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Inhomogeneous Assessment of New Mechanism of Adaptive Detection of Partially-correlated χ^2-Targets

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Abstract: Owing to its merits in fluctuating radar targets detection, the scenario of fusion structure has rapidly become a methodology of choice. The base goal of this paper is to analyze the linear type of this methodology, which is termed as linear fusion (LF). The target of interest along with fallacious ones is assumed to be fluctuating obeying χ^2-model of two-degrees of freedom in their fluctuation, with particular attention on partially-correlated target returns. Closed-form expression is derived for the detection performance of the proposed processor. The analytical results are validated with computer simulation. Our simulation results demonstrate that the LF model yields impressive detection performance in terms of detection performance and CFAR loss, in comparison with the conventional schemes in the case where the operating environment is free of or contaminated with interferers. Additionally, the LF homogeneous performance outweighs that of Neyman-Pearson (N-P) detector, which is the yardstick of the CFAR world. Moreover, the LF structure has the capability of holding the rate of false alarm fixed against the presence of interferers. The ability to obtain improved performance compared to existing models is the major contribution of this research.

Index Terms: Adaptive detection, post-detection integration, χ^2-distribution of 2-degrees of freedom, fluctuating targets, Swerling models, partially-correlated χ^2-targets, target multiplicity environments.

1. Introduction

Radar is a remote sensing technique. It acts as a powerful eye, where it is capable of gathering information about objects located at remote distances from the sensing device. It is a useful device for detecting and ranging, tracking and searching. It is beneficial for remote sensing, weather forecasting, speed trapping, fire control and astronomical abbreviations. It operates by transmitting a particular type of waveform and detecting the nature of the signals reflected back from objects. A portion of the transmitted signal is intercepted by a reflecting object (target) and is reradiated in all directions. The antenna collects the returned energy in the backscatter direction and delivers it to the receiver [1-5].

From this briefly scientific overview about radar system, it is seen that it is a crucial device. Therefore, it is recommended to maximize its detection probability simultaneously with guaranteeing a constant false alarm rate. Therefore, the trials to achieve such emergency have unabated continued till now. In this regard, the use of CFAR variants in parallel allows detecting targets in different clutter types through the fusion of the results into a single decision. It is well-known that fusion of particular decisions of the single CFAR detectors by appropriate fusion rules provides a better detection performance. Recently, a new model of the linear fusion (LF) is introduced as a CFAR detector [6-10]. The new approach is based on parallel operation of cell-averaging (CA), order-statistics (OS), and trimmed-mean (TM) schemes.

In aerospace detection, on the other hand, the targets have complicated structures. They reflect scatterers with different radar cross section (RCS). Peter Swerling described the statistical properties of the RCS of the targets by five different models [11-15]. Here, we are concerned with two (SWI & SWII) of them. Since the probability of detection is sensitive to the degree of correlation among the target echoes, partially-correlated target returns are of primary concern. This paper is devoted to the analysis of LF-CFAR strategy in the case where the radar receiver uses post-detection integration of M pulses to carry out its decision with special emphasis on partially-correlated target returns. The primary as well as outlying target obeys χ^2-statistic of two-degrees of freedom (SWI & SWII models) in its fluctuation. Closed-form performance expressions, of the new structure as well as its individual variants in the absence as well as in the presence of outliers, are derived. A comparison of these schemes along with Neyman-Pearson (N-P) processor is also portrayed under similar conditions. The paper proceeds as follows. Section 2 discusses the literature review associated with our problem of research. The methodology of resolving is outlined in section 3. Section 4 is devoted to formulate the problem of detection as well as the basic assumptions. The detection performance of the tested processor along with its fundamental variants is analyzed in section 5. Our numerical simulations are portrayed in section 6 to evaluate the accuracy of the theoretical derivation and substantiate the effectiveness of the proposed schemes. Finally, our useful conclusions are drawn in section 7.

2. Literature Review

In radar and sonar systems, it is desirable to maximize their detection performance. To fulfill this principal goal, lots of CFAR algorithms have been proposed. The mean-level (ML) operation represents the simplest way that uses arithmetic averaging to extract the unknown noise power [11]. The most well-known ML algorithm is the CA which averages all the reference cells. This feature of CA donates the optimal performance given that the operating environment is homogeneous. However, it doesn't operate well in heterogeneous cases which are frequently created by clutter edges and the appearance of spurious targets. To reduce the negative effects of these problems, many modifications of the conventional CA scheme have been suggested to cope with such diverse inhomogeneous environments. Generally, these modifications can be classified into numerous categories. The first one consists of those algorithms that employ the averaging scenario [12]. The second category is associated with those techniques that use order-statistics (OS) mechanism [13]. Although these modifications have an enhanced detection performance, they don't still succeed in robustly combating the environment changes. Because of the diversity of the radar search environment (multiple target, abrupt changes in clutter, etc.), there exists no universal CFAR scheme. The development of composite CFAR algorithms represents awesome solution. Therefore, the third group is concerned with some strategies which are combination of the above mentioned procedures with the aim of reducing the effects of the underlined problems [8-9, 14]. This category is interested in developing models that have some kind of fusion centers in their processing. The And- and Or-CFAR processors use AND & OR binary gates to achieve data fusion from CA and OS scenarios which operate in parallel [15]. Also, a procedure of parallel operation of CA, GO and SO variants with one fusion center based on neural network gives a superior detection performance than the single operation of each one of them [11]. In addition, the CA_TM version is a combination of CA and TM schemes [16]. This modified model has very simple fusion center and provides better results in its detection performance [17-18]. It is realized by parallel operation of CA and TM scenarios. Recently, a new model of the linear fusion (LF) has been introduced as a CFAR scheme. The new approach is based on parallel operation of CA, OS, and TM processors. Each processor carries out a decision about the presence of the reflected signal from the target in the tested cell. The three decisions are simultaneously transmitted to the fusion center, where a final decision about the presence/absence of the target in the cell under test (CUT) is achieved. This type of CFAR processors gives satisfied results in the detection of closely spaced targets [19]. M-sweeps performance of LF-CFAR strategy is analyzed in [20] when the target of interest as well as interferers fluctuates following SWI or SWII model and the numerical results demonstrate that it possesses excellent results in both homogeneous and heterogeneous events.

3. Methodology

Since multistatic radar systems offer some merits in comparison with the more classical concentrated systems, the most recent robust surveillance systems are composed of several spatially distributed sensors and a data fusion center; that combines and controls the information supplied by each sensor. The merits of such systems include greater volume of coverage, increase in system reliability and robustness to target fading, as well as system reconfiguration which results in greater flexibility. Therefore, the proposed approach is based on simultaneous operation of the well-known CFAR processors and a fusion center with fusion rule. Simple block diagram of the linear fusion (LF) detector is depicted in Fig. 1. In this figure, it can be seen three branches. In each one of these branches, there is one type of the celebrated CFAR procedures (CA, TM or OS) that are running in parallel. Each one of these algorithms is combined with a clutter model adapting threshold, for the purpose of achieving minimum probability of false alarm and maximum probability of detection.

