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CFAR Threshold Optimization by EMS-GA in Non Homogeneous Backgrounds

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Abstract: The problem of the optimisation in distributed systems had taken an important place for the estimation of the detection threshold. As a result, a big variety of mathematical methods are proposed in literature, in an attempt to achieve the optimum without any prior assumptions. Recently Genetic Algorithms (GAs) were proposed and processed as an optimization tool for a large variety of domains. We propose in this study, an optimization of the CFAR (OS-CFAR and CML-CFAR) threshold by an EMS-GA in non homogeneous backgrounds, for which the environment is characterized by the presence of interfering targets. The EMS-GA was applied to estimate the order statistic (K) and the multiplied factor (T) in a distributed system that contains more than one detector, then the performance of such method is analysed in different situations of multiple targets case. In spite of the efficiency and flexibility of the GA to resolve such problems the CML-CFAR system has given best results over the OS-CFAR system. In the other hand the overall probability of detection was largely influenced by the presence of interfering targets and the best results were found in the case of the OR fusion rule on a wide interval of SNR (Signal to Noise Ratio). The increase of the number of detectors in a distributed system improves its performance and the quality of the detection is affected in the sense of an increase of the detection probability in a critical situation with a presence of big number of interfering targets that saturate all the detectors.

Key words: Distributed CFAR system, non homogeneous environment, threshold optimisation, genetic algorithm, EMS scheme

INTRODUCTION

Distributed sensor systems were originally motivated by their applications in military surveillance, with respect to command, control and communication. But in recent years, they are being employed in a wide variety of applications and their utility has spurred great research interest in this topic[1]. The parallel and the serial architectures for distributed detection systems are discussed in[2].

The problem of decision in distributed sensor systems, assuming that the sensors decisions are independent from each other, was considered by Thomopoulos *et al.*[3]. This study provided a general proof that the optimal decision scheme which maximizes the probability of detection at the fusion centre, for a fixed false alarm probability, consists of a Neyman-Pearson test at the fusion centre and a likelihood-ratio tests at the local sensors.

In practical radar signal detection systems, by using a fixed threshold, a weak increase in the total noise power results in a corresponding increase of several orders of magnitude in the probability of false alarm. This undesirable increase, leads to steer for an adaptive threshold techniques in order to maintain a Constant False Alarm Rate (CFAR). A configuration of a CFAR processor is represented in Fig. 1.

In literature, the CFAR detection problem has been studied extensively for both homogenous and non homogenous backgrounds[4,5]. At the CFAR detector, the threshold is set adaptively, based on the noise power level estimated from the surrounding cells of the test cell.

Also, distributed detection systems have been largely considered because of their capability to improve reliability, speed and to handle a large area of coverage. As a matter of fact, the distributed CFAR systems with fusion centre have been receiving a lot of attention by a big number of studies. Begging with Barkat and Varshney[6], who have developed a first attempt for the theory of CA-CFAR detection using two sensors with data fusion, according to the "AND" and the "OR" fusion rules, in homogenous environment. The results have showed an improvement of the performance in distributed multiple sensor systems with data fusion, over a single sensor system. However in non homogenous environment, where noise and clutter powers at each distributed sensor are unknown and possibly varying, the CA-CFAR detection performance, degrade considerably.

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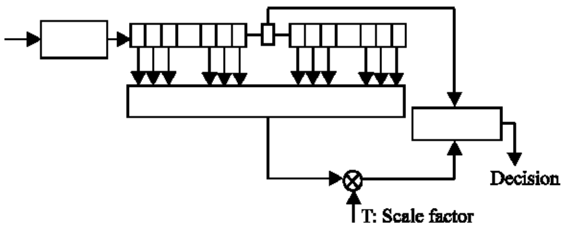

Fig. 1: CFAR detector algorithm

So it became inadequate in region of clutter edges and closely spaced multiple targets environment. Rohling proposed in[7] the Ordered Statistics (OS-CFAR) detector that takes an appropriate reference cell to estimate the background clutter power level. To estimate the performance of CFAR detection in both homogenous and non homogenous background, Üner and Varshney[4,5] developed a comparative study between the CA-CFAR and the OS-CFAR, in which they showed that in non homogenous case and for several scenarios, consisting of multiples targets and clutter-edges environments, the performance of the distributed CFAR improves dramatically if the distributed OS-CFAR system is used instead of the distributed CA-CFAR detection system. For the situation of multiple targets, the Censored Mean Level Detector (CML-CFAR) is a detector in which the largest noise samples are censored and the noise level estimation is obtained by the remaining noise samples. For a fixed number of interfering targets, the detection performance of the CML-CFAR is robust than the performance of the OS-CFAR[8].

