Threshold Optimization in Distributed TM-CFAR Adaptive Acquisition Serial Search System Using Particles Swarm Optimization Technique

Identical case

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Abstract— **This work investigates the detection threshold optimization of the distributed trimmed-mean constant false alarm rate (TM-CFAR) algorithm. The algorithm TM-CFAR is chosen to solve the serial acquisition of the PN sequences problem. The acquisition system uses several identical sensors; every individual sensor makes a local decision. The overall decision, which is zero or one, is obtained at the data fusion center, which is grounded by "AND" and "OR" fusion rules, in the case where signals are independent from sensor to other. Under Rayleigh fading channel assumption, the analytic expressions of false alarm and detection probabilities are derived. The proposed system generates non-linear multi-variable equations, which are difficult to optimize using conventional optimization methods. To overcome this problem, an efficient methodology for simulation based particles swarm optimization (PSO) is suggested from a variety of meta-heuristic techniques. The obtained results demonstrate that, the proposed optimization method shows a powerful and useful tool to solve such problem in terms of achieving lower false alarm probabilities and higher detection probabilities.**

Keywords— ATM-CFAR, identical case, PN sequences, code acquisition, particles swarm optimization, Rayleigh fading channel.

I. Introduction

The acquisition of PN sequence task is one of the most popular techniques. It is used in several applications, such as cellular network, optic communication and satellite communication systems. The acquisition of PN codes can be considered as a signal detection problem. The signal detection is a procedure which can be implemented in various applications such as radars, sonars, and communication systems. The Main goal of this procedure is thus the design of an optimal receiver according to certain criteria, which are determined by the type of signal detection environments.

Achieving acquisition is one of difficult problems in low signal to noise ratio (SNR) environments. Also, the performance measurements of interest (i.e., the probability that the H_1 decision is a correct detection "P_D" and the probability that it is a false alarm "P_{FA}") degraded in these conditions [1]. Thus, constant false alarm rate (CFAR) algorithms are used in this work.

The goal in distributed CFAR systems is to maximize the total probability of detection (P_d) while keeping the total probability of false alarm P_{fa} constant. So, the mathematical development of both the overall P_d and the overall P_{fa}, for a distributed system that contains more than one sensor, generates a system of non-linear equations, which is difficult to optimize. Consequently, the classical methods become inadequate to find the global optimum and so, the use of stochastic search techniques such as Genetic Algorithms (GAs) or Evolutionary Strategies (ESs) becomes necessary [2]. These techniques are based on the selection of better solutions, which are achieved using the reproduction operators. Not far from the latter techniques, the meta-heuristic method of particle swarm optimization (PSO) was introduced by Eberhart and Kennedy in 1995 [3] and was inspired from the social behavior of living beings.

Recently, some work on adaptive acquisition of PN sequence using multi-censor processing has been reported in [4]. In this work, authors develop the theory of order statistics CFAR (OS-CFAR) and censored mean level detector CFAR (CMLD-CFAR) detection using multiple sensors and data fusion, where detection decisions are transmitted from each OS-CFAR or CLMD detector to the data fusion center. The overall decision is obtained at the data fusion center based on "And" and "Or" fusion rule. They maximize the global probability of detection for a given fixed global probability of false alarm by optimizing both the scaling factor T and the estimated noise level K of the above processors using PSO.

The goal of the present work is to propose the use of this simple and efficient approach for the optimization of the distributed TM-CFAR detector thresholds efficiency, by optimizing the scaling factor T, the k_1 cells trimmed from the lower end and the k_2 cells trimmed from the upper end of each TM-CFAR processor. In this study, a particle swarm optimization algorithm is coupled with multi-censor adaptive acquisition serial search of PN sequence simulation program by means of a MATLAB code to enhance performances of the acquisition system.

The paper is organized as follows: In Sect. 2, the proposed distributed adaptive acquisition system based on TM-CFAR processor is presented and described. In Sect. 3, this system is analyzed, and expressions for the detection and false alarm probabilities are given as a function of T, k_1 and k_2. In Sect. 4, the particle swarm optimization technique is reviewed. In Sect. 5, we evaluate the acquisition and detection performances of the proposed schemes based on simulation results. In Sect. 6, the concluding remarks are given.

II. System Model

The proposed system (Fig.1) is composed of N censors (antenna elements), each one is followed by an adaptive detector (AD) with correlation tap size R. Each AD consists of two blocks: the first block contains the conventional non-coherent matched filter (MF) correlator; it is composed of two independent branches: the inphase and the quadrature phase.