The radar returns are sampled and simultaneously processed by the selected CFAR schemes. Depending on the required probability of false alarm, the power of the clutter and signal value in the CUT, each processor makes a decision about the presence of the reflected signal from the target in the tested cell. The three decisions are simultaneously arrived at the fusion center, where a final decision about the presence of the target in the CUT is achieved. The new style takes the final decision by the appropriate fusion rules.

The output of the CA detector is taken as reference for the fusion center because it assures high probability of detection. However, sometimes when CA output is "1", there is a possibility for a false alarm caused by multiple targets or change of clutter features. To eliminate such case of false alarm, an "AND" logic gate is implemented between CA output and the output obtained by applying an "OR" logic gate between TM and SO outputs. On the other hand, there is a real possibility that target is present but CA output is "0" because strong clutter interference or multiple neighborhood targets. To avoid such occurrence, an "AND" logic gate is applied between TM and OS outputs for the target lost to be eliminated.

According to Swerling's models, if only one pulse per scan hits a target, SWI cannot be distinguished from SWII. However, if multiple pulses are transmitted per antenna scan, the problem of detecting slow fluctuating targets (SWI) and fast fluctuating targets (SWII) can be easily overcome. Nevertheless, it is of importance to take into account the partial correlation of the target returns; otherwise the processor fails to predict the actual system performance.

The performance evaluation of the underlined scheme is based on the calculation of the moment generating function of its noise level estimate. Therefore, our objective in this research is focused on evaluating this important parameter for the conventional (CA, OS, TM) algorithms along with their modified (LF) version when each one of these processors based its decision on integrating, non-coherently, M consecutive pulses. This is the main contribution of this work in the CFAR world.

4. Problem Formulation

Modern radars perform target detection automatically. This automation has the feature of automatically adjusting its sensitivity in accordance with the interference power variation. Thus, the key factor of this technique lies in estimating the background power level and adaptively setting the threshold based on this estimation. Whatever the structure of the adaptive model is, the framework of sliding window is regarded as its basic arrangement. As Fig.1. depicts, this window moves throughout the coverage area, and contains a set of reference cells around the central cell, which is called as cell under test (CUT). To alleviate self-interference in a real target echo, some guard cells enclose CUT are used as buffer between it and the training cells. They are excluded from the background computation to insure that the CUT doesn't affect the threshold calculation. Each resolution cell has the chance to occupy the position of CUT. In this regard, the reference cells that have been already processed constitute the leading subset, whilst those that have not yet occupied the center organize the lagging subset. The size selection of the sliding window is dependent upon rugged knowledge of the typical clutter background. Generally, the window length *(N)* should be as large as possible for the estimation process to be of good modality. Meanwhile, *N* is preferred to be compatible with the typical range extension of homogeneous clutter zones for the demand of identically distributed random variables to be statistically verified. The typical value of *N* is within the range of 16-32 cells [2]. The detection threshold is established as the product of the estimated noise power *(Z)* by an adjustment factor *T*, which is chosen to guarantee the desired false alarm rate, as Fig.1. shows. By comparing the content of CUT with the resulting threshold, the procedure will recommend that the signal is belonging to a target, if the magnitude of the CUT surpasses the calculated threshold, otherwise the received signal is purely clutter.

Most modern radar systems are of coherent type. This means that they receive the returned signal as a polar (amplitude and phase). In the radar receiver, the synchronous detector generates in-phase (I) and quadrature (Q) components from the received signal. Under the null hypothesis (H_0), the received noise for both I and Q channels is modeled as an independent and identically distributed (IID) Gaussian random process with zero mean and of variance ψ/2. In addition, I and Q channels are statistically independent. Thus, the received noise is a complex Gaussian signal $(x_n=I+iQ)$ with μ=0 and $\sigma_n^2=\psi$.

After pulse compression, the signal passes through a rectifier, which converts the complex signal into an amplitude and phase. There are different types of rectifiers. In modern radar systems, the essential types are linear and square-law detectors. The linear detector measures only the magnitude (voltage) of the complex received signal, which follows the Rayleigh distribution. The square-law detector, on the other hand, measures only the square (power) of the linear detector, the distribution of which is exponential. For both linear and square-law detectors, the phase is uniformly distributed in the interval $[-\pi, \pi]$.

In order to analyze the adaptive variant in inhomogeneous background, it is assumed that the square-law detected output for any range cell (ν_0) has a probability density function (PDF) with parameter η, the formulation of which is:

$$f_{\nu_0}(\nu) = \frac{1}{\eta}\exp\left(-\frac{\nu}{\eta}\right) U(\nu) \tag{1}$$

In the above formula, U(.) denotes the unit-step function. The value of η depends on the case of operation and can be assigned as:

$$\eta \triangleq \begin{cases} \psi & for \quad Clear\ Background \\ \psi(1+A) & for \quad Object\ Under\ Test \\ \psi(1+I) & for \quad Spurious\ Background \end{cases} \tag{2}$$

In the preceding formula, "A" denotes the SNR of the tested target return, whereas "I" symbolizes the interference-to-noise ratio (INR) of the spurious target return.

The echo from a target in motion is almost never constant. Variations are caused by meteorological conditions, lobe structure of the antenna, equipment instability and the variation in target's radar cross-section (RCS). Cross section of complex targets is sensitive to aspect. Usually, the targets have complicated structures, which reflect scatterers with different RCS. A description of a good estimate of target reflection models was introduced by Swerling for scanning data. He described the statistical properties of the RCS of the targets by five different models (SWJ; J=I-V) based on χ^2-distribution with 2κ degrees of freedom as a parameter. These models specify the statistical features of the RCS of different types of targets. They treat, roughly, the target as a large reflector combined with a group of small ones, or a large reflector over a small range of aspect values. They are verified for a wide range of targets and have the property that they are more strengthened about their mean as κ increases.

We start our formulation by assuming that M-pulses strike the target of interest which follows χ^2-model (with κ =1) in its fluctuation. This target will return a statistical signal that is characterized by a moment generating function (MGF); the mathematical formula of which is given by [16]:

$$M_{\nu_0}(S) \triangleq E_{\nu_0}\{ exp(-\nu_0 S)\} = \prod_{j=1}^{M} \frac{1}{1+(1+\lambda_j A)S} \tag{3}$$

Here, ν_0 represents the content of CUT, $E_\nu\{.\}$ stands for the mathematical expectation over a random variable (RV) ν_0, and λ_i's symbolizes the nonnegative eigenvalues of the correlation matrix **Λ**. To statistically formulate this matrix, the target signal is assumed to be of stationary state that allows us to model it as a first-order Markov chain. This assumption makes **Λ** to be Toeplitz nonnegative definite matrix of the form [17]:

$$\Lambda = \begin{bmatrix} 1 & \rho & \rho^2 & \dots\dots\dots . & \rho^{M-2} & \rho^{M-1} \\ \rho & 1 & \rho & \dots\dots\dots. & \rho^{M-3} & \rho^{M-2} \\ \rho^2 & \rho & 1 & \dots\dots \quad \dots. & \rho^{M-4} & \rho^{M-3} \\ & & & & & \\ \rho^{M-2} & \rho^{M-3} & \rho^{M-4} & \dots\dots\dots & \rho^2 & \rho \\ \rho^{M-1} & \rho^{M-2} & \rho^{M-3} & \dots \quad \dots\dots & \rho & 1 \end{bmatrix} \quad 0 \le \rho \le 1 \tag{4}$$