The problem of the threshold optimization represents an important part of the global problem toward the improvement of the quality of detection and many mathematical methods were proposed in literature. Among them we can find the Newton method and the Conjugate gradient method, in which only one of the parameters to optimize is fixed and the others are varying. In such way an important disadvantage is encountered by which the solution may be far from the global optimal.

At the present time, heuristic techniques including GAs are showing their efficiency for solving optimization problems in many areas. However this efficiency is widely depending on the computational complexity of the problem, the reproduction manner (schemes of crossover) and therefore the replacement methods to run toward the best solution. In[9] Lieu and al have proposed a flexible approach employing a GA to both the CA-CFAR and the OS-CFAR detectors in homogeneous environment. This study showed that the application of GA is much more effective compared to other methods using either exhaustive search or some crude approximations. Also in[10] we have considered a solution based on three kinds of GA (BMW, AFP and EMS) for two methods of replacement, for the OS-CFAR and the CML-CFAR detectors, in a distributed system that contains 2, 3 and 5 detectors. This work had showed that the EMS-GA was more flexible to generate the best solution in a distributed system.

To our knowledge, all previous works on the application of GAs have being proposed for the homogeneous case of study. We propose in this work to analyze the efficiency of the EMS-GA to improve the performance of a distributed system for both "AND" and "OR" fusion rules in non homogenous backgrounds, by integration of interfering targets in a homogeneous environment. Assuming Rayleigh target, for a case with independent observations from sensor to sensor, an EMS-GA scheme of crossover had been applied with elitist deterministic method of replacement.

In the next study, we describe the OS-CFAR and CML-CFAR processor in non homogeneous background.

Cfar processor in nonhomogeneous backgrounds: A CFAR detector contains a number (N+1) of cells, divided into two references windows. The leading (N/2) cells and the lagging (N/2) cells containing samples that are processed to estimate the total noise power. In the middle of the detector there is a test cell whose sample allows making a decision, by a comparison with the adaptive threshold obtained by the multiplication of a scale factor (T) and the estimated total noise power. In the OS-CFAR processor, the reference window cell samples are first rank ordered according to increasing magnitudes as: $X_{(1)} \le X_{(2)} \le \cdots \le X_{(k)} \le \cdots \le X_{(N)}$, in order to select K^{th} ordered value, $X_{(k)}$ as the statistic Z that estimates the background noise. This estimate is multiplied by a constant (T) to yield the adaptive threshold against which the output of the cell under test will be compared.

We assume that the target in the test cell is slowly fluctuating Swerling type I model. So the probability density function of the out put of the square law detector is given in[4] by:

$$f(x) = (1/2\lambda)\exp(-x/2\lambda) \quad x \ge 0 \tag{1}$$

The detection may be done into two different situations either in homogenous or non homogenous background environment. In the first case, under hypothesis H_0 (absence of target in the test cell), λ is the total background clutter-plus-thermal noise, denoted by σ. Under hypothesis H_1 (presence of target in the test cell), λ is σ (1+S) where S is the SNR.

In a CFAR processor, the probability of false alarm P_f and the probability of detection P_d are given by:

$$P_f = \int_0^{\infty} \Pr(Y \succ TZ/Z, H_0) f_Z(Z) dZ \quad (2)$$

And

$$P_d = \int_0^{\infty} \Pr(Y \succ TZ/Z, H_1) f_Z(Z) dZ \quad (3)$$

Respectively, where is $\Pr(Y \succ TZ/Z, H_i)$ the conditional probability of $Y>T.Z$ given Z and H_i, i= 0, 1 and $f_z(Z)$ is the pdf of Z, the estimate of total noise power. In a non homogenous background, the reference window samples are no identically distributed and this non homogeneity is generally represented by the two different situations[11].