The second uses the constant false alarm rate technique to adjust the adaptive threshold of the decision process. The received PN signal is corrupted by noise and multipath interferences; it arrives at the input of each censor at the same time. Each AD makes a local decision, which is zero (no synchronization) or one (synchronization). The global decision to continue or to stop searching for the proper code alignment is made in the fusion center using the considered fusion rule (And or Or).

If the fusion center declares that the present cell is the correct one (H_1 cell), then the decision is made to stop search, the tracking loop is triggered, the phase of the local PN code is retarded by ΔT_C, where T_C is the chip time of the PN code, the next cell is then examined, and the whole testing procedure is repeated. The parameter Δ is usually take the values 0.25, 0.5 or 1, in our case Δ is equal to 1. On the other hand, if the fusion center fails to indicate that the present cell is the correct one (H_0 cell), the acquisition scheme automatically adjusts the local and the incoming code phases to the next offset position and the search of the synchronized cell is repeated.

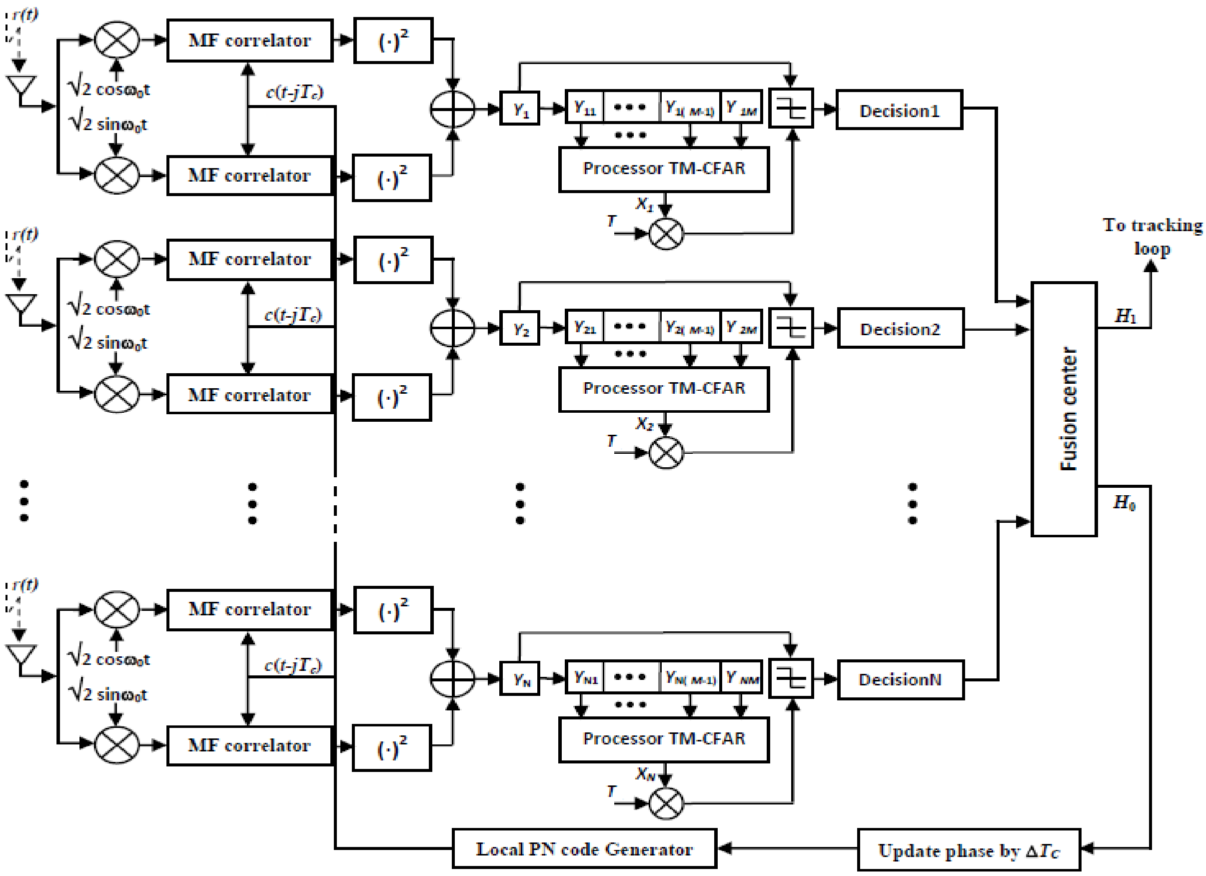

Fig.1. Proposed multi-censor adaptive acquisition system.