On the other hand, moderately fluctuating radar targets (i.e. intermediate between SWII and SWI models) are regarded as an important category of targets and their detection is of primary concern. This prompts the necessity to investigate the evaluation of λ_i's of **Λ** for the partially-correlated processor performance to be evaluated as Eq.(3) reveals. For simplicity, Eq.(3) can be reformatted as:

$$\boldsymbol{M_{\nu_0}(S) = \prod_{\ell=1}^{M} \frac{\delta_\ell}{S + \delta_\ell}} \tag{5}$$

In accordance with Eq.(2), the parameter δ_ℓ can be defined as:

$$\boldsymbol{\delta_j \triangleq \begin{cases} 1 & for \quad Clear\ Background \\ 1/(1+\lambda_j A) \triangleq \alpha_j & for \quad Object\ Under\ Test \\ 1/(1+\lambda_j I) \triangleq \beta_j & for \quad Spurious\ Background \end{cases}} \tag{6}$$

In the world of detection, each processor is characterized by two fundamental parameters: the probability of detection P_d and that of false alarm P_{fa}. Due to its crucial role in satisfying a needed level of operation, P_{fa} has the first priority. Therefore, the designer fixes a certain rate of false alarm firstly and then tries to ameliorate the level of detection. Actually, P_d tends to P_{fa} in the absence of the target signal ($A=0$). Thus, P_d is more general than P_{fa}. Thus, we are going to evaluate it.

For χ^2-target fluctuation with two-degrees of freedom (κ =1), the moderately fluctuating radar target P_d has a form given by [18]:

$$\boldsymbol{P_d = \sum_{j=1}^{M} \prod_{\substack{i=1 \\ i\neq j}}^{M} \frac{\alpha_i}{\alpha_i - \alpha_j} \Phi_Z(S) \Big|_{S = T\alpha_j} \& \Phi_Z(S) = \frac{M_Z(S)}{S}} \tag{7}$$

Here, $\Phi_Z(.)$ refers to the Laplace transform of the cumulative distribution function (CDF) of the noise level estimate *Z*. The computation of the scale factor *T*, for a pre-setting rate of false alarm, necessitates the formulation of P_{fa}. As a non-coherent integration of M-pulses is applied, the needed formula is [20]:

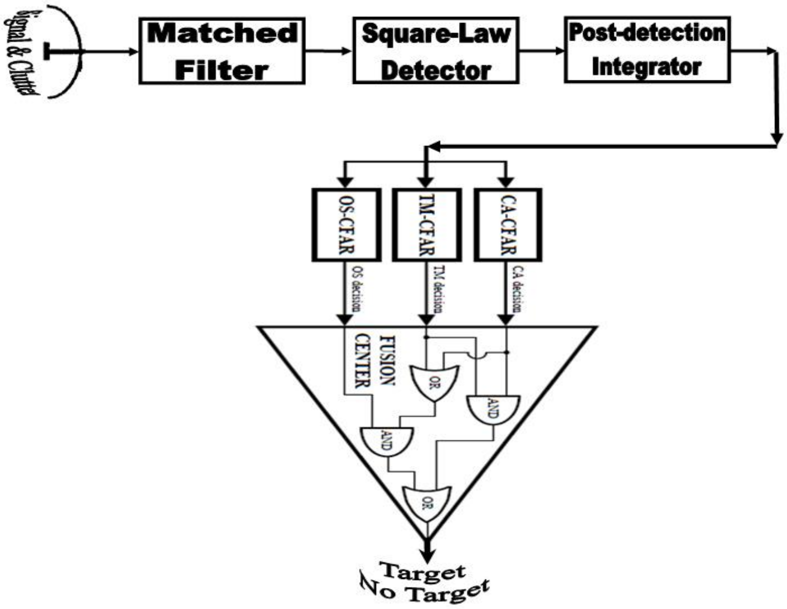

Fig.1. Architecture of linear fusion (LF) adaptive strategy with post-detection integration.

$$\boldsymbol{P_{fa}} = \sum_{j=0}^{M-1} \frac{1}{\Gamma(j+1)} \frac{d^j}{dS^j} \{M_Z(-T\,S)\} \Big|_{S=-1} \tag{8}$$

$\Gamma(x)$ stands for the standard Gamma-function of argument x. Formulas (7 & 8) demonstrate that $M_Z(S)$ is regarded as the cornerstone of the processor performance evaluation. Therefore, the upcoming section is focused on the determination of this crucial parameter for the examined variants.

5. Processor Performance Evaluation

Target masking in CFAR detection processing is a major limitation in most CFAR detection schemes. More robust CFAR detection algorithms, that mitigate or eliminate target masking, have been devised with the drawback of either SNR loss or the number of targets that can be detected at once. The most familiar variants of this class are CA, OS, and TM. These styles are commonly used as standards against which, the reaction of any developed model is compared. However, they exhibit problems when facing clutter edges or target multiplicity events that may exist in real operations. The impossibility of existing a unique CFAR mechanism to cope with diverse noise circumstances has led to the emergence of composite CFAR designing. The analysis of the CA, OS, and TM schemes as well as some of their composite versions is our goal here.

Normally, the efficiency of the CFAR alternative is measured in the perfect situation of operating conditions or in the presence of some of fallacious targets beside the target of interest. Since the ideal situation can be treated as a special case of heterogeneous operation, it is preferable to analyze the processor performance in inhomogeneous background. This is actually the state that we are going to follow in the upcoming subsections.

5.1 Single Adaptive Processors

5.1-1 Order-Statistics (OS)

This strategy of CFAR processors is robust and well performing in both heterogeneous clutter and multiple target cases. It estimates the noise level by extracting the K^{th} largest sample from the elements of the reference window. This extraction is achieved by ranking the reference cells in an ascending order, in such a way that:

$$\nu_{\langle \ell \rangle} \leq \nu_{\langle \ell+1 \rangle} \;\&\; \ell \in [1, 2, \dots\dots\dots\dots\dots, N-1] \tag{9}$$

In this ordered samples, $\nu_{(1)}$ is regarded as the lowest noise sample whereas $\nu_{(N)}$ represents the highest one. After the sorting process, it is desirable to censor one or more of the top samples and pick the K^{th} one to denote the unknown noise power level. Thus, the OS test statistic takes the form:

$$Z_{\langle OS\rangle} = \nu_{\langle K\rangle} \; \& \; K \in [1, 2, \dots\dots, N] \tag{10}$$