Clutter-edge case: Clutter edges is linked to the case where only thermal noise appears in some of the reference cells with $\lambda = \sigma = \sigma_0$ and the remaining reference cells have clutter-plus-thermal noise with $\lambda = \sigma_0(1 + C)$, where C is the clutter-to-thermal Noise Ratio (CNR). It is assumed that there is only one type of clutter in the reference window.

Two scenarios will represent the clutter-edge situation. In the first one, it is assumed that the clutter-edge is parallel to the beam direction of the Local Detector 2 (LD2), which means that the LD2 always observes a homogenous background while the LD1 observes the clutter-edge in its reference window. The second scenario represents another form of situation, in which the clutter-edge was assumed to be parallel to the straight line joining the two local detectors so that both local detectors observed the same number of clutter-plus-noise samples in their reference windows.

Multiple-target case: The multiple targets in a non homogenous environment, is a situation in which interfering targets appears in the reference window. In this case, it is assumed that the background is homogenous and it consists of either only thermal noise or clutter-plus-thermal noise. Also the amplitudes of all interfering targets fluctuate according to the Swerling type I and the parameter λ is equal to $\sigma(1+I)$ where σ is the total noise power and I is the interference-to-total Noise Ratio (INR). In the multiple targets case, the estimate of the background noise power level is higher than its actual values and which leads to an increasing of the local threshold value and then results in a decreasing of the false alarm rates. Also the global P_d and P_f decreases, resulting in the so called masking effect.

Genetic algorithms: Researchers into the application of GAs and simulated annealing have grown more numerous in the past few years. Holland[12] laid the foundation of GAs with the goal to create computer algorithms by simulating the characteristics of a natural system. It was intended that, if nature can produce from a random population, a population with individuals that are better fit to the environment it is possible to develop an algorithm to solve complex problems by utilizing the concept from nature. A GA randomly generates a set of possible solutions to the problem which is being investigated. This is termed the initial generation of solutions (chromosomes), advanced by the conventional genetic operators and each successive incremental improvement in a solution structure becomes the basis for the next generation. Standard GA consists of three main operators: Selection, crossover and mutation. The selection is used to detect which individuals, of the current population will be authorized to reproduce (the parents). In literature a variety of schemes of selection were proposed among what, the EMS-GA (Emperor Mate Selective)[9]. In this crossover scheme the best individual gets to mate with every other even sample in the population. The evaluation, that consists to calculate (or estimate) the quality of the individuals already created is based on the optimization of the fitness function. The transition from one generation to other is done throughout the replacement methods. The usual methods consist in maintaining a given percentage of the best individuals, of the current population in the following population. We mention here that the method used for the replacement is the elitist deterministic one, consisting in managing the elitism by the means of the best individuals of the current population and the best individuals of the descendant population.

SIMULATION RESULTS

We have considered in this paper two different distributed detection systems consisting of OS-CFAR and CML-CFAR local detectors, using the "AND" and the "OR" fusion rules, in non homogeneous background conditions (multiple targets situation). We have analyzed the performance of these systems in different situations, in the sense of the number of the interfering targets in each local detector. Assuming Rayleigh targets, the detectors are non identical with independent observations.

A computation of the threshold is done with an EMS-GA by using the fitness function defined as:

$$\text{Fitness}(N,k,T) = \text{abs}(1 - P_d) + \frac{1}{\alpha_0}\text{abs}(P_f - \alpha_0) \quad (4)$$

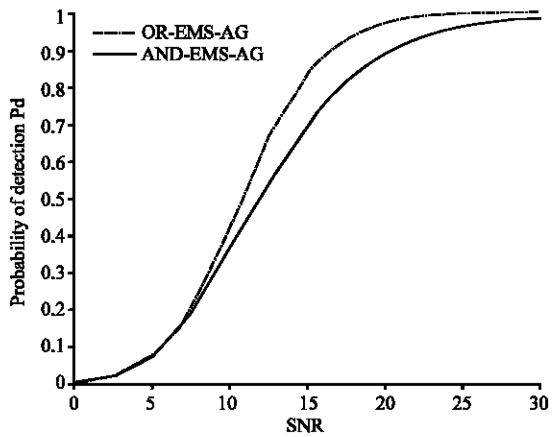

Fig. 2: Comparison between the AND and the OR fusion rules in Homogeneous case OS-CFAR system

