Progress In Electromagnetics Research C, Vol. 107, 273–286, 2021

Inhomogeneous Performance Evaluation of a New Methodology for Fluctuating Target Adaptive Detection

Mohamed B. El-Mashade*

Abstract—The ideality of operating environment of radar systems is extremely scarce while the demand for these systems is growing at a rapid pace. Technology of adaptation is therefore of primary concern in the design of their future strategies. The difficulty in finding a solution based on a single adaptive algorithm to deal with diverse noise environments has led to the development of composite adaptive procedure. Therefore, fusion of particular decisions of the single adaptive variants through appropriate rules provides a better final detection. This paper is intended to analyze the fusion strategy of cell-averaging (CA), order statistics (OS), and trimmed-mean (TM) schemes in heterogeneous environments. The tested target and the spurious ones are assumed to follow χ^2-distribution with two- and four-degrees of freedom in their fluctuations. A closed form processor performance is derived. The results show that for the heterogeneous operation, this approach is more realistic. Particularly in multi-target situations, it exhibits higher robustness than CA, OS, or TM architecture. Additionally, our results reveal that it exhibits a homogeneous performance outperforming that of the Neyman-Pearson (N-P) detector which is the yardstick in the world of adaptive detection.

1. INTRODUCTION

Radar is an electromagnetic sensor that uses radio waves to detect the presence of a target and measure its position along with other properties. The possibility of large surveillance areas as well as continuous operation, irrespective to day or night and in all weather conditions, makes this sensor play a key role in many civilian and military applications. In these situations, the mission of a radar is to detect targets of interest and to discard those that do not concern a particular application. The automation of the detection process is the cornerstone of any radar system. This automation can take different forms. A simpler variety is to set a fixed threshold for input signals, while the most complex sort is to determine an adaptive detection threshold through the measurement of the mean and variance of signals that are returned from the local environment. Irrespective of whether the operating environment is ideal or not, radar processors always seek to ensure a constant rate of false alarm (CFAR). This is the principal goal of an ideal system of automatic detection of radar targets. The benefit of this lies in establishing the signal strength, relative to the background noise, which is necessary for actual detection in the given environment. On the other hand, owing to the statistical nature of clutter, a CFAR detection device must provide a high detection threshold to hold a reasonably low false alarm rate. A rate of 10^{-6} to 10^{-8} is typically needed at the input of an automatic tracking system. However, detections of small- and medium-sized targets may fail for these levels of false alarm rate [1–5].

CFAR processors make a worthwhile contribution to the radar target detection. These algorithms have a feature that automatically adjusts their sensitivity according to variety of the interference power. In such detectors, the threshold is the product of the local background noise/clutter power and a constant scale factor based on the desired rate of false alarm. The way in which the threshold

Received 1 November 2020, Accepted 21 December 2020, Scheduled 29 December 2020
* Corresponding author: Mohamed Bakry El-Mashade (mohamed.b.elmashade@azhar.edu.eg).
The author is with the Electrical Engineering Department, Faculty of Engineering, Al Azhar University, Nasr City, Cairo, Egypt.

is estimated represents the technique that makes one CFAR scheme different from another. The cell-averaging (CA) detector is a classical procedure, in which the background level is estimated through the arithmetic averaging operation. Although it is optimum in homogeneous situation, it suffers performance degradation in heterogeneous operation. In order to enhance the CA performance under certain situations, such as multi-target and inhomogeneous clutter, many scholars have put forward various improved cell average CFAR scenarios. Order Statistics (OS) method has good detection performance in multi-target situation, but at the same time it has a certain loss in ideal operation. On this basis, the scholars put forward many new CFAR methods based on automatic censoring technique. Trimmed-mean (TM) detector is an attempt to combine the CA and OS techniques in order to benefit from averaging when the background noise is homogeneous and from ordering, when the operating environment has outlying targets along with the target of interest [6].

The hardness of an existing single CFAR algorithm to deal with diverse noise environments has led to the development of composite CFAR procedure. Distributed detection based on a number of local detectors and a fusion center exhibits several merits such as reliability, survivability, an increase in the number of targets under consideration, a smaller in communications bandwidth, and a better area of coverage. In other words, the combination of information from multiple sensors, known as data fusion, introduces redundancy, potentially increasing the confidence and robustness of the system as a whole. Thus, the fusion of particular decisions of the single CFAR detectors by appropriate fusion rules provides a better final detection [7].

This manuscript is intended with the analysis of the fusion CA-OS-TM version of automatic detection of radar targets obeying their fluctuation χ^2-distribution with two- and four-degrees of freedom when mono-pulse operation is considered. The remainder of this paper proceeds as follows. Section 2 discusses the fusion processor along with the formulation of the detection problem. The heterogeneous performance of the tested algorithm is analyzed in Section 3. Section 4 is devoted to our numerical results which depict the effects of the detector parameters on its performance in homogeneous as well as heterogeneous backgrounds. Finally, our concluded remarks are summarized in Section 5.

2. BASIC ASSUMPTIONS AND PROBLEM FORMULATION

Using an adaptive threshold with the CFAR property is unavoidable in most radar and automatic detection systems. These sliding window based techniques play an important role in handling the detection purposes. Regardless of the employed CFAR alternative, the applied sliding window mechanism is the same. The window moves throughout the coverage region and contains a group of reference cells around a central cell that is used to decide the presence of a target. The reference cells that have not yet occupied the center form the lagging window, whilst those that have been already evaluated constitute the leading window. Each radar resolution cell has a chance to occupy the central position. The noise power is estimated from the neighboring cells of that cell. Then the detection threshold is established by weighting the resulting estimation by an adjustment factor which is chosen in such a way that the requested false alarm rate is guaranteed. As a consequence of this behavior, the threshold is adapted to the received data. However, the heterogeneities of the background clutter can distort the evaluation of the estimated power from the reference cells, and this in turn deteriorates the detector's performance owing to the deviation of the operational false alarm rate from the original value upon which the design is achieved [2].

Generally, the square-law detected signal is sampled in range, and the range samples are sent serially into a shift register of length $N + 1$ as shown in Fig. 1. The leading $N/2$ samples and the lagging $N/2$ cells constitute the reference window. The data available in that window are processed to extract the estimate of the background level "Z". The detection threshold is established by scaling the statistic "Z" with a scale factor "T" which is chosen in such a way that the required rate of false alarm is realized. In other words, the "T" parameter is a function of the CFAR type, the probability of false alarm, and the error distribution of the threshold estimate [4]. The test cell "ν" from the centre tap is compared with the constituted threshold to make a decision about the presence or the absence of a target in the cell under test (CUT).

The basic parameters that characterize any radar detector are the detection "P_d" and false alarm "P_{fa}" probabilities. These probabilities are of relationship of proportionality inverse. This means that