To evaluate the OS performance, the PDF of the K[th] sample out of N ones is needed, given that these samples are independent but not identically distributed. Let r extraneous target returns, with power level of $\psi(1+I)$, are among the elements of the reference window and the remainder, q=N–r, cells contain clear background with power level ψ. Under these assumptions, the CDF of the K[th] ordered sample is given by [4]:

$$F_K^{NH}(t,N;r) = \sum_{i=K}^{N} \sum_{j=Max(0,i-r)}^{Min(i,q)} \binom{q}{j} \binom{r}{i-j} \sum_{n=0}^{j} \binom{j}{n} (-1)^n \sum_{m=0}^{i-j} \binom{i-j}{m} (-1)^m \{1 - F_c(t)\}^{q-n} \{1 - F_e(t)\}^{r-m} \tag{11}$$

In the above formula, $F_c(.)$ denotes the CDF of the cell that contains clutter background whereas $F_e(.)$ denotes to the same thing for the cell that has extraneous target return. The RV's representing returns from clutter background and extraneous targets have the same form as that given in Eq.(5) for their MGFs taking into account Eq.(6). As Eq.(7) demonstrates, the Laplace transformation of the CDF of ν_0 is given by its MGF divided by the Laplace transformation parameter S. Thus, $F_C(.)$ has a formula given by:

$$F_c(t) = 1 - \sum_{j=0}^{M-1} \frac{t^j}{\Gamma(j+1)} e^{-t} U(t) \tag{12}$$

On the same manner, $F_e(.)$ can be obtained as:

$$F_e(t) = L^{-1}\left\{ \frac{1}{S} \prod_{i=1}^{M} \frac{\beta_i}{S + \beta_i} \right\} \tag{13}$$

In the preceding formula, L^{-1} stands for the Laplace inverse operator. The Laplace inverse processing yields:

$$F_e(t) = 1 - \sum_{j=1}^{M} \zeta_j \exp(-\beta_j t) \; U(t) \; \& \; \zeta_j \triangleq \prod_{\substack{i=1 \\ i\neq j}}^{M} \frac{\beta_i}{\beta_i - \beta_j} \tag{14}$$

The substitution of Eqs.(12 & 14) into Eq.(11) results:

$$F_K^{NH}(t;N,r) = \sum_{i=K}^{N} \sum_{j=Max(0,i-r)}^{Min(i,q)} \binom{q}{j} \binom{r}{i-j} \sum_{\varepsilon=0}^{j} \sum_{\ell=0}^{i-j} \binom{j}{\varepsilon} \binom{i-j}{\ell} (-1)^{i-\varepsilon-\ell} \left\{ \sum_{m=0}^{M-1} \frac{t^m}{\Gamma(m+1)} e^{-t} \right\}^{q-\varepsilon} \left\{ \sum_{n=1}^{M} \zeta_n e^{-\beta_n t} \right\}^{r-\ell} \tag{15}$$

With the aid of binomial theorem, the bracketed quantities can be expanded as a polynomial of t. Following this technique of expansion, Eq.(15) takes a new form as:

$$F_K^{NH}(t;N,r) = \sum_{i=K}^{N} \sum_{j=Max(0,i-r)}^{Min(i,q)} \binom{q}{j} \binom{r}{i-j} \sum_{n=0}^{j} \binom{j}{n} \sum_{m=0}^{i-j} \binom{i-j}{m} (-1)^{i-n-m} \sum_{u_0=0}^{q-n} \sum_{u_1=0}^{q-n} \dots \sum_{u_{M-1}=0}^{q-n} \frac{\Xi(q-n;\, u_0,\, u_1, \dots\dots,\, u_{M-1})}{\prod_{\sigma=0}^{M-1} [\Gamma(\sigma+1)]^{u_\sigma}} \sum_{\nu_1=0}^{r-m} \sum_{\nu_2=0}^{r-m} \dots\dots\dots \sum_{\nu_M=0}^{r-m} \Xi(r-m;\, \nu_1, \nu_2, \dots\dots, \nu_M) \prod_{\eta=1}^{M} (\zeta_\eta)^{\nu_\eta} \, t^{\sum_{\tau=0}^{M-1} \tau u_\tau} exp\left[-\left(q - n + \sum_{\delta=1}^{M} \nu_\delta \beta_\delta \right) t \right] \tag{16}$$

Finally, the Laplace transformation of the above formula leads to:

$$\boldsymbol{\Phi_K^{NH}(S;N,r)} = \sum_{i=K}^{N} \sum_{j=Max(0,i-r)}^{Min(i,q)} \binom{q}{j} \binom{r}{i-j} \sum_{n=0}^{j} \binom{j}{n} \sum_{m=0}^{i-j} \binom{i-j}{m} (-1)^{i-n-m} \sum_{u_0=0}^{q-n} \sum_{u_1=0}^{q-n} \dots \sum_{u_{M-1}=0}^{q-n} \frac{\Xi(q-n;\, u_0,\, u_1, \dots\dots,\, u_{M-1})}{\prod_{\sigma=0}^{M-1} [\Gamma(\sigma+1)]^{u_\sigma}}$$

$$\sum_{\nu_1=0}^{r-m}\sum_{\nu_2=0}^{r-m}\ldots\ldots\ldots\ldots\sum_{\nu_M=0}^{r-m}\Xi(r-m;\ \nu_1,\nu_2,\ldots\ldots,\nu_M)\ \prod_{\eta=1}^{M}\left(\zeta_\eta\right)^{\nu_\eta}\ \frac{\Gamma\left(\sum_{\tau=0}^{M-1}\tau\,u_\tau+1\right)}{\{S+q-n+\sum_{\delta=1}^{M}\nu_\delta\beta_\delta\}^{\left(\sum_{\tau=0}^{M-1}\tau\,u_\tau+1\right)}}$$

(17)

In the preceding mathematical expressions, the factor $\Xi(I;\ i_1, i_2, \ldots\ldots, i_M)$ is defined as:

$$\Xi(I;\ i_1,i_2,\ldots\ldots\ldots,i_M)\triangleq\begin{cases}\frac{\Gamma(I+1)}{\prod_{\ell=1}^{M}\Gamma(i_\ell+1)} & if\quad \sum_{j=1}^{M}i_j\ =\ I\\ 0 & Otherwise\end{cases} \tag{18}$$

Once Eq.(17) is obtained, the false alarm and detection performances are completely evaluated, as Eq.(7) indicates. The major drawback of this scheme is the high processing time that is taken in performing the sorting mechanism.