The threshold value of the comparator in each AD is adjusted in accordance with the magnitude of the incoming signals. Accordingly, the noncoherent detectors outputs are sent serially into the N shift registers, each of length M+1 called reference windows. Each first register, denoted Y_i, i=1,2,…, N, stores the output of the test phase. The acquisition system stores the output of the previous M offset positions in the following M registers, denoted by Y_{ij}, i=1,2, …, N and j = 1, 2, …, M. Using the TM-CFAR algorithm in each AD, the system can estimate the background noise power of incoming signals and reject automatically the interfering cells, without a priori information about the channel characteristics. In order to make a decision about the presence or the absence of the desired signal, the adaptive threshold values are calculated dynamically according to the desired false alarm rate values of the TM-CFAR used by the N adaptive detectors. M and N are the number of censors and the number of reference cells in each AD, respectively.

III. Analysis of Decision Processors

The received signal is then processed by the in-phase and quadrature phase channels, assuming a correlated chi-square signal with two degrees of freedom embedded in Rayleigh fading channel. Referring to Fig.1, the probability density function "pdf" of the hypothesis H_1, $f_Y(y/H_1)$, in the output of each non-coherent detector can be expressed as [5]

$$f_Y(y/H_1) = \frac{1}{1+\mu}\exp\left(\frac{-y}{1+\mu}\right),\ \ y \geq 0 \tag{1}$$

where μ denotes the average signal to noise ratio (SNR), and the pdf of the sample H_0 is

$$f_Y(y/H_0) = \exp(-y),\ y \geq 0 \tag{2}$$

Using the algorithm TM-CFAR, the reference cells of each AD are ranked firstly in ascending order according to their magnitude to form the ordered samples

$$Y_i(1) \leq Y_i(2) \leq \cdots \leq Y_i(M), \quad i = 1, 2, \ldots, N \tag{3}$$

Then each TM-CFAR processor trims k_1 cells from the lower end and k_2 cells from the upper end, the remaining ones are summed to estimate the noise power level, as:

$$X_i = \sum_{j=k_1}^{M-k_2} Y_i(j) \tag{4}$$

where, all ADs have the same number of reference cells M, and k_2, can be considered as the estimate numbers of samples containing multipath replicas, generated by the censoring block of each AD. Hence, the values of k_1 and k_2 are used to yield the statistics X_i, i=1, 2, ,…, N, and the scaling factor value T which realize the desired false alarm probabilities (P_{fa_i}, i=1, 2,…, N) of each AD, and then the desired global false alarm rate P_{fa}.

The ordered samples are not independent and identically distributed (*iid*) random variables even when the original samples Y_{ij}, i=1,2, …, N and j = 1, 2, …, M, are *iid* random variables. However, the following transformation results in independent quantities [6]:

$$W_{ip} = k'_p Z'_{ip} \tag{5}$$

where, $k'_p = M - k_1 - k_2 + 1 - p$, $p = 1, 2, \ldots, M - k_1 - k_2$, and

$$\begin{aligned} Z'_{i1} &= Y_{i(k_1+1)} \\ Z'_{i2} &= Y_{i(k_1+2)} - Y_{i(k_1+1)} \\ &\vdots \\ Z'_{i(M-k_1-k_2)} &= Y_{i(M-k_2)} - Y_{i(M-k_2-1)} \end{aligned} \tag{6}$$

The estimate values of the noise power level X_i are obtained by the remaining $(M - k_1 - k_2)$ cells in each AD (non censored), as:

$$X_i = \sum_{p=1}^{M-k_1-k_2} W_{ip},\ i = 1,2,...,N \tag{7}$$

Each value X_i, i=1, 2, …, N, is then multiplied by the constant T in order to the desired false alarm probability P_{fa_i}, i=1, 2,…, N. Considering these conditions, the false alarm rate is found to be:

$$P_{fa_i} = \prod_{j=1}^{M-k_1-k_2} M_{V_j}(T), \quad i = 1,2,...,N \tag{8}$$

where,

$$M_{V_1}(T) = \frac{M!}{k_1!(M-k_1-1)!(M-k_1-k_2)} \times \sum_{l=0}^{k_1} \frac{\binom{k_1}{l}(-1)^{k_1-l}}{\frac{M-l}{M-k_1-k_2}+T} \tag{9}$$

and

$$M_{V_j}(T) = \frac{a_j}{a_j+T},\quad j = 2,...,M-k_1-k_2 \tag{10}$$

where,

$$a_j = \frac{M - k_1 - j + 1}{M - k_1 - k_2 - j + 1} \tag{11}$$

The detection probability P_{di} is obtained by replacing T with $T/(1+\mu)$ in (8). To obtain the global decision, two fusion rules are considered: "And" and "Or".