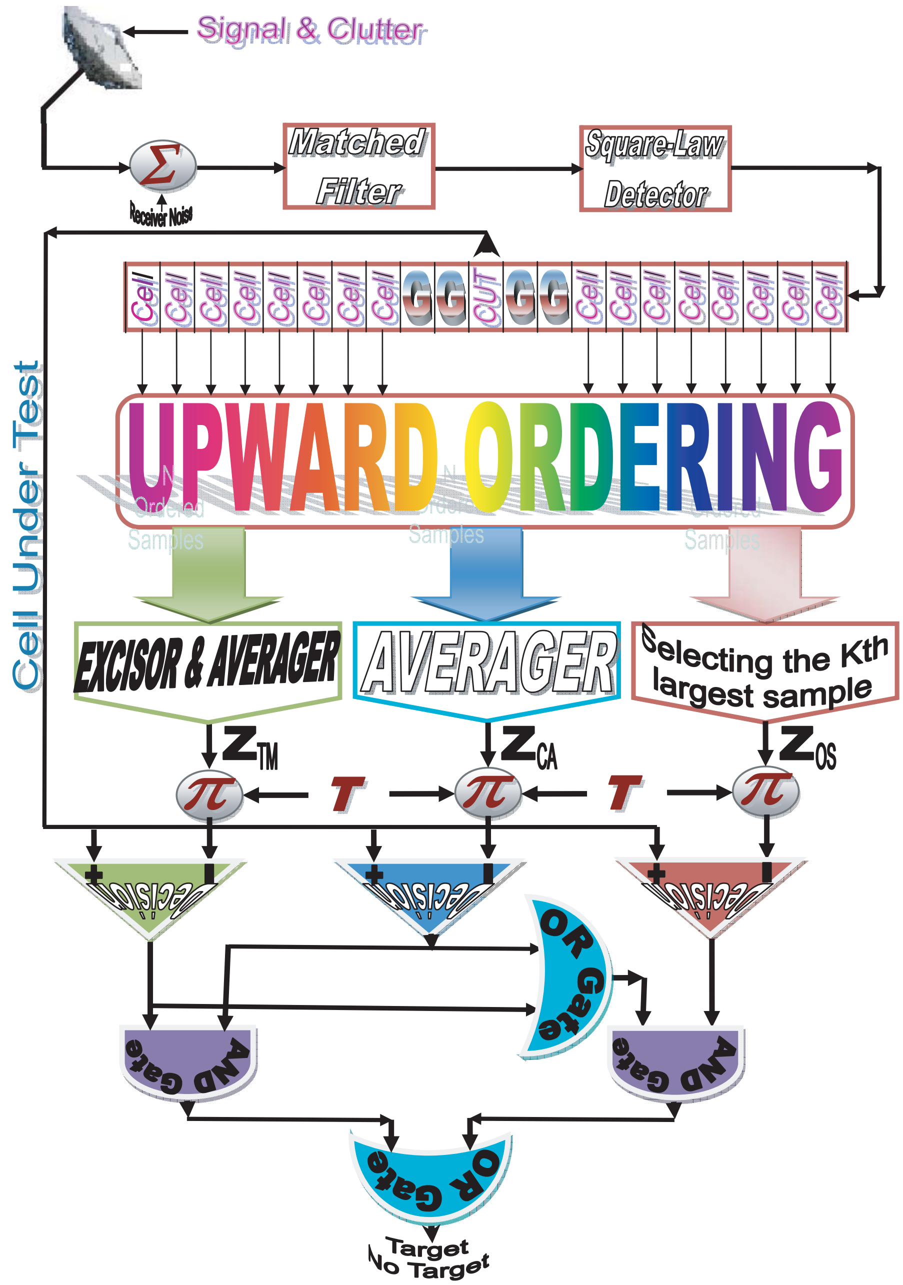

Figure 1. Architecture of the linear fusion (LF) adaptive processor.

one can be enhanced at the cost of sacrificing the other. As the N-P criterion is based on, the false alarm probability takes the precedence. In other words, ensuring a preassigned level of false alarm has the main designer's priority over searching other means to improve the level of detection [7].

Usually, the structures of the targets are complicated. These structures reflect scatterers with different radar cross sections (RCSs). Swerling [8] introduced a good estimate of target reflection models for scanning data. He suggested five different models, I-V/0, for the statistical properties of the RCS of the targets. The χ^2-distribution, with 2κ degrees of freedom, is used to characterize such models. This statistical model has the property that the distribution is more concentrated about the mean as the value of the parameter κ is increased.

In single sweep operation, $\kappa = 1$ represents SWI & SWII models, whilst $\kappa = 2$ indicates SWIII & SWIV states. For these important cases, the χ^2 distribution has a probability density function (PDF) of the form [9]:

$$p_{\nu}(x) = \begin{cases} a\exp(-ax)) & \& \quad a \triangleq \dfrac{1}{1+S} \quad for \quad \kappa = 1 \\ b^2\left[\exp(-bx) + (1-b)\,x\exp(-bx)\right] & \& \quad b \triangleq \dfrac{1}{1+S/2} \quad for \quad \kappa = 2 \end{cases} \tag{1}$$

In the above expression, "v" denotes the content of CUT, and "S" stands for the signal-to-noise ratio (SNR).

A detector's performance is measured by its ability to achieve a certain probability of detection for a given SNR and a specified rate of false alarm. For the PDF defined by Eq. (1), the probability of detection is given by [3]:

$$P_d = T\begin{cases} a\Psi_z(\omega)\Big|_{\omega=aT} & for \quad \kappa = 1 \\ b^2\left[\Psi_z(\omega) + T(1-b)\dfrac{d}{d\omega}\Psi_z(\omega)\right]\Bigg|_{\omega=bT} & for \quad \kappa = 2 \end{cases} \tag{2}$$

In the above mathematical expression, $\Psi_z(\cdot)$ denotes the Laplace transformation of the cumulative distribution function (CDF) of the statistic Z. Actually, the detection probability tends to be the false alarm probability in the absence of the tested target ($S = 0$). From Eq. (2), it is of importance to note that the Laplace transformation of the CDF of the noise power level estimate "Z" is the fundamental parameter that makes the processor performance easily evaluated, and the CFAR algorithm operates in either homogeneous or heterogeneous background environments. Therefore, our goal in the following subsections is to execute this important parameter for the examined CFAR detection schemes.

3. PROCESSOR PERFORMANCE ANALYSIS

The real work on detection is coming up with an appropriate threshold. Owing to the cost associated with a false detection, it is desirable to construct a detection threshold that both satisfies the maximization of the detection probability and keeps the false alarm rate below a preset level. On the other hand, time changes of radar as well as target background characteristics imply that a static detection threshold is not practically convenient and must be replaced by a dynamic mechanism for the false alarm rate to be maintained constant irrespective to the circumstances. Therefore, CFAR technology addresses the required issues. In this scenario of detection, the detection threshold will increase or decrease in proportion to the noise power in the training cells for the CFAR property to be controlled [3].

To simultaneously benefit the merits of the well-known CFAR detectors, a new category, which has some kind of a fusion center in its procedures, is developed. The approach of this new fusion CFAR processor is based on parallel operation of CA, OS, and TM standard techniques. For this reason, this new version is called fusion CA_OS_TM detector. A simple block diagram of the developed scheme is illustrated in Fig. 1. In this figure, there exist three branches. Each branch is associated with one of the associated detectors. Depending on the needed rate of false alarm, the clutter level along with the signal value in the CUT of each detection scheme is used to make a decision about the presence of the reflected signal from the target in the CUT. According to the appropriate fusion rules, the decisions of the three algorithms are simultaneously combined at the fusion center to employ them in achieving the final decision about the presence of the target in the CUT. In this regard, the potential outputs of fusion CA_OS_TM detector are outlined in Table 1. Since the CA procedure satisfies the highest homogeneous detection performance, it is taken as a reference for the fusion center. However, there is a false alarm possibility caused by target multiplicity or change of clutter features even though the output of CA scheme is high. To eliminate this false alarm case, an "AND" logic gate is introduced between CA output and those outputs obtained through the application of "OR" gate between OS and TM options. Because of strong clutter interference or multiple neighborhood targets, the CA output is low even though the real possibility indicates that the target is present. To overcome this situation, an "AND" gate is applied between TM and OS detectors.

Events that represent the target detection (rows 4, 6, 7, & 8) are mutually exclusive since the occurrence of one of them excludes the occurrence of the others. Taking into account that the CA, OS,

Table 1. Possible outputs of fusion CA_OS_TM processor.