5.1-2 Trimmed-Mean (TM)

In this style of CFAR techniques, the ordered range cells of a particular reference window are trimmed from both the upper and the lower ends and the threshold is estimated by averaging the remaining cells. The TM variant may be considered as an amended version of the OS scenario. Thus, the elements of the reference set are ranked and then N_L lower cells and N_U upper ones are excised before summing the remaining cells to achieve the noise level estimate. Thus, the statistic Z_{TM} has the form [2]:

$$Z_{TM}(N_L,N_U)\triangleq\sum_{\ell=N_L+1}^{N-N_U}\ \nu_{(\ell)} \tag{19}$$

Clearly, the ordered statistics $\nu_{(1)}$, , , $\nu_{(K)}$,. . . . , $\nu_{(N)}$ are neither independent nor identically distributed random variables even if the original samples ν_1, . . . , ν_N are IID. However, on the assumption that the samples ν_1, ν_2,, . . . , ν_N are IID and exponentially distributed, the independent quantities can be obtained through the transformation [19]:

$$W_\ell\triangleq\ \nu_{(N_L+\ell)}-\ \nu_{(N_L+\ell-1)}\ U(\ell-2)\ \&\ \ell\ \epsilon\ [1,2,\ldots\ldots\ldots,N-N_L-N_U] \tag{20}$$

In terms of W_i's, Eq.(19) can be written as:

$$Z_{TM}=\sum_{j=1}^{N_T}\ \left(N_T-j+1\right)\ W_j\ \&\ N_T\ \triangleq\ N-N_L-N_U \tag{21}$$

As a function of the S-domain representation of the CDF of $\nu_{(i)}$'s, the MGF of the RV W_j's becomes [19]:

$$M_{W_\ell}(S)=\begin{cases}S\ \Phi_{N_L+1}^{NH}(S;N,r) & for\qquad \ell=1\\ \frac{\Phi_{N_L+\ell}^{NH}(S;N,r)}{\Phi_{N_L+\ell-1}^{NH}(S;N,r)} & for\qquad 1<\ell\ \le N_T\end{cases} \tag{22}$$

Since W_j's are statistically independent, the MGF of the noise level estimate Z_{TM} is:

$$M_{Z_{TM}}(S;\ N_L,\ N_U)=\prod_{\ell=1}^{N_T}\ M_{W_\ell}(S)\Big|_{S=\ (N_T-\ell+1)\,S} \tag{23}$$

The main drawback of TM scenario is, as previously mentioned in OS, the high processing power demanded to achieve the sorting algorithm. As a solution to this problem, the reference set is symmetrically divided into two subsets about the CUT. The candidates of each subset are separately processed and the statistic Z may be chosen by further processing the two subsets outputs. The subset output is simply the trimmed sum of its ordered range cells. The final estimate of the noise power is obtained by taking the mean value of the two noise level estimates. In this situation, assume that r_1 cells contain outlying target returns, q_1= N/2-r_1 ones immersed in thermal noise, Q_L censored cells from the lower end and Q_U excised samples from the top end of the ordered statistics of the leading subset. Similarly, the lagging subset is assumed to have r_2 interfering cells, q_2=N/2-r_2 clear samples, its associated ordered statistics is trimmed from its ends, where the lowest T_L ordered cells are removed and T_U largest ranked cells are nullified. Under these circumstances, the MGF's of their noise level estimates, Z_1 and Z_2, have the same form as that given by Eq.(23) after replacing its argument with the corresponding parameter values for the leading and lagging subsets. Finally, the two noise level estimates are combined through the mean-level operation to investigate the final noise level estimate. Thus,

$$Z_f = Mean\,(Z_1,\ Z_2) \tag{24}$$

Since the two noise level estimates are statistically independent, the MGF of Z_f is:

$$M_{Z_f}(S) = M_{Z_{TM}}(S;\ Q_L,\ Q_U)\ \ M_{Z_{TM}}(S;\ T_L,\ T_U) \tag{25}$$

Once the S-domain representation of the PDF of the resultant noise level estimate is investigated, the processor performance is completely evaluated, as Eq.(7) demonstrates.

5.1-3 Cell-Averaging (CA)

The CA is the best CFAR scheme that has the top, relative to OS and TM, homogeneous performance, given that the clutter is exponentially distributed and the contents of the reference window are IID. It uses the maximum likelihood estimate of the noise power to set the adaptive threshold. The CA detector is used as a baseline to compare the more-robust detectors. However, it has a degraded performance in the presence of clutter edges as well as in multi-target situations [7].

Since CA is a special case of TM scheme, we can exploit the analysis of the TM variant to evaluate the performance of the CA detector, where all of its ordered samples are activated. Thus, under the same conditions of the double-window TM scenario, the MGF of the double-window CA processor is [20]:

$$M_{Z_{CA}}(S) = M_{Z_{TM}}(S;\ 0,0)\ \ M_{Z_{TM}}(S;\ 0,0) \tag{26}$$

As the MGF of the CA technique is computed, both the detection and false alarm probabilities are easily calculated as outlined in Eqs.(7 & 8), respectively.

5.2 Combined CFAR Schemes

5.2-1 CA_OS & CA_TM Developed Versions

There are different CFAR variants and each of which has its own application. Some of these procedures combine couple of CFAR scenarios in one processor and make the resulting model to adaptively vary in accordance with the background environment. Generally, there is no one CFAR processor that is always better than all the other ones. Each radar system designs its CFAR processor based on the application. The hardness of existing an efficient CFAR strategy is the prime motivation of developing a new structure of adaptive schemes. In this vein, the use of multiple sensors is widely applied in surveillance systems. The base goal of employing this technology is to enhance the system reliability and speed of reaction, as well as achieving a larger area of coverage. This strategy is implemented by parallel operation of the selected types of CFAR models. Here, the CA model is combined with either OS or TM scenario to emanate CA_OS or CA_TM novel modes. In any one of them, the two candidates carry out their processing, independently and simultaneously, in such a way that the scaling factor T is common for constructing their own detection threshold against which the content of CUT is compared to independently decide the presence/absence of the target of interest. The final decision is achieved in the fusion center which is an "AND" logic gate, according to the truth table of which, the existence of the target in the CUT is declared iff both of the single decisions of the fusion center are positive. Otherwise, the fusion center's decision is negative and target is not at the location which corresponds to the CUT [15]. In other words, the global decision is concluded in accordance with:

$$v_0 \ \underset{<\ Target\ Absent}{\overset{>\ Target\ Present}{}}\ V_T\ ,\ V_T \triangleq T\,Z_{CA} \wedge T\,Z_{DT}\ \ \&\ DT \in [OS, TM] \tag{27}$$

In the previous formula, "v_0" denotes the content of the CUT, "V_T" represents the detection threshold, Z_{DT} designates the background estimate of the detector DT, and "∧" stands for the algebraic Boolean of AND gate. Since the two single decisions are statistically independent, the global detection and false alarm probabilities can be easily evaluated as:

$$P_{GP}^{CA\_DT} = P_{GP}^{CA}\ \ P_{GP}^{DT}\ \ ,\ GP \in [fa, d]\ \ \&\ DT \in [OS, TM] \tag{28}$$

As a function of the performances of CA, OS, and TM detectors, the performances of CA_OS and CA_TM mechanisms are completely analyzed, as Eq.(28) confirms.