✓ *And rule :* In this case, the global probabilities of detection and false alarm are given by

$$P_d = \prod_{i=1}^{N} P_{di} \qquad (12)$$

$$P_{fa} = \prod_{i=1}^{N} P_{fai} \qquad (13)$$

✓ *Or rule :* The global probabilities P_d and P_{fa} can be expressed as

$$P_d = 1 - \prod_{j=1}^{N} \left(1 - P_{dj}\right) \qquad (14)$$

$$P_{fa} = 1 - \prod_{j=1}^{N} \left(1 - P_{faj}\right) \qquad (15)$$

It is clear from these equations that the thresholds of the detectors TM-CFAR used in ADs have a nonlinear property according to the estimated parameters of the noise power. The classical method can give an estimate value of the detection threshold far from the optimum. For improving the detection performances, we propose the use of an intelligent system for the optimal estimate of the detection thresholds. The optimal threshold is obtained by achieving a higher global detection probability and keeping the global false alarm rate in a desired lower value, using particles swarm optimization (PSO) algorithm. In the sense of the Neyman-Pearson, the objective function (or fitness) to be minimized by the PSO algorithm is defined by [2]

$$Fitness(T, k_1, k_2) = \left|1 - P_d(T, k_1, k_2)\right| + \frac{1}{\alpha_0} \cdot \left|P_{fa}(T, k_1, k_2) - \alpha_0\right| \qquad (16)$$

where, α_0 is the global desired false alarm probability.

IV. PSO Technique

Particle swarm optimization (PSO) algorithm is a powerful approach inspired from the collective behavior of social animals living in swarm and their aptitude to optimize a total objective by collaborative research in a space. The PSO is a stochastic search technique, characterized by its simplicity and efficacity, applicable to solve problems with several variables, and in a space of research to one or several dimensions, it has many similarities with the evolutionary strategies. These solutions are used in an algorithm of update in order to optimize an objective in future generations. However, instead of using evolutionary operators to manipulate individuals, like other algorithms of evolutionary calculation, the PSO rests on the exchange of information between individuals, who are particles of a population called swarm [3]. Each particle, which represents a potential solution, moves in the space of research with an adaptive speed while following the current optimal particles. Fig. 2 demonstrates the workflow of PSO algorithm. The position of each particle $x_i(t)$ is calculated using the following expression [3, 4]

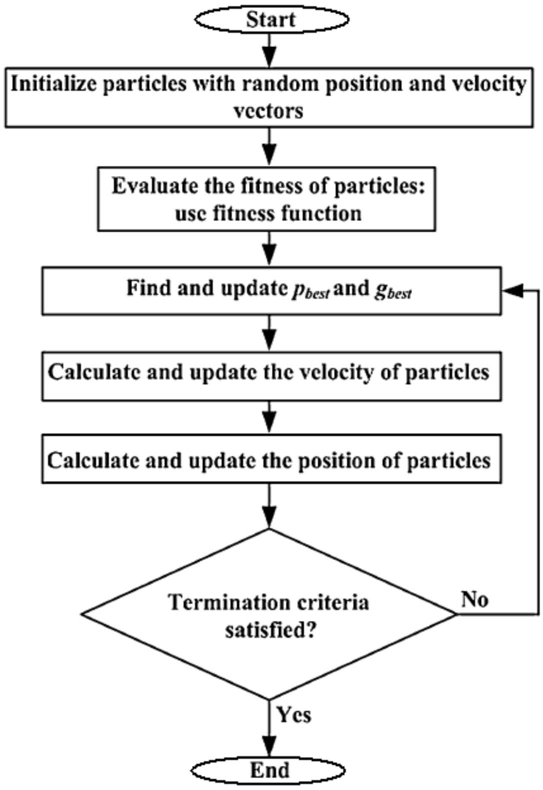

Fig. 2. Flowchart depicting the general PSO algorithm.