CA Scheme	**OS Algorithm**	**TM Procedure**	**FUSION RULE**
Absence	*Absence*	*Absence*	*Absence*
Absence	*Absence*	***Presence***	*Absence*
Absence	***Presence***	*Absence*	*Absence*
Absence	***Presence***	***Presence***	***Presence***
Presence	*Absence*	*Absence*	*Absence*
Presence	*Absence*	***Presence***	***Presence***
Presence	***Presence***	*Absence*	***Presence***
Presence	***Presence***	***Presence***	***Presence***

and TM decisions are also independent events, the detection probability "P_{dF}" of the proposed fusion CFAR algorithm can be evaluated according to the Boolean algebra as [7]:

$$\begin{aligned} P_{d_{FUSION}} &= (1-P_{d_{CA}})\,P_{d_{OS}}P_{d_{TM}}+P_{d_{CA}}\,(1-P_{d_{OS}})\,P_{d_{TM}}+P_{d_{CA}}P_{d_{OS}}\,(1-P_{d_{TM}})+P_{d_{CA}}P_{d_{OS}}P_{d_{TM}} \\ &= P_{d_{CA}}(P_{d_{OS}}-2P_{d_{OS}}P_{d_{TM}}+P_{d_{TM}})+P_{d_{OS}}P_{d_{TM}} \end{aligned} \tag{3}$$

It is of importance to note that all the parameters of the above formula must be calculated for the detection performance of the underlined scheme to be analyzed.

In order to compute any parameter in Eq. (3), it is sufficient to determine its associated $\Psi_Z(\omega)$ as demonstrated in Eq. (2). Thus, we are going to evaluate this interesting function for CA, OS, and TM procedures.

In heterogeneous situation, it is of practical interest to concern with transitions in background power as well as the presence of multitarget in the reference set. In the first case, a single transition state, from a lower level of background power to a higher level, is considered. In this event, it is assumed that a portion "r" of the reference cells arise from a clutter background along with thermal noise so that their power level is $\psi(1+\alpha)$, with α being the clutter-to-noise ratio (CNR), whilst the remaining $(N-r)$ cells have thermal noise only with power level ψ. Under these circumstances, the total noise power is estimated as [2]:

$$Z_{CA}=\sum_{j=1}^{r}x_j+\sum_{\ell=r+1}^{N}y_\ell\triangleq X+Y \tag{4}$$

Generally, Each one of the samples x_i's and y_ℓ's has a characteristic function (CF) given by:

$$C_x(\omega)=\frac{1}{(1+\alpha)\,\omega+1}\quad \&\quad C_y(\omega)=\frac{1}{\omega+1} \tag{5}$$

The samples of each category are assumed to be independent. Since the two categories are statistically independent, this will allow us to calculate $\Psi_z(\cdot)$ of the processor CA as:

$$\Psi_{Z_{CA}}(\omega)=\frac{C_X(\omega)\,C_Y(\omega)}{\omega},\quad C_X(\omega)=[C_x(\omega)]^r\quad \& C_Y(\omega)=[C_y(\omega)]^{N-r} \tag{6}$$

In multitarget environment, on the other hand, the amplitudes of all the targets present in the reference set are assumed to be fluctuating. The common interference-to-total noise ratio (INR) of all extraneous targets is denoted by "**I**". In this situation, the interfering target return has a CF given by:

$$C_x(\omega)=\begin{cases}\dfrac{g}{\omega+g} & \&\quad g\triangleq(1+I)^{-1}\quad for\quad \kappa=1\\[2ex] h^2\dfrac{\omega+1}{(\omega+h)^2} & \&\quad h\triangleq(1+I/2)^{-1}\quad for\quad \kappa=2\end{cases} \tag{7}$$

The motivation of using OS scheme in CFAR detection is to avoid the possibility of violating the assumptions on the distribution or the homogeneity of the clutter samples which may be invalid. In this mechanism of detection, the Kth sample level is picked to represent the unknown noise power in the reference set, i.e., $Z_{OS} = x_{(K)}$. In this regard, the Kth ordered-statistics out of N samples has the Laplace transformation of the CDF of which is [9]:

$$\Psi_K^{NH}(\omega; N, r) = \begin{cases} \sum_{i=K}^{N} \sum_{j=\max(0,i-r)}^{\min(i,N-r)} \binom{N-r}{j} \binom{r}{i-j} \sum_{n=0}^{j} \sum_{m=0}^{i-j} \binom{j}{n} \binom{i-j}{m} (-1)^{i-n-m} \\ \frac{1}{\omega + N - r - n + g(r-m)} \quad for \quad \kappa = 1 \\ \sum_{i=K}^{N} \sum_{j=\max(0,i-r)}^{\min(i,N-r)} \binom{N-r}{j} (r) \sum_{n=0}^{j} \sum_{m=0}^{i-j} \binom{j}{n} \binom{i-j}{m} (-1)^{i-n-m} \sum_{\ell=0}^{r-m} \binom{r-m}{\ell} (-\varepsilon)^{\ell} \\ \frac{1}{[\omega + N - r - n + h(r-m)]^{\ell+1}}, \quad \varepsilon \triangleq h(1-h) \quad for \quad \kappa = 2 \end{cases} \tag{8}$$

The TM scheme was introduced as an attempt to combine the CA and OS schemes in order to benefit from averaging, as in the CA, when the background noise is homogeneous and in order to exploit the good behavior of OS in multitarget situation. In other words, the motivation of using TM algorithm is to combine the merits of averaging and ordering along with excising [10]. Thus, the statistic Z_{TM} is formulated by censoring N_1 lower cells and N_2 upper ones and then forming a sum of the remaining cells. Thus,

$$Z_{TM}(N_1, N_2) \triangleq \sum_{\ell=N_1+1}^{N-N_2} x_{(\ell)} \tag{9}$$

Evidently, the ordered cells $x_{(i)}$ are neither independent nor identically distributed. So, the performance evaluation becomes complicated. As a solution to this problem, $x_{(i)}$ must be transformed to other samples Q_i that satisfy the property of independent and identically distributed (IID) [1]. In terms of these new variables Q_i, Eq. (9) can be reformulated as:

$$Z_{TM}(N_1, N_2) = \sum_{j=1}^{N_T} (N_T - j + 1) Q_j \quad \& \quad N_T \triangleq N - N_1 - N_2 \tag{10}$$

As a function of the ω-domain representation of the CDF of $x_{(i)}$, the CF of the random variables Q_j takes the form [9]:

$$C_{Q_j}(\omega) = \begin{cases} \omega \Psi_{N_1+1}^{NH}(\omega; N, r) & for \quad \ell = 1 \\ \frac{\Psi_{N_1+\ell}^{NH}(\omega; N, r)}{\Psi_{N_1+\ell-1}^{NH}(\omega; N, r)} & for \quad 1 < \ell \leq N_T \end{cases} \tag{11}$$

Since Q_j are statistically independent, $\Psi_z(\cdot)$ of the processor TM becomes:

$$\Psi_{Z_{TM}}(\omega; N_1, N_2) = \frac{1}{\omega} \prod_{\ell=1}^{N_T} C_{Q_\ell}(\omega) \big|_{\omega=(N_T-\ell+1)\omega} \quad \& \quad N_T \triangleq N - N_1 - N_2 \tag{12}$$

Notwithstanding that the TM-CFAR scheme has good performance, the long processing time, which is taken in ordering the elements of the reference window, limits its practical applications. To decrease the processing time, the leading and trailing sub-windows are processed separately to estimate the noise power of each one of them, and the two noise power estimates are combined through a mathematical operator to extract the final background noise level. In this regard, suppose that the leading sub-window has r_1 cells from outlying target returns, $N/2 - r_1$ ones from thermal background. Also, L_1 and L_2 samples are trimmed from the lower and upper, respectively, ends of its ordered-statistic.

Similarly, assuming that the trailing subset has r_2 interfering cells, $N/2-r_2$ samples containing clutter, its associated ordered-statistic is excised from its ends, where the lowest T_1 ordered cells are censored, and T_2 largest ranked cells are nullified. Taking these assumptions into consideration, the CFs of their noise power level estimates, Z_1 and Z_2, have the same form as that given by Eq. (12) after replacing its common parameters with their corresponding values for the leading and trailing sub-windows. Finally, the two noise level estimates are combined through the mean-level operation to establish the final noise power estimate. Thus,

$$Z_f = Z_1 + Z_2 \tag{13}$$

Because the two noise level estimates are statistically independent, the final noise level estimate has a CF given by:

$$C_{Z_f}(\omega) = C_{Z_{TM}}(\omega; L_1, L_2)\, C_{Z_{TM}}(\omega; T_1, T_2) \tag{14}$$

where

$$C_{Z_{TM}}(\omega; M_1, M_2) = \prod_{j=1}^{M_T} C_{Q_j}(\omega)\left|_{\omega=(M_T-j+1)\omega}\right. \quad \& \quad M_T \triangleq \frac{N}{2} - M_1 - M_2 \tag{15}$$

Once the ω-domain representation of the PDF of the resultant noise level estimate is formulated, the processor false alarm and detection performances are completely evaluated, as demonstrated in Eq. (2), where

$$\Psi_{Z_f}(\omega) = \omega^{-1} C_{Z_f}(\omega) \tag{16}$$

Now, the processor performance of the fusion CA_OS_TM is completely evaluated.