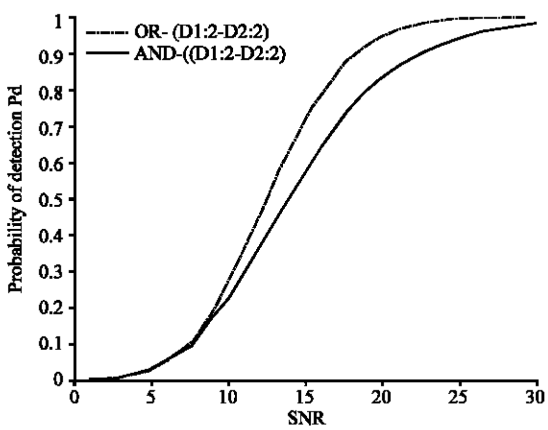

Fig. 3: P_d performance in case of interfering targets: LD1:2 and LD2:2

Where P_d and P_f are the global probabilities of detection and false alarm respectively, N is the number of estimation cells at the local detector, K is the rank order and T is the detection threshold for a fixed P_f equal to 10^{-4}. The initial population, included 100 random chromosomes is generated for N_1=12 and N_2=16 and a variation of the other parameters K and T. A linear crossover is performed for a probability P_c = 1 and a Gaussian mutation with a probability P_m = 0.1 by using a discrete crossover for K and an arithmetic one for T.

The first application represented by Fig. 2 was dedicated to a comparison between the "AND" and the "OR" fusion rules in homogeneous environment. This results showed an improvement of the performance for the "OR" fusion rule in relation to the "AND" fusion rule on almost all the interval of the variation of the SNR. Though, before SNR equal to 5_{dB} the performance is reversed with a slight difference between the two rules.

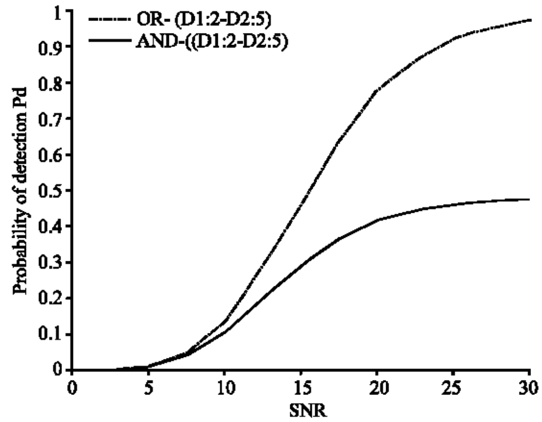

Fig. 4: P_d performance in case of interfering targets: LD1:2 and LD2:5

The next application is linked to the assumption of a non homogeneous background with the presence of interfering targets and the performance of the P_d of the system is analysed for five different situations. Here the test cell and interfering targets were assumed to have the same average power (S/I = 1).

We represent here three cases of these five tests. In Fig. 3 it was assumed that the two detectors LD1 and LD2 observed 2 interfering targets within their reference window. Always the "OR" fusion rule performs better with a slight degradation of the probability of detection which do not seem to be noticed between the two layouts.

The saturation of one detector is supposed for the second detector LD2 with the assumption of 5 interfering targets and the first detector LD1 observed 2 interfering targets as represented by the Fig. 4. The degradation is more observed than the previous study for the two fusion rules, with a conservation of the superiority of the "OR" fusion rule and also the difference between the two rules is bigger than previously.

At last, in Fig. 5, the two detectors LD1 and LD2 are saturated with observing 5 interfering targets in their reference windows. And the degradation in this situation is more considerable linked to the fact that the two local detectors are saturated and thus they are more affected by the number of interfering targets.

In order to show the influence of the number of interfering targets on the P_d performance of the distributed system, we have compared all the tested situations for each fusion rule. For the "AND" one, by increasing the number of interfering targets in the reference window the performance degrades more as represented in Fig. 6. Nevertheless, for the "OR" fusion rule the difference of the last situation and the other cases is very remarkable. Also we can notice that there is an intersection between