5.2-2 Linear Fusion (LF) Emerged Strategy

A robust detector should not only pick out targets but also diminish false alarms. For target detection in complex background, it is difficult to realize high level of detection simultaneously with holding low rate of false alarm. An effective detector dictates an incorporation of different features in such a way that each aspect resolves one of the challenges that enface the detection characteristics. In this regard, the fusion strategy has rapidly become a methodology of choice for detecting fluctuating radar targets. In other words, an architecture involving decentralized processing at multiple sensor locations provides the proper choice of optimum results in heterogeneous situation. Such establishment involves higher reliability and survivability, improved system performance at low latency. In this scenario of CFAR technology, a new pattern of CA, OS, and TM variants has been recently appeared [19]. This structure is called as linear fusion (LF). In this new strategy, each one of its processors carries out its local binary decision, and sends it to the fusion center which performs the overall decision based on the local ones.

Fig.1. illustrates the detailed architecture of such developed model. In this layout, there are three individual arms in accordance with the standard detectors. Depending on the required rate of false alarm, the detection threshold along with the signal strength of the CUT of each local scheme is used to attain the final decision about the *presence/absence* of the target under research. According to the appropriate fusion rule, the three local decisions are simultaneously mixed in the fusion center to reach the final decision. As the circuit in Fig.1. depicts, the potential outputs of fusion CA_OS_TM strategy are summarized in Table 1. This table illustrates the inputs to the fusion center (CA, OS, TM) and the corresponding outputs of the fusion rule, where a value of "1" represents the presence of the target, whilst a value of "0" denotes no target.

Since the CA scheme provides a low false alarm rate and a high level of detection, its output is taken as a baseline for the fusion center. When the CA output is "1", there is a possibility of occurrence of false alarm, caused by clutter transition or multi-targets. To eliminate this eventuality, the AND fusion rule-I, indicated in Eq.(29), can be applied. This rule necessitates the application of an AND logic gate between the CA output and that obtained by applying an OR logic gate between the outputs of OS and TM scenarios. On the other hand, when the CA output is "0", there exists the possibility of a target lost caused by clutter interference. To avoid such occurrence, an AND fusion rule-II, exhibited in Eq.(29) is applied. This necessitates the application of an AND logic gate between the outputs of OS and TM variants.

$$Rule - I = CA \wedge (OS \vee TM) \ \& \ Rule - II = OS \wedge TM \tag{29}$$

In the previous mathematical expression, "$\vee$" stands for the algebraic Boolean of OR gate whilst "$\wedge$" represents the same thing of AND gate.

Table 1. Possible Outputs of Fusion CA_OS_TM Strategy

CA Scenario	OS Procedure	TM Strategy	FUSION RULE
0	0	0	0
0	0	1	0
0	1	0	0
0	1	1	1
1	0	0	0
1	0	1	1
1	1	0	1
1	1	1	1

The presence of the target of interest is indicated by the outcomes of rows 4, 6, 7, and 8. Since the occurrence of one of them excludes the occurrence of the others, they are mutually exclusive. Taking into account that the decisions of CA, OS, and TM approaches are independent events, the global detection probability "P_{DG}" of the new implementation is given by:

$$\begin{aligned} P_{DG} &= (1 - P_{d_{CA}})\ P_{d_{OS}}\ P_{d_{TM}} + (1 - P_{d_{OS}})\ P_{d_{CA}}\ P_{d_{TM}} + (1 - P_{d_{TM}})\ P_{d_{CA}}\ P_{d_{OS}} + P_{d_{CA}}\ P_{d_{OS}}\ P_{d_{TM}} \\ &= \left(P_{d_{OS}} - 2\, P_{d_{OS}}\ P_{d_{TM}} + P_{d_{TM}} \right)\ P_{d_{CA}} + P_{d_{OS}}\ P_{d_{TM}} \end{aligned} \tag{30}$$

All the parameters of Eq.(30) are previously executed. So, the detection performance of the *LF-CFAR* strategy is completely analyzed. The upcoming section is focused on numerically simulating the derived formulas through a PC device using C++ programming language to see the new contribution of the *LF* mechanism in the CFAR world.

6. Processor Performance Assessment

To demonstrate the robustness of LF version, we carry out some numerical results for its detection performance, in the absence as well as in the presence of fallacious targets. To see to what extent the non-coherent integration can ameliorate the reaction of the CFAR scheme against fluctuating targets, the CFAR circuit is provided by a non-coherent integrator of two pulses (M=2).

In our simulation results, it is assumed that the reference window has a size of 24 cells, the desired P_{fa} is 10^{-6} and the simulation is performed for the state of homogeneous and multi-target situations. For OS scenario, the 10^{th} ordered sample is chosen to represent its noise level estimate of each reference sub-window. For TM scheme, the two lower cells as well as the two upper ones are rejected from the ordered set of each sub-window before adding the remaining ones to extract its background power. Additionally, symmetrical parameter values are supposed for the leading (Q_L=Q_U=2, K_1=10) and trailing (T_L=T_U=2, K_2=10) reference sub-windows. In the presence of fallacious targets, it is assumed that each reference sub-window is contaminated with one outlying return (r_1=r_2=1) and the performance is achieved for a possible practical situation where the interfering returns have the same correlation strength (ρ_p=ρ_s) as well as the same signal power (INR=SNR) as the returns of the target of interest.

Since the final background estimation is obtained via the averaging operation and this is common for all the schemes presented here, it is preferable to omit this property in the variant representation. Therefore, in the forthcoming scenes, each alternative will be nominated by its sub-window noise level estimation rule. As a reference of comparison, the performance of the Neymann-Pearson (N-P) style is incorporated into the contents of each one of upcoming plots. In addition, to see to what extent the non-coherent integration can ameliorate the processor performance, the single-pulse (M=1) characteristics of the tested variants along with N-P scheme are accompanied. Now, we are in position that allow us to display our simulation results.

6.1 Homogeneous Background

This category of curves includes Figs.2-7. Fig.2. plots P_d against SNR of the CFAR under consideration, along with N-P detector, in the absence of post-detection integration (M=1). For weak signal strength, it is observed that the N-P has the highest level of detection till SNR=11dB above which, the LF algorithm surpasses it and presents the top performance in the examined group. All the other variants give lower, relative to N-P scheme, level of detection. The CA_TM(2, 2) modified model has the best (very close to the N-P) performance, whilst the ordinary OS(10) gives the worst (relative to CA_OS(10), standard CA, and normal TM(2, 2)) probability of detection.