4. SIMULATION RESULTS DISCUSSION

Let us simulate the derived formulas through a PC device using C++ programming language to have an idea about the new contribution of the novel strategy of adaptive schemes. In all our presented results, the size of the reference set "N" is taken as 24 samples, and the underlined processors are designed to have a rate of false alarm of 10^{-6}. In our presentation, each scenario will be denominated by the rule based on which its noise level is estimated from each subset since the final background power is obtained through the mean-level "ML" operation, and this is common for all the processors under examination. For simplicity, the symbol that refers to ML is ignored from the indication of the tested procedure. In this regard, an indication TM (N_1, N_2) on a specified curve signifies that it is associated with a CFAR algorithm, whose threshold is constructed by weighting the ML of symmetrically adding the ordered cells between N_1 and $N/2-N_2$ from each reference subset. Taking these assumptions in mind, let us go to discuss the behavior of the constituents of each scene of the displayed categories.

The diagnostic performance of a detector or its accuracy to discriminate diseased cases from normal situations is effectively evaluated through receiver operating characteristics (ROCs). In other words, the ROC curve, in which the detection probability is plotted as a function of the false alarm probability for different cut-off points of the SNR, is a fundamental tool for diagnostic performance evaluation. This category of figures includes Figs. 2 and 3. The former of these plots is associated with the graphical tracing of ROC for the tested schemes in homogeneous situation when the primary target fluctuates obeying χ^2-distribution with two degrees of freedom, whilst the second scene shows the same characteristics for the same processors in the case where the target follows χ^2-distribution with four degrees of freedom in its fluctuation. In both cases, the primary signal strength is taken as 10 dB. For the purpose of comparison, the ROC curve of Neyman-Pearson (N-P) detector is included amongst the candidates of these figures under the same conditions of operation. The displayed results of these two scenes indicate that the N-P has the top ROC behavior for lower values of false alarm rate. As the rate of false alarm increases, the processor CA_OS(10)_TM(2, 2) surpasses the N-P processor in its detection processing. This behavior is common either the target under research obeys two or four degrees of freedom for its χ^2 fluctuation model with more superiority in fourth degree of freedom. Additionally, the novel version CA_TM(2, 2) surpasses the N-P detector in its ROC for false alarm rate greater than 10^{-6} given that the primary target follows χ^2-distribution with 4-degrees of freedom. Moreover, the normal OS(10) scheme presents the worst ROC curve in the two situations of target fluctuation.

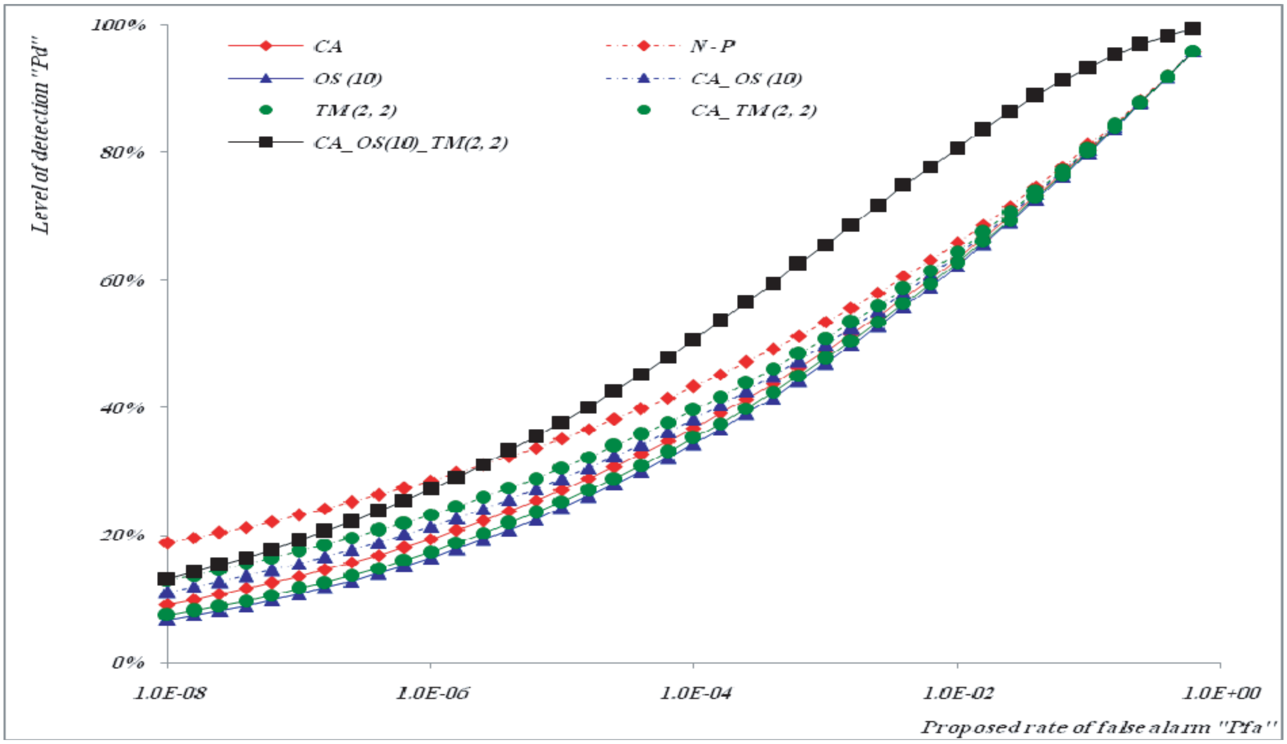

Figure 2. Single pulse ROC's of the conventional as well as developed versions of adaptive schemes for χ^2 fluctuating targets with two degrees of freedom when $N = 24$ and $SNR = 10\,\text{dB}$.