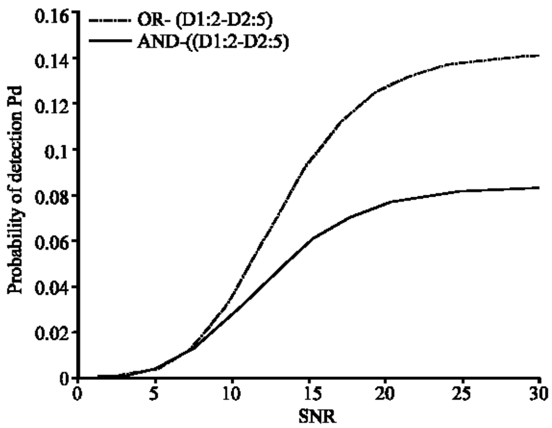

Fig. 5: P_d performance in case of interfering targets: LD1:5 and LD2:5

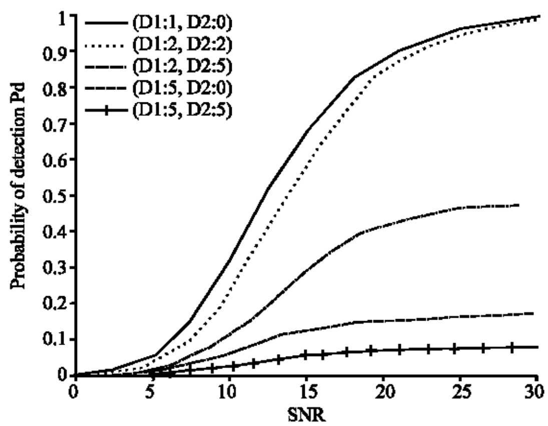

Fig. 6: Comparison between different cases of interfering targets for the AND fusion rule.

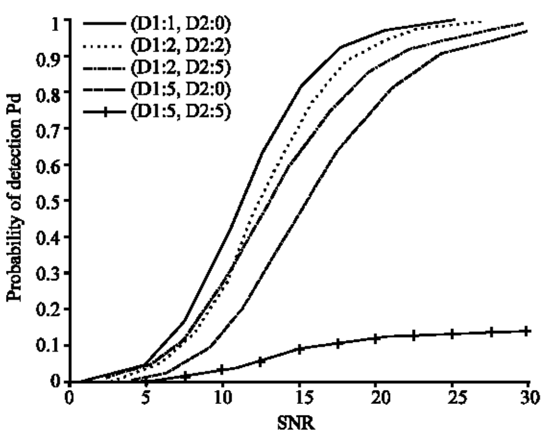

Fig. 7: Comparison between different cases of interfering targets for the OR fusion rule

the layout of the second situation (LD1:2; LD2:2) and the forth one (LD1:5; LD2:0) nearly the value SNR = 10_{dB}. So the P_d of the forth situation is better than the second

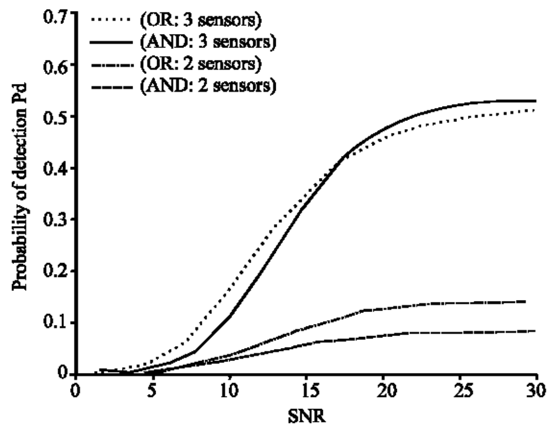

Fig. 8: Comparison between 2 sensors and 3 sensors OS-CFAR systems for case: LD1:5 and LD2:5

before this value and better than the third situation on the total interval of SNR Fig. 7.

In the previous steps, we have considered a system that contains two local detectors, so to verify the advantage of a distributed system and the influence of the number of detectors in such systems and also because the optimization here is done by genetic algorithms that resolve the problem of global optimization in systems that contains more than two detectors, we propose as a test, a graph of P_d performance for a system that contains three local OS-CFAR detectors (N_1=12; N_2=16 and N_3=14) for the last case of interfering targets, represented in Fig. 8.

This application has showed that the addition of one detector to the previous system has largely improved the quality of the detection with a remark concerning the superiority of the "OR" fusion rule toward the "AND" fusion rule which occurs after an SNR value of 10_{dB}

The second system performed in this paper contains two CML-CFAR local detectors. The same steps of work as the previous one are considered. The first remark in the case of a homogeneous environment, as represented in Fig. 9, is that the superiority of the "OR" fusion rule is conserved. We can also notice that the results in the case of the CML-CFAR are better, with better values of P_d for the same SNR, so that for 0_{dB} P_d is positive. Also there is an inversion in the layouts at the beginning of graph instead for the OS-CFAR system.

