>( K_{1} = 12, K_{2} = 18 )</td>
</tr>
<tr>
<td></td>
<td>( \sigma^{2} P_{f} (0) = 1.500e-3 )</td>
<td></td>
</tr>
<tr>
<td>( 10^{-1} )</td>
<td>( T_{1} = 4.6611, T_{2} = 4.1103 )</td>
<td>( K_{1} = 12, K_{2} = 18 )</td>
</tr>
<tr>
<td></td>
<td>( \sigma^{2} P_{f} (0) = 1.860e-4 )</td>
<td></td>
</tr>
<tr>
<td>( 10^{0} )</td>
<td>( T_{1} = 5.7803, T_{2} = 5.2269 )</td>
<td>( K_{1} = 12, K_{2} = 18 )</td>
</tr>
<tr>
<td></td>
<td>( \sigma^{2} P_{f} (0) = 2.1506e-5 )</td>
<td></td>
</tr>
</tbody>
</table>

#### 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

<table>
<thead>
<tr>
<th>( P_{f} )</th>
<th>BBO method</th>
<th>GA method [5]</th>
</tr>
</thead>
<tbody>
<tr>
<td>( 10^{-3} )</td>
<td>( T_{1} = 6.1382, T_{2} = 6.9298 )</td>
<td>( K_{1} = 13, K_{2} = 18 )</td>
</tr>
<tr>
<td></td>
<td>( \sigma^{2} P_{f} (0) = 2.53e-2 )</td>
<td>( \sigma^{2} P_{f} (0) = 1.162e-2 )</td>
</tr>
<tr>
<td>( 10^{-4} )</td>
<td>( T_{1} = 5.9420, T_{2} = 7.6778 )</td>
<td>( K_{1} = 15, K_{2} = 18 )</td>
</tr>
<tr>
<td></td>
<td>( \sigma^{2} P_{f} (0) = 2.900e-3 )</td>
<td>( \sigma^{2} P_{f} (0) = 1.418e-3 )</td>
</tr>
<tr>
<td>( 10^{-5} )</td>
<td>( T_{1} = 8.2147, T_{2} = 10.6284 )</td>
<td>( K_{1} = 15, K_{2} = 18 )</td>
</tr>
<tr>
<td></td>
<td>( \sigma^{2} P_{f} (0) = 3.3683e-4 )</td>
<td>( \sigma^{2} P_{f} (0) = 1.662e-4 )</td>
</tr>
<tr>
<td>( 10^{-6} )</td>
<td>( T_{1} = 10.8955, T_{2} = 14.0889 )</td>
<td>( K_{1} = 15, K_{2} = 18 )</td>
</tr>
<tr>
<td></td>
<td>( \sigma^{2} P_{f} (0) = 3.7978e-5 )</td>
<td>( \sigma^{2} P_{f} (0) = 1.873e-5 )</td>
</tr>
</tbody>
</table>

#### 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.
REFERENCES


[10] S. Dan, “A Probabilistic Analysis of a Simplified Biogeography Based Optimization Algorithm,” Department of Electrical and computer Engineering, Cleveland state University, Cleveland, Ohio, 44115, USA.


Authors short biographies

Amel Gouri was born in M’sila, Algeria, on January 5, 1991. She received the Master degree in Electronics/systems control from the University of Mohamed Boudiaf-M’sila, Algeria in 2015. She is a doctorate student in Telecommunication at the University of M’sila since 2015. Her main research interests include radar signal processing, Parameter estimation of statistical models and CFAR detection.

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Houcine Oudira was born in Constantine, Algeria, on November 05,1980. He received the Engineering degree in Electronics/Communication, Magister degree and the Doctorate degree in semiconductor sensor in biomedicine from the University of Constantine, Algeria, in 2003, 2005 and 2009 respectively. He joined the Department of Electronics, the University Mouhamed Boudiaf of M’sila, in 2009 as a full-time Professor. He is a member of the LGE (Laboratoire de Génie Electrique) Laboratory, University Mouhamed Boudiaf of M’sila. Currently his main research interests include signal processing and renewable energy.