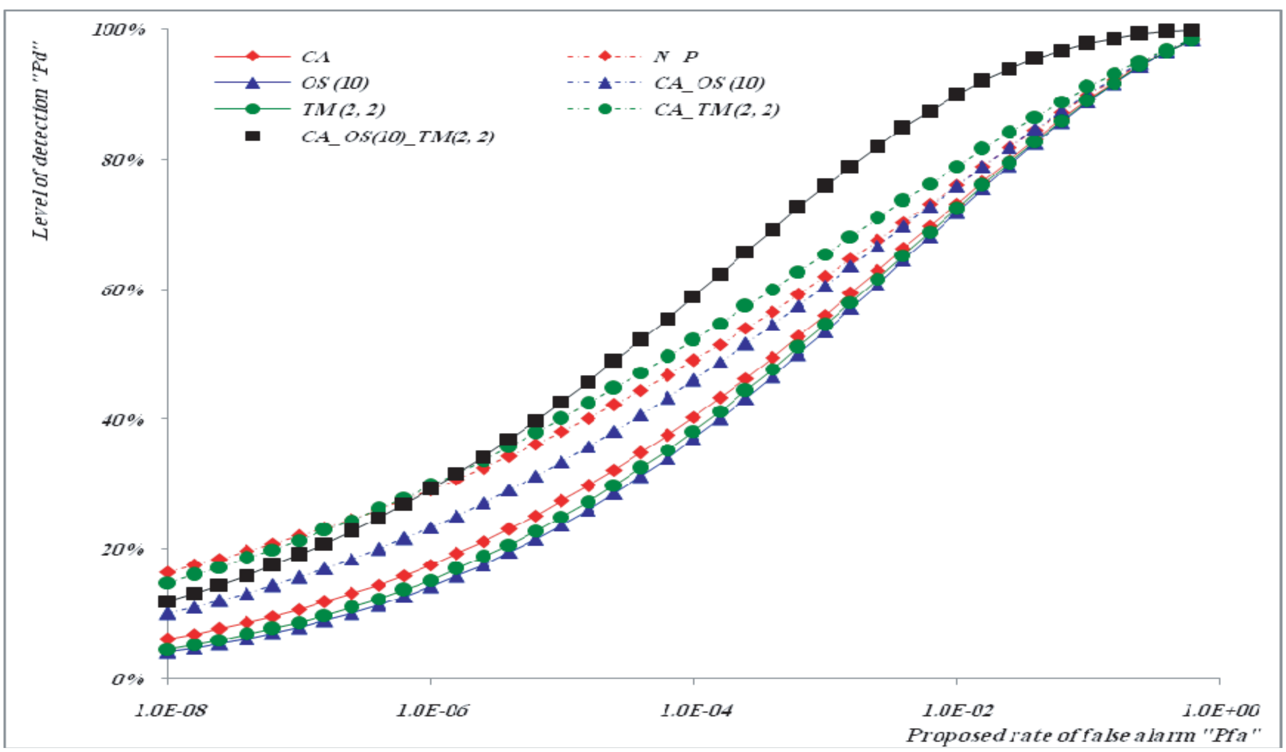

Figure 3. Single pulse ROC's of the conventional as well as developed versions of adaptive schemes for χ^2 fluctuating targets with four degrees of freedom when $N = 24$ and $SNR = 10\,\text{dB}$.

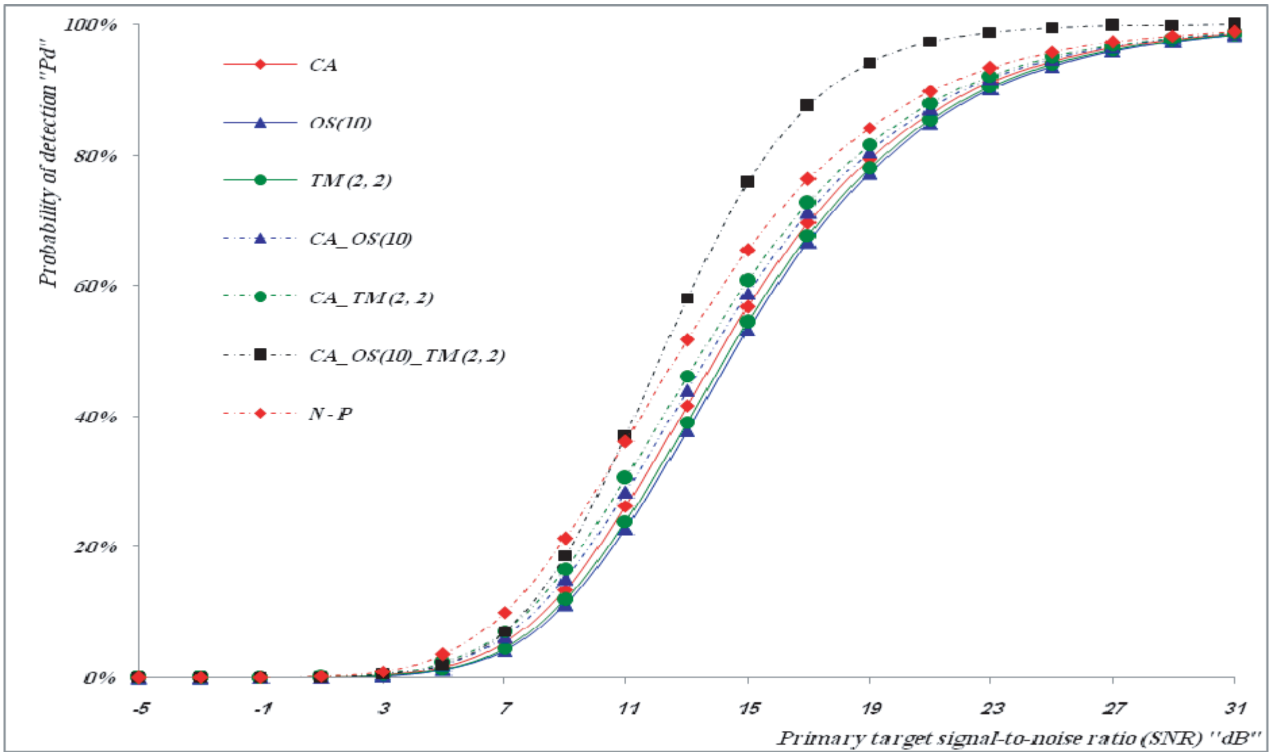

Figure 4. Single sweep ideal performance of the conventional as well as developed versions of adaptive schemes for χ^2 fluctuating targets with two degrees of freedom when $N = 24$ and $P_{fa} = 10^{-6}$.

The next category of curves is concerned with plotting the most important characteristics that measure the capability of the processor in detecting targets when the background reference channels are ideal. In the radar terminology, this characteristic is known as detection performance. We have depicted this relationship by graphing the level of detection (P_d) against the strength of the target return (SNR) as shown in Figs. 4 and 5. Fig. 4 is devoted to the performance of the examined CFAR schemes for 2 degrees of freedom fluctuation model, whilst the other fluctuation case is depicted in Fig. 5, given that the operating circumstances are held unchanged. To see which processor gives the highest performance, the N-P algorithm is added to the curves of these two plots. A big insight into the variation of the elements of these figures illustrates that the N-P has the top performance for low SNR till 11 dB after which the fusion CA_OS(10)_TM(2, 2) model exceeds the N-P in its level of detection. This behavior is common either the target fluctuates with 2 or 4 degrees of freedom for its χ^2-model. Additionally, Fig. 5 also shows the superiority of the novel version CA_TM(2, 2) to the optimum processor for signal strengths greater than 11 dB which verify the preceding results presented in Fig. 3. Furthermore, the standard OS(10) architecture has the worst detection performance for the two cases of target fluctuations, as we have previously demonstrated in Figs. 2 and 3.

Let us now turn our attention to another type of characteristics which is involved with the capability of the CFAR processor to detect targets in the presence of spurious ones. The present category contains Figs. 6–7. In multiple target situation, it is assumed that there is one sample amongst the elements of each reference subset ($r_1 = r_2 = 1$) that is corrupted by interfering target return of the same strength as that returned from the primary target (INR=SNR). Fig. 6 depicts the detection performance of the underlined processors, along with the N-P algorithm, when the primary as well as the outlying targets fluctuate in accordance with χ^2-distribution with two degrees of freedom. From visualized results, it is apparent that the fusion CA_OS(10)_TM(2,2) model has the highest performance after the optimum detector whilst the ordinary CA scheme presents the worst. Additionally, the fusion model exceeds the normal TM(2, 2) processor in detecting fluctuating targets in the presence of interferers. Fig. 7 exhibits