Also for different situations of interfering targets, the performance of the global probability of detection is drawing Fig. 10-12 and the degradation of P_d is less clear than in the case of the OS-CFAR system. In the last case in which the two local detectors are saturated, we can easily notice that the intersection point between the

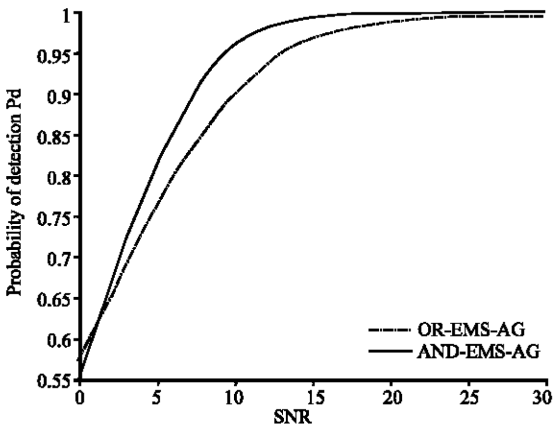

Fig. 9: Comparison between the AND and the OR fusion rules in Homogeneous case for CML-CFAR system

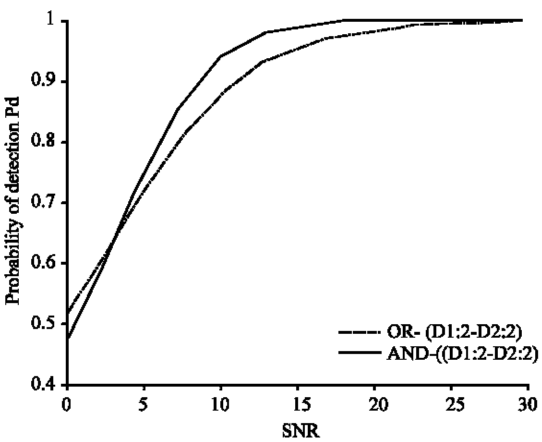

Fig. 10: P_d performance in case of interfering targets: LD1:2 and LD2:2

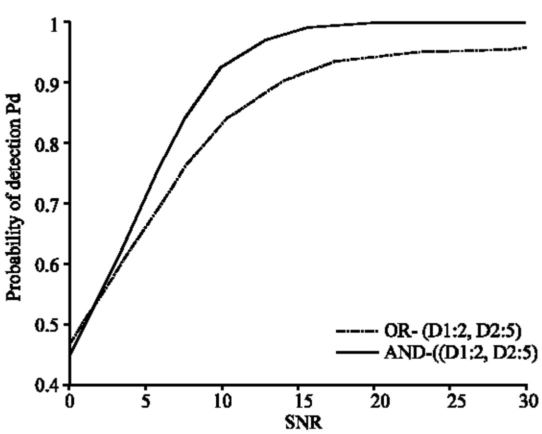

Fig. 11: P_d performance in case of interfering targets: LD1:2 and LD2:5

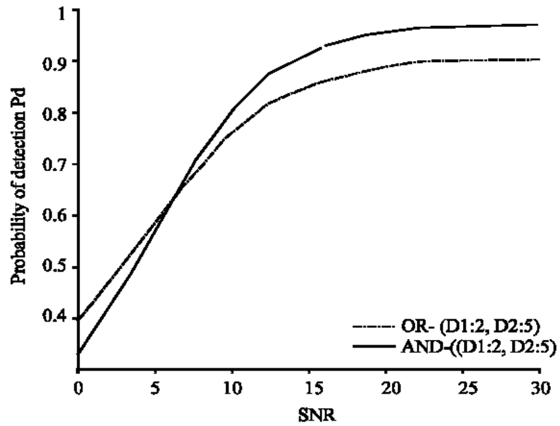

Fig. 12: P_d performance in case of interfering targets: LD1:5 and LD2:5

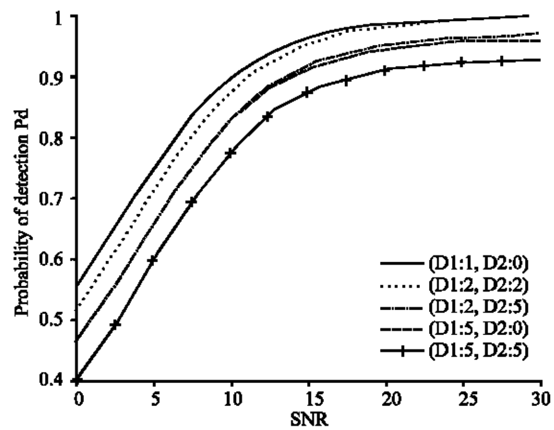

Fig. 13: Comparison between the different cases for the AND fusion rule

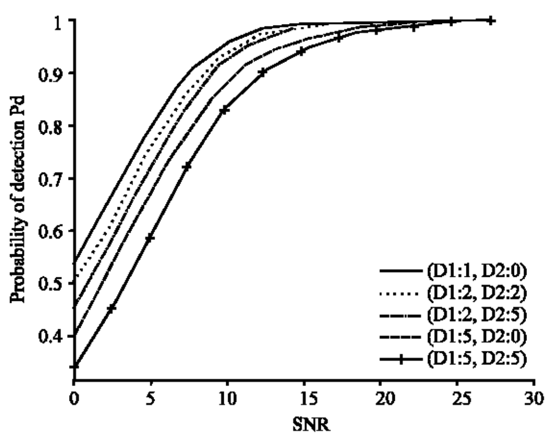

Fig. 14: Comparison between the different cases for the AND fusion rule

layouts of the "OR" and the "AND" fusion rules and by which there is an inversion of the performance, is exceeding 5_{dB}.

The comparison between the five situations tested in this study for the CML-CFAR system for each fusion rule is represented by Fig. 13 and 14. The main idea given by

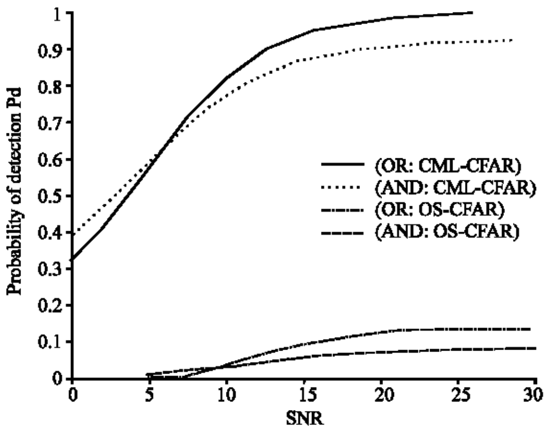

Fig. 15: Comparison between OS-CFAR and CML-CFAR systems for case: LD1:5 and LD2: 5

the last results is that the CML-CFAR system performs better than the OS-CFAR system, as represented by Fig. 15 which shows the difference between the two kinds of systems in the case of the saturation of the two local detectors.

CONCLUSION