$$x_i(t) = x_i(t-1) + v_i(t) \qquad (17)$$

where the velocity vector is defined as

$$v_i(t) = \omega v_i(t-1) + c_1.r_1[P_{best_i}(t-1) - x_i(t-1)] + c_2.r_2[G_{best_i}(t-1) - x_i(t-1)] \qquad (18)$$

where ω is the inertia weight to control the effect of the particle previous velocity on the current one, $P_{best_i}(t-1)$ is the best previous position of each particle named particle best position, $G_{best_i}(t-1)$ is the best position of all the particles (called the global best particle), c_1 and c_2 are accelerations usually defined as positive constants, r_1 and r_2 are random values in the range of 0 and 1.

V. Performances evaluation

In this section, we will employ the PSO algorithm described in the previous section for the optimization of local thresholds of distributed TM-CFAR detectors. First, the research intervals are set to $T \in [0,10]$, $k_1 \in [1,(M/2)-1]$ and $k_2 \in [1,(M/2)]$, where M is the reference window size of each detector. The initial population is composed of about 30 particles, where equation (16) is used as the objective function, in the sense of the Neyman-Pearson criterion. The maximum generation is set equal to 100 and ω is fixed as a decreasing linear function of time from 0.9 to 0.4. The SNR/Chip is fixed at the value 10 dB for "And" and "Or" fusion rules to compute the values of T, k_1 and k_2 on off-line leading to best performance.

Tables 1 and 2 below show the corresponding optimal values of T, k_1 and k_2 in different situations for the fusion rule “And” and “Or”, respectively. For the acquisition system, the uncertainty region q is set to 1023, R to 64, Δ to 1 and the penalty factor K to 1000, with a rate of 1 Mbits/s.

In this case, it is noted that the best results are those obtained for the system which has a large number of local detectors. Also, the performances of detection are degraded by decreasing the desired probability of false alarm; and when we compare the results of Tables 1 and 2, we observe a clear improvement in the results of the detection probability (P_d) using the fusion rule “Or”, i.e., the fusion rule “Or” gives the best detection results compared to the fusion rule “And”.

The evolution of the global probability of detection P_d according to the SNR/Chip (dB) variation is represented, for the fusion rules “And” and “Or”, by Figs. 3 and 4 respectively, for various values of P_{fa}, a fixed value of the number of reference cells M = 16, and supposing that the system contains two identical detectors (N = 2). According to these two figures, it can be observed that there is a significant degradation of the detection probability value, for the two fusion rules “And” and “Or”, imposed by the reduction in the probability of false alarm P_{fa}.

Figs. 5 and 6 represent the evolution of the global detection probability versus the SNR/Chip (dB), for the fusion rules “And” and “Or”, respectively. From these two figures it is shown that, plus the number of detectors in the distributed system is high, plus the detection performance is improved. Thus, the system using the fusion rule “Or” with 5 detectors has better performances, compared to the fusion rule “And”.

TABLE I. ESTIMATED PARAMETERS OF DISTRIBUTED TM-CFAR DETECTORS, USING PSO ALGORITHM FOR THE FUSION RULE “AND”.

Number of detectors	$N = 2$		$N = 3$		$N = 5$	
P_{fa}	Estimated parameters	P_d	Estimated parameters	P_d	Estimated parameters	P_d
10^{-2}	$T = 0.5326$ $k_1 = 4$ $k_2 = 5$	0.9283	$T = 0.1651$ $k_1 = 3$ $k_2 = 2$	0.9278	$T = 0.1158$ $k_1 = 1$ $k_2 = 3$	0.9291
10^{-3}	$T = 0.5179$ $k_1 = 4$ $k_2 = 3$	0.8850	$T = 0.3100$ $k_1 = 2$ $k_2 = 3$	0.8899	$T = 0.1477$ $k_1 = 2$ $k_2 = 3$	0.8942
10^{-4}	$T = 0.5730$ $k_1 = 4$ $k_2 = 2$	0.8452	$T = 0.3742$ $k_1 = 5$ $k_2 = 2$	0.8532	$T = 0.2254$ $k_1 = 6$ $k_2 = 2$	0.8593
10^{-5}	$T = 0.7139$ $k_1 = 2$ $k_2 = 5$	0.8027	$T = 0.5067$ $k_1 = 6$ $k_2 = 2$	0.8152	$T = 0.3100$ $k_1 = 2$ $k_2 = 3$	0.8233

TABLE2: ESTIMATED PARAMETERS OF DISTRIBUTED TM-CFAR DETECTORS, USING PSO ALGORITHM FOR THE FUSION RULE “OR”.