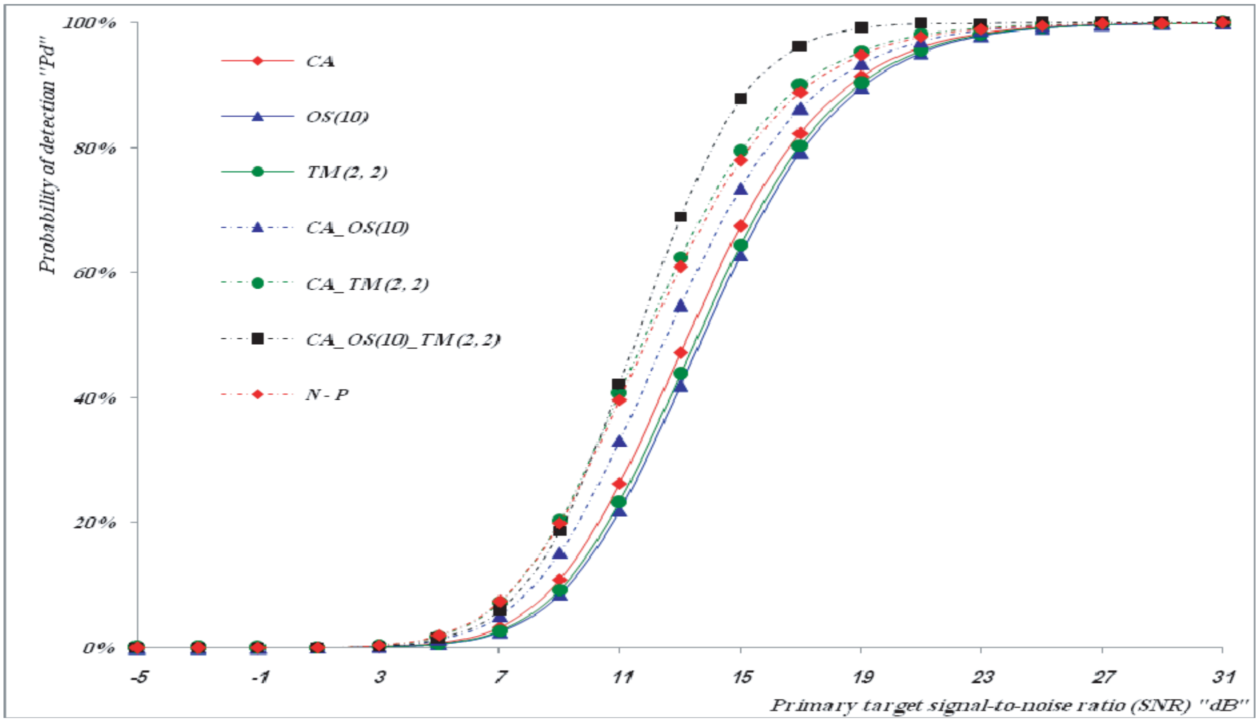

Figure 5. Single sweep ideal performance of the conventional as well as developed versions of adaptive schemes for χ^2 fluctuating targets with four degrees of freedom when $N = 24$ and $P_{fa} = 10^{-6}$.

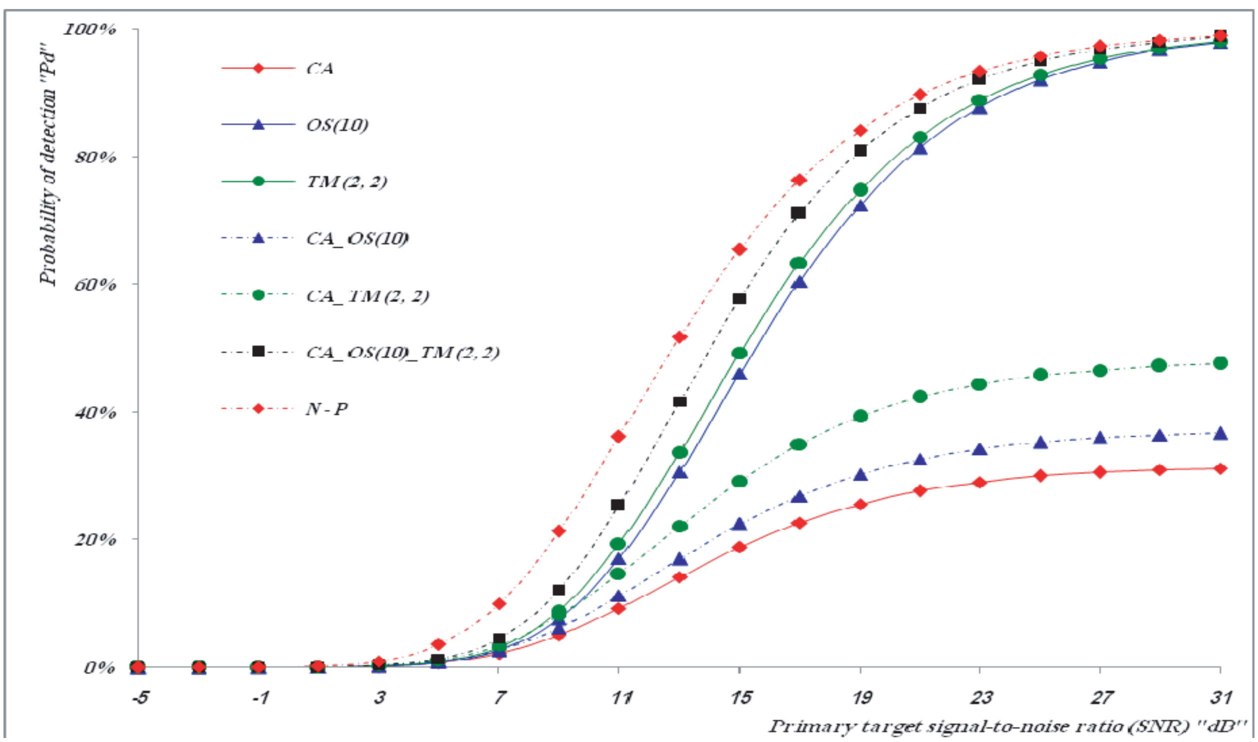

Figure 6. Single sweep multitarget performance of the conventional as well as developed versions of adaptive schemes for χ^2 fluctuating targets with two degrees of freedom when $N = 24$, $r_1 = r_2 = 1$, and $P_{fa} = 10^{-6}$.

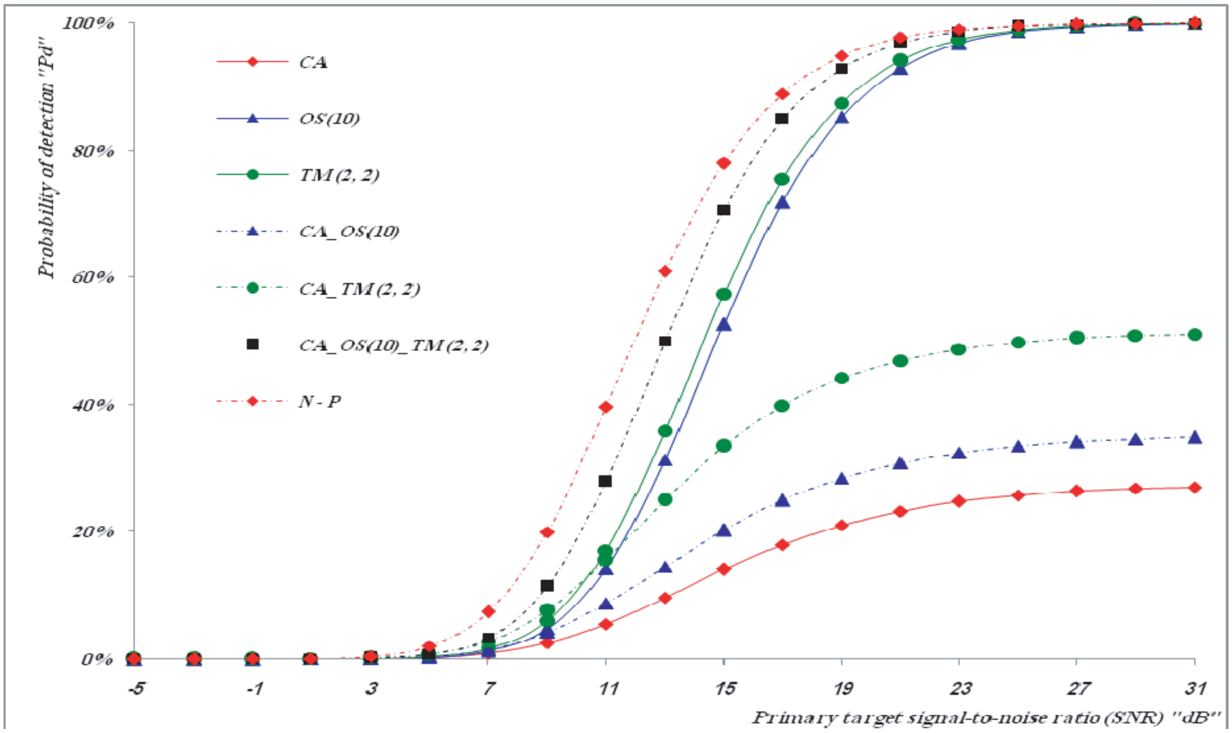

Figure 7. Single sweep multitarget performance of the conventional as well as developed versions of adaptive schemes for χ^2 fluctuating targets with four degrees of freedom when $N = 24$, $r_1 = r_2 = 1$, and $P_{fa} = 10^{-6}$.

the same characteristics as Fig. 6 with the exception that the considered targets obey χ^2-distribution with four degrees of freedom in their fluctuation. The curves of this figure behave like the corresponding ones in the preceding plot with some enhancements.