In this analyse, we have compared the performance of two different distributed CFAR systems, composed in one case by OS-CFAR local detectors and in the other case by CML-CFAR local detectors. The fusion centre is considered for both the "AND" and the "OR" fusion rules with non identical local detectors. In non homogeneous background for which the number of cells covered by the interfering targets changed, we have proposed several situations. The optimization of the two parameters K and T is done by an EMS-GA with using a Gaussian mutation and an elitist deterministic replacement.

The results had showed that in spite of the flexibility of the GA to estimate the parameters, the situations proposed for different number of interfering targets in the reference windows influences largely the quality of the detection. Also a more considerable degradation is observed in the case of the saturation of the detectors, when the number of cells affected by interfering targets exceeds the order K.

The main conclusion showed in this paper is that the distributed system performs better when the number of detectors is increased and so in such problems it is important to have adequate optimization methods that may give a global optimization for a system that contains more than two detectors. In this way the GA have presented a big flexibility mentioned by the results of the three OS-CFAR local detectors system. In the other hand, a comparison between the OS-CFAR system and the CML-CFAR one for the critical case in which the local detectors are saturated by a number of interfering targets, has showed a remarkable improvement in the quality of the detection, by an increase of the P_d in the case of the second system over the case of the first one in a considerable SNR variation interval.

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