Number of detectors	$N = 2$		$N = 3$		$N = 5$	
P_{fa}	Estimated parameters	P_d	Estimated parameters	P_d	Estimated parameters	P_d
10^{-2}	$T = 1.0209$ $k_1 = 2$ $k_2 = 4$	0.9903	$T = 0.6254$ $k_1 = 6$ $k_2 = 1$	0.9990	$T = 3.7091$ $k_1 = 1$ $k_2 = 8$	0.9999
10^{-3}	$T = 1.2647$ $k_1 = 1$ $k_2 = 3$	0.9781	$T = 2.0017$ $k_1 = 5$ $k_2 = 4$	0.9958	$T = 1.1789$ $k_1 = 2$ $k_2 = 2$	0.9999
10^{-4}	$T = 0.8959$ $k_1 = 4$ $k_2 = 0$	0.9641	$T = 0.9159$ $k_1 = 2$ $k_2 = 0$	0.9922	$T = 2.1586$ $k_1 = 3$ $k_2 = 3$	0.9994
10^{-5}	$T = 1.6367$ $k_1 = 5$ $k_2 = 1$	0.9370	$T = 1.5765$ $k_1 = 0$ $k_2 = 1$	0.9821	$T = 2.5163$ $k_1 = 6$ $k_2 = 2$	0.9981

To see More clearly the difference between the obtained results of the two fusion rules “And” and “Or”, we represent the variation of the total detection probability as function of the SNR/Chip (dB) for the distributed TM-CFAR system. The performance of the distributed TM-CFAR system, in terms of the detection probability is represented on Fig. 7, considering

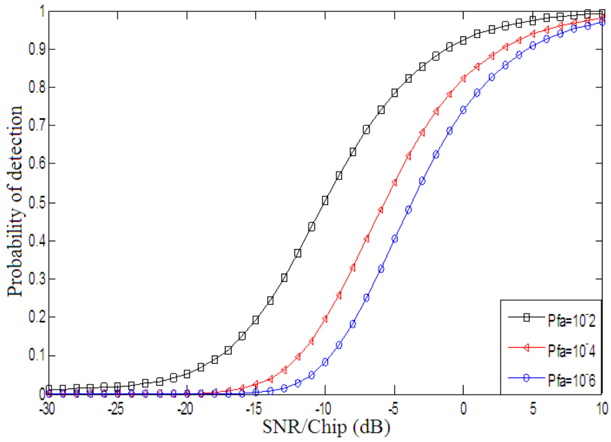

Fig. 3. Probability of detection according to the SNR/Chip(dB) for various values of P_{fa}, considering the “And” fusion rule.

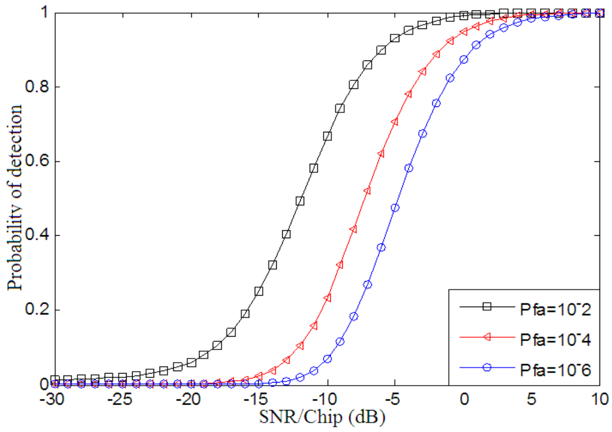

Fig. 4. Probability of detection according to the SNR/Chip(dB) for various values of P_{fa}, considering the “Or” fusion rule.