The scope of the next characteristic of the CFAR processors is the variation of the false alarm rate when the contents of the reference samples are assumed to be nonhomogeneous. In radar terminology, this situation of operation is known as clutter edge. This edge is characterized by a single transition from a lower total noise background power level to a higher level. To simulate this situation, a special case, where the lagging sub-window is assumed to have thermal noise only with background power "ψ", and the leading sub-window arises from a clutter background combined with thermal noise so that its power level is $\psi(1 + \alpha)$, is considered. Fig. 8 illustrates the false alarm rate performance in a region of clutter power transition of $CNR = 5$ dB as a function of the number of clutter cells present in the window. As the reference window sweeps over the clutter edge, the CUT is from the clutter background for $r \geq N/2$. The false alarm rate exhibits a sharp discontinuity at $r = N/2$ as expected. A big insight into the behavior of the curves of this figure demonstrates that the false alarm rate of the OS(10) processor is the nearest one to the designed value, and the modified version CA_TM(2, 2) has the worst false alarm rate performance, whilst the fusion CA-OS(10)-TM(2, 2) model gives an intermediate performance for this type of CFAR characteristics.

The upcoming category has two plots, Figs. 9 and 10, which are corresponding to the two situations of primary target fluctuation. Fig. 9 plots the required signal strength to reply a preassigned level of detection for the conventional as well as their derived versions of CFAR detectors given that the primary target fluctuation obeys two-degrees of freedom χ^2 model. Each one of the curves of this figure is linearly increased with variable slope according to the given level of detection. The operating range of detection can be classified in three distinct zones. The first zone is characterized by weak level of detection, $P_d < 20\%$, and the second zone extends from 20% to 80% ($0.20 \leq P_d < 0.80$), whilst the third zone is specified by strong detection levels, $P_d \geq 80\%$. In the first zone, the rate of increase of the signal

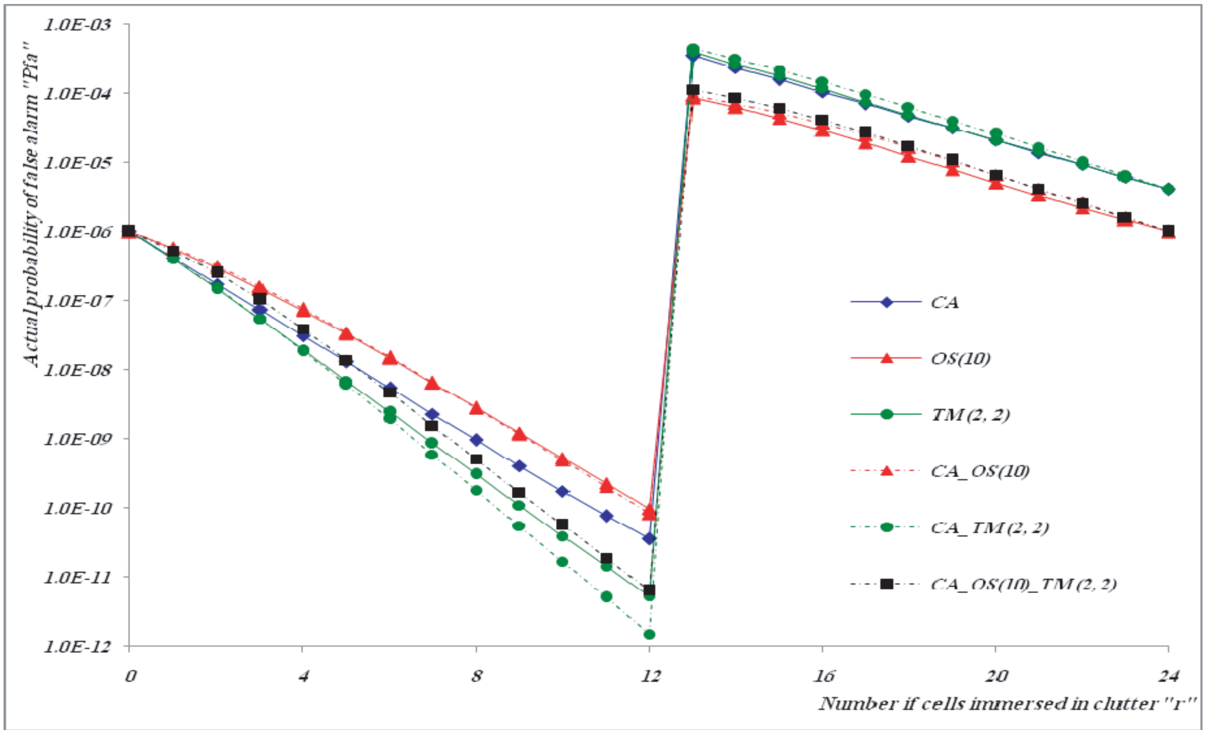

Figure 8. Single pulse false alarm performance of the conventional as well as developed versions of adaptive schemes at clutter edge of strength 5 dB when $N = 24$ and design false alarm probability of 10^{-6}.

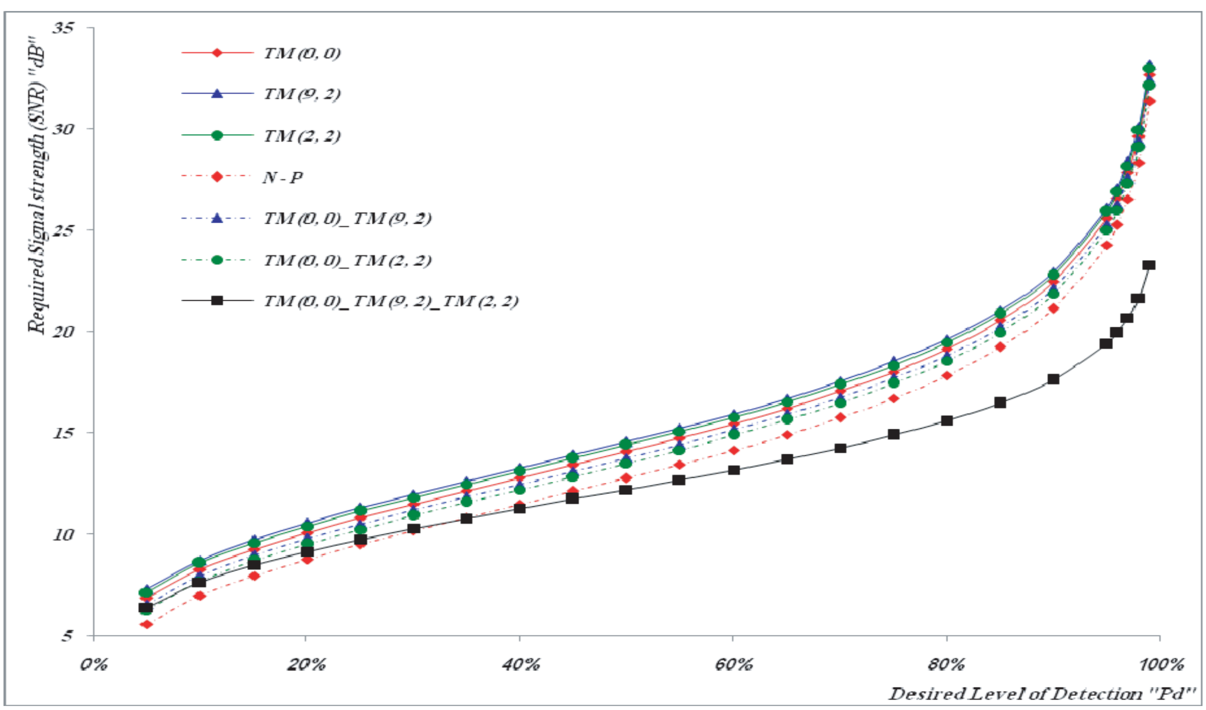

Figure 9. Single pulse request signal strength to reply a required detection level of the conventional along with modified versions of CFAR schemes for two degrees of freedom χ^2 fluctuating targets when $N = 24$ and $P_{fa} = 10^{-6}$.