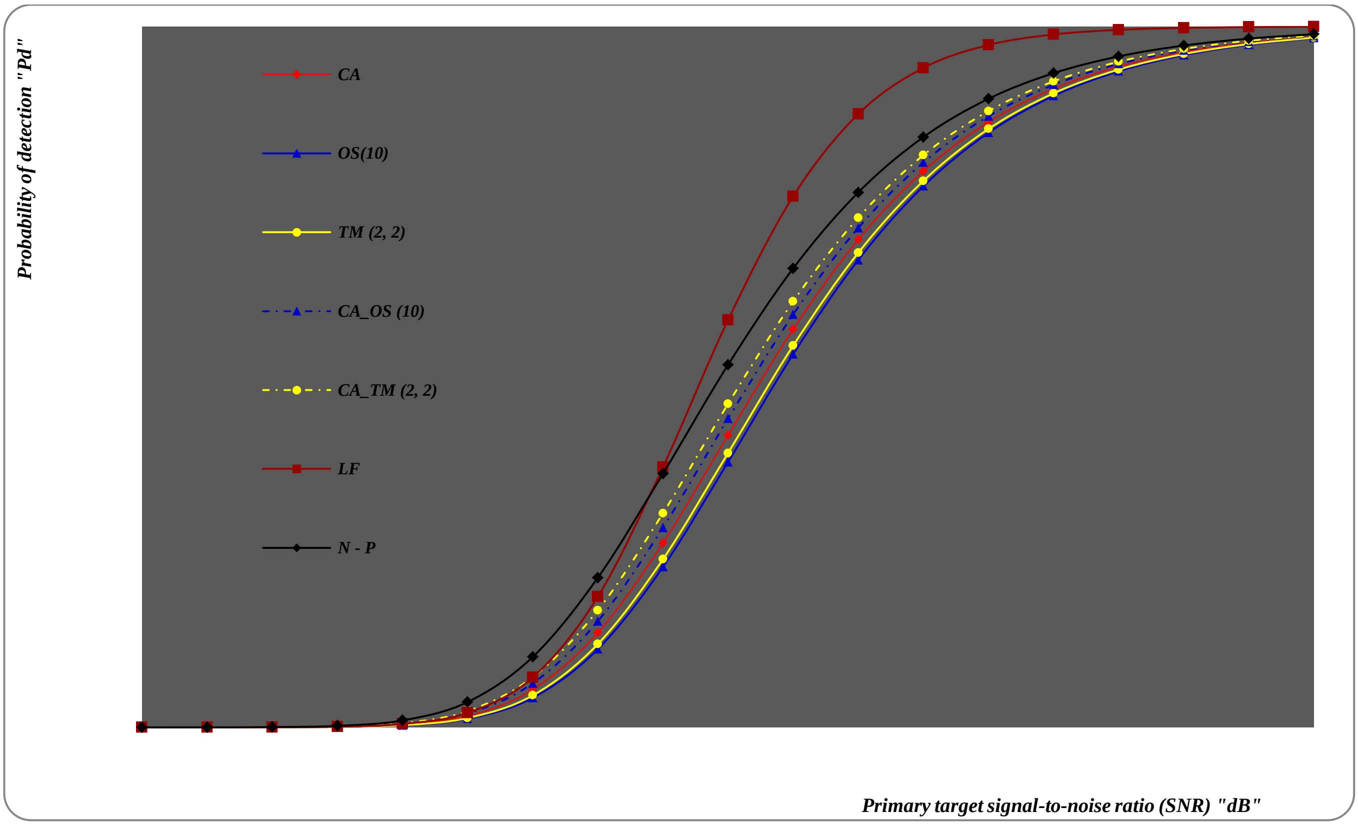

Fig.2. Mono-pulse homogeneous performance of the conventional as well as developed versions of adaptive schemes for χ^2 fluctuating targets with two degrees of freedom when N=24, and P_{fa}=10^{-6}

Now, we turn our attention to the partially-correlated χ^2 target returns of two-degrees of freedom. Fig.3. describes the detection performance of the above mention processors when the radar receiver based its decision on integrating two de-correlated (ρ_s=0) successive pulses (M=2). For weak signal strength (SNR<8dB), both CA_TM(2, 2) and N-P schemes have detection level superior to that of LF algorithm. For SNR>8dB, the new modified model gives the top level of detection and the derived version CA_TM(2, 2) occupies the next location. The N-P detector reserves the third position, whereas the other mechanisms remain in their positions as in Fig.2. When the correlation among the target returns increases (ρ_s=0.65), the modified version CA_TM(2, 2) recedes to become below N-P till SNR=10dB after which, it surpasses the ideal (N-P) detector, as Fig.4. portrays. On the other hand, the LF scenario possesses the highest performance for signal strength greater than 7dB, whilst the remaining processors keep their locations without any changes. Fig.5. depicts the processor detection performance when the correlation among target returns is more strengthened (ρ_s=85%).

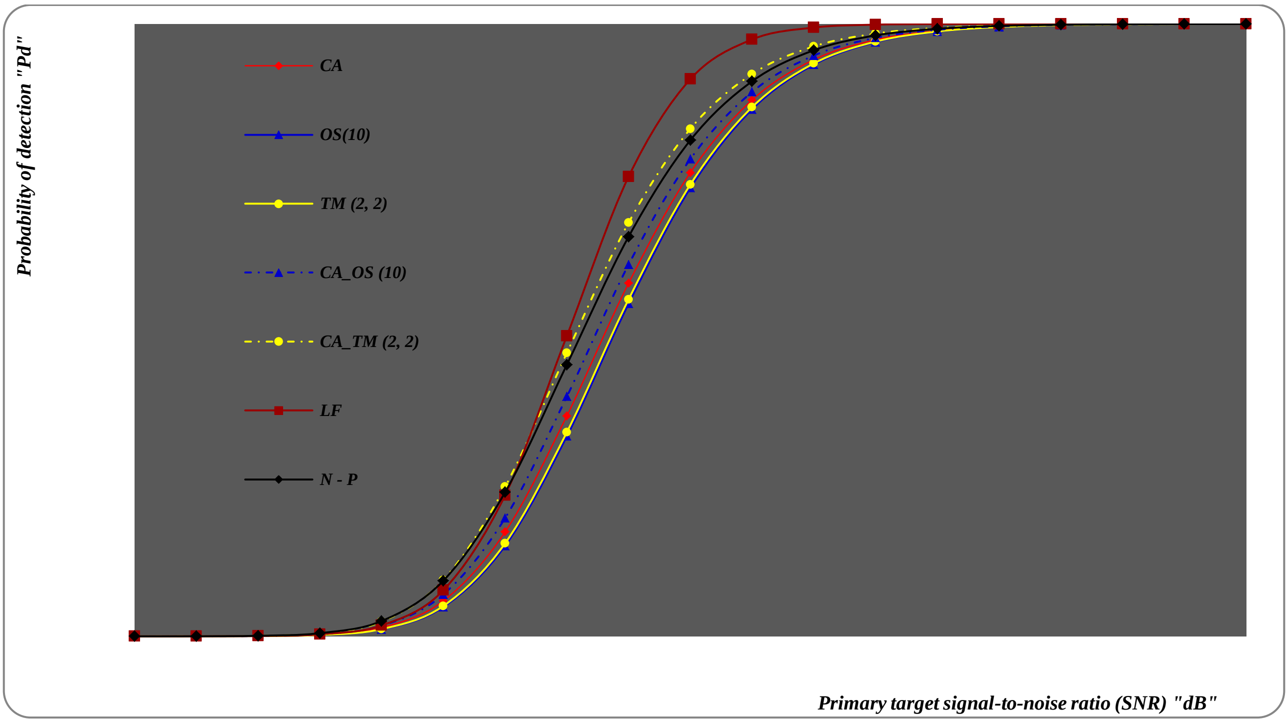

Fig.3. Multi-pulse homogeneous performance of the conventional as well as developed versions of adaptive schemes for partially-correlated χ^2 fluctuating targets when N=24, M=2, ρ=0, and P_{fa}=10^{-6}