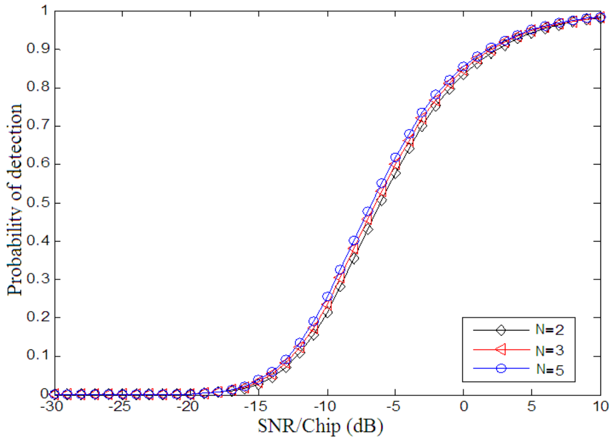

Fig. 5. Probability of detection according to the SNR/Chip(dB) for various number of local detectors *N*, considering the "And" fusion rule.

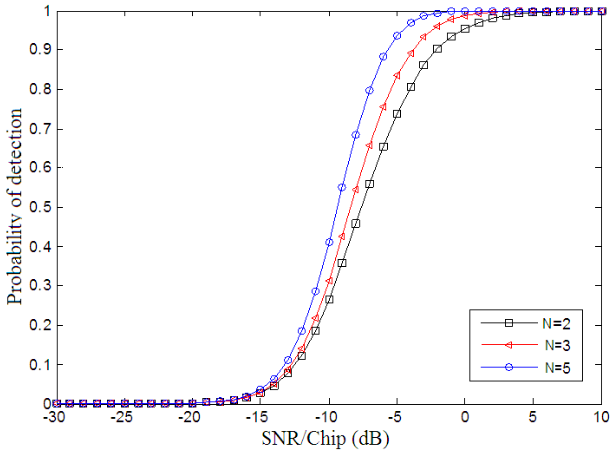

Fig. 6. Probability of detection according to the SNR/Chip(dB) for various number of local detectors *N*, considering the "Or" fusion rule.

two identical detectors (N = 2) with a value of the P_{fa} =10^{-4}, a number of reference cells M = 16 and R = 64 during 100 iterations of the algorithm PSO. Through the results of this figure, which represent the variation of the probability of detection according to the signal to noise ratio, for the "And" and "Or" fusion rules, we can observe that, the superiority of the detection probability is given by the fusion rule "Or", compared to the results of the fusion rule "And".

VI. Conclusion

In this work, an attempt to improve the effectiveness of an approach based on the swarm intelligence is presented for the optimization of the detection threshold in distributed TM-CFAR systems. In this context, an alternative of the standard algorithm PSO, which consists in applying an inertia factor to control the speed of particles, is used in order to define the distributed TM-CFAR detector parameters, and then determine the optimum detection threshold. To this end, and in order to highlight the quality of the obtained results using this technique, various simulations were carried out and the obtained performances, for the studied case, were compared and analyzed.

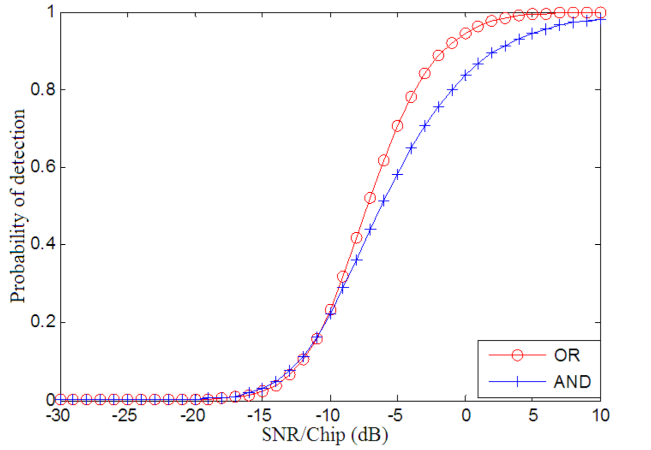

Fig. 7. Probability of detection according to the SNR/Chip(dB), consideringthe "And" and "Or" fusion rules.

An algorithm PSO adapted to the treated this problem was proposed here. So, the components of each particle of the swarm represent the parameters of the distributed TM-CFAR system, which we want to define. The criterion of Neyman-Pearson was adopted like an evaluation function and the initial parameters were selected in an empirical way. Thus, we studied the influence of a certain number of factors able to modify the system properties. Where, the effect of the number of detectors TM-CFAR, the effect of the SNR value variation and the effect of the desired P_{fa} are taken into account. The impact of the two fusion rules "And" and "Or" is also studied here. It is clear that the best performances of detection were obtained for the system which contains a high number of detectors, for the "Or" fusion rule in the majority of situations.

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