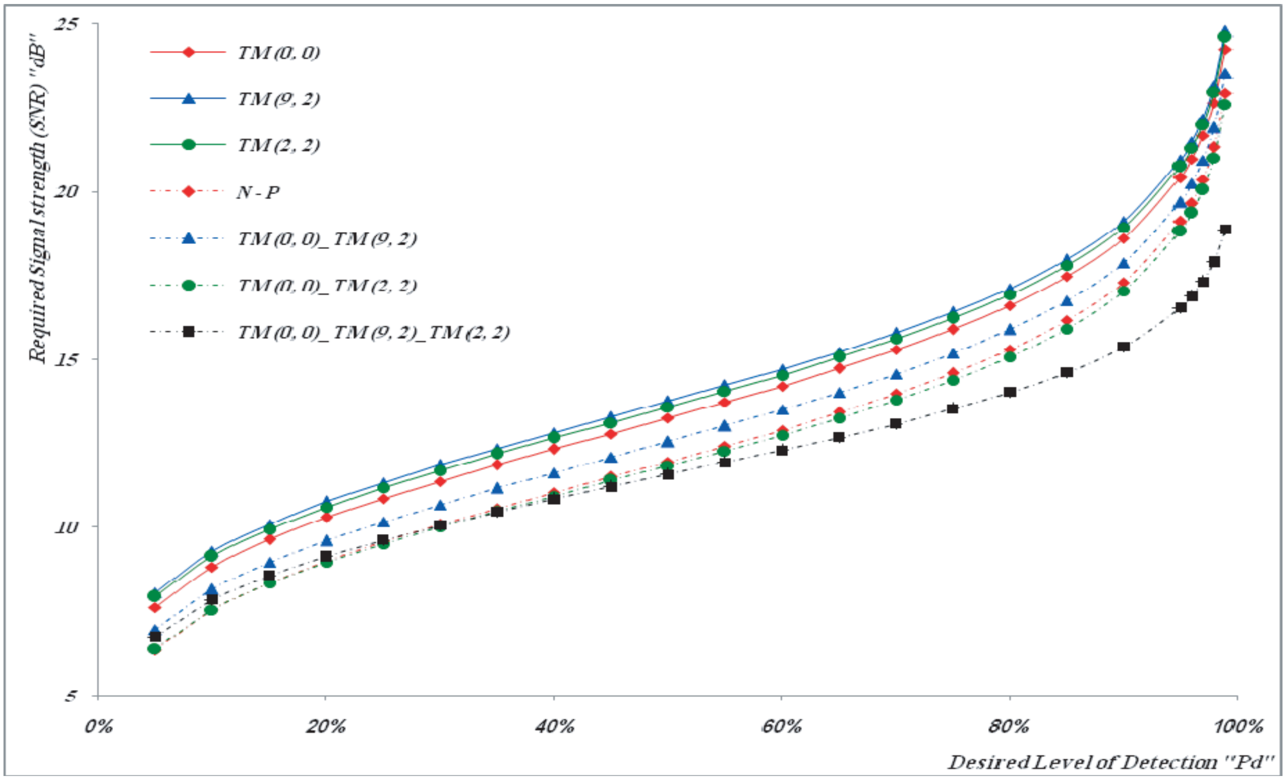

Figure 10. Monopulse request signal strength to reply a required detection level of the standard along with modified versions of CFAR schemes for four degrees of freedom χ^2 fluctuating targets when $N = 24$ and $P_{fa} = 10^{-6}$.

strength is higher than that of the second zone, in which the change of the needed SNR to verify a specified level of detection is modest, whilst the third zone is characterized by the highest increasing rate. It is evident that the N-P scheme needs the minimum signal power, to satisfy the preassigned detection level, till $P_d = 35\%$ beyond which the fusion CA_OS(10)_TM(2, 2) model requires less signal strength than that attained by the N-P algorithm to reply the same level of detection. In addition, the traditional OS(10) processor requests the highest signal strength to accomplish the given probability of detection. On the other hand, Fig. 10 displays the same results as that presented in Fig. 9 except that the tested target following χ^2-distribution with four degrees of freedom in its fluctuation. It is of importance to note that the same concluded remarks, extracted from the behavior of the curves of Figs. 4 and 5, can be demonstrated from the variation of the candidates of this figure.

5. CONCLUSIONS

In this paper, a detailed analysis of the detection performance of the new developed version of CFAR processors in the absence, as well as in the presence of extraneous targets, is given taking into account that the primary and secondary interfering targets fluctuate in accordance with χ^2-distribution of two and four degrees of freedom model. Closed form expression is derived for its detection performance in heterogeneous situation. The simulation results indicate that the fusion model enjoys the same property of CA procedure in giving top homogeneous performance. Additionally, it provides good multitarget performance as the TM technique whatever the number of spurious targets does not exceed the number of excising cells from the top end. Moreover, the fusion CA_OS_TM mode surpasses, in its homogeneous detection performance, the N-P detector which is taken as a reference for any new processor in the CFAR world. Furthermore, the fusion model has the ability of keeping the false alarm rate constant in face of interferer returns of strengthened signal.

REFERENCES

1. El Mashade, M. B., "Monopulse detection analysis of the trimmed mean CFAR processor in nonhomogeneous situations," *IEE Proc. Radar, Sonar Navig.*, Vol. 143, No. 2, 87–94, April 1996.
2. Wang, W. Q., *Radar Systems: Technology, Principals and Applications*, Nova Science Publishers, Inc, 2013.
3. Gerlach, K. and K. Gerlach, "Adaptive detection of range distributed targets," *IEEE Transactions on Signal Processing*, Vol. 47, No. 7, July 1999.
4. El Mashade, M. B., "Performance analysis of OS structure of CFAR detectors in fluctuating target environments," *Progress In Electromagnetics Research C*, Vol. 2, 127–158, 2008.
5. Machado-Fernández, J. R. and N. Mojena-Hernández, "Evaluation of CFAR detectors performance," *ITECKNE*, Vol. 14, No. 2, 170–178, December 2017.
6. Islam, Md. M. and M. Hossam-E-Haider, "Detection capability and CFAR loss under fluctuating targets of different swerling model for various gamma parameters in radar," *International Journal of Advanced Computer Science and Applications (IJACSA)*, Vol. 9, No. 2, 90–93, 2018.
7. D. Ivković, B. Zrnić, and M. Andrić, "Fusion CFAR detector in receiver of the software defined radar," *Frequenz*, Vol. 68, Nos. 3–4, 125–136, 2014.
8. Swerling, P., "Radar probability of detection for some additional fluctuating target cases," *IEEE Transactions Aerospace and Electronic Systems*, Vol. AES-33, No. 2, 698–709, April 1997. This reference is included in chapter 2 of [2].
9. El Mashade, M. B., "Performance superiority of CA_TM model over N-P algorithm in detecting χ^2 fluctuating targets with four-degrees of freedom," *Int. J. Systems, Control and Communications*, Vol. 11, No. 1, 92–118, 2020.
10. El Mashade, M. B., "Heterogeneous performance analysis of the new model of CFAR detectors for partially-correlated χ2-targets," *Journal of Systems Engineering and Electronics*, Vol. 29, No. 1, 1–17, February 2018.