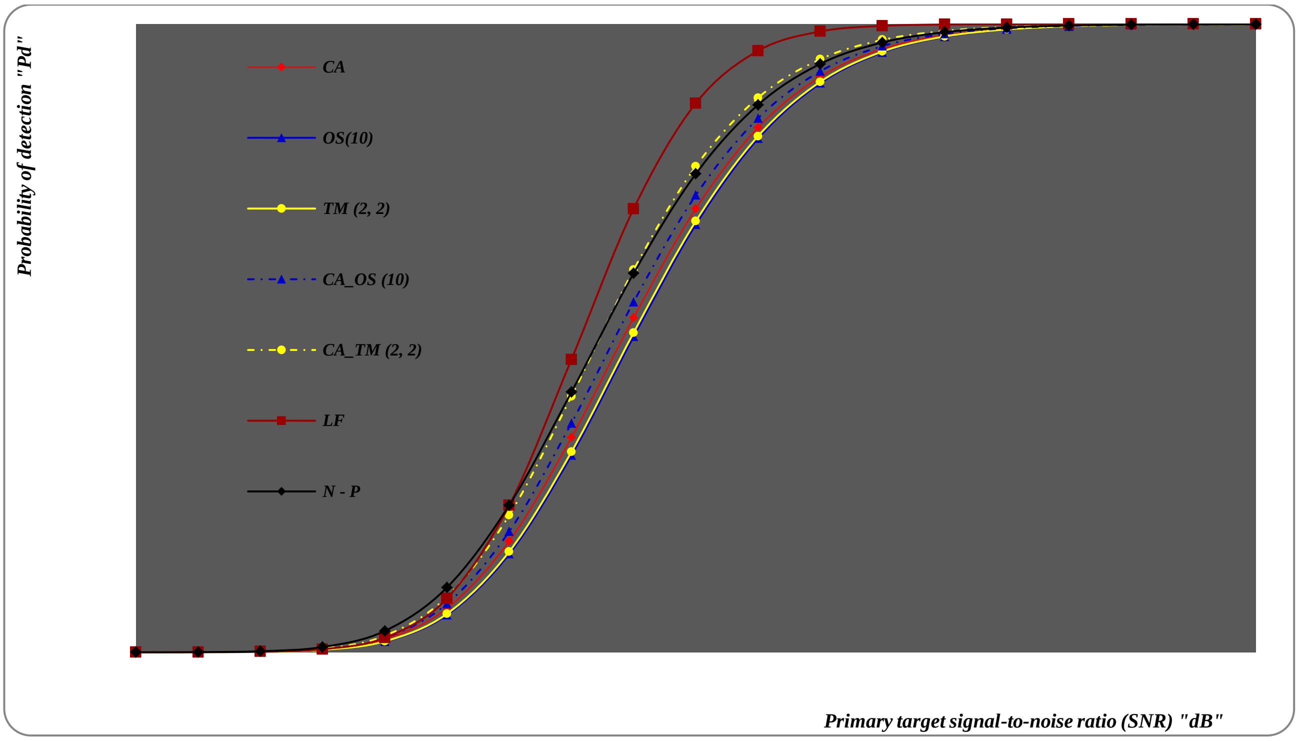

Fig.4. Multi-pulse homogeneous performance of the conventional as well as developed versions of adaptive schemes for partially-correlated χ^2 fluctuating targets when N=24, M=2, ρ=0.65, and P_{fa}=10^{-6}

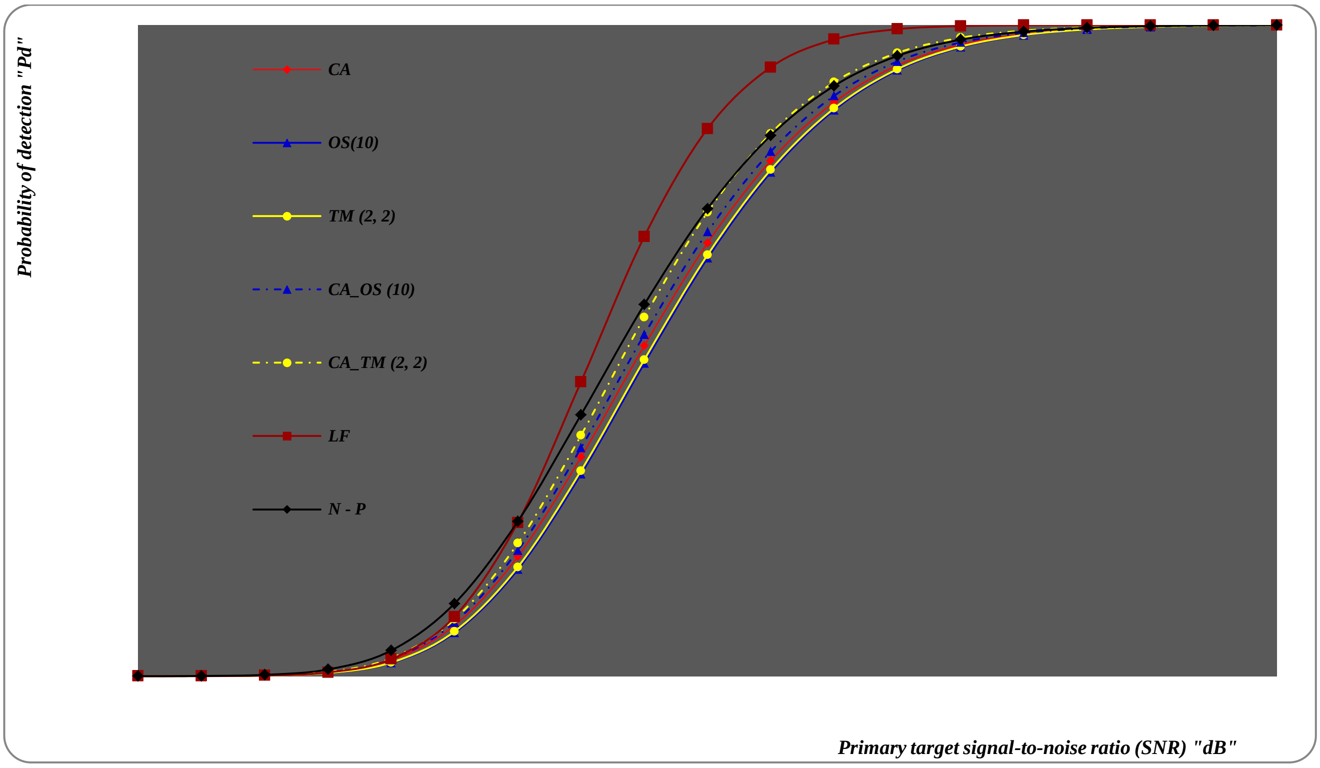

Fig.5. Multi-pulse homogeneous performance of the conventional as well as developed versions of adaptive schemes for partially-correlated χ^2 fluctuating targets when N=24, M=2, ρ=0.85, and $P_{fa}=10^{-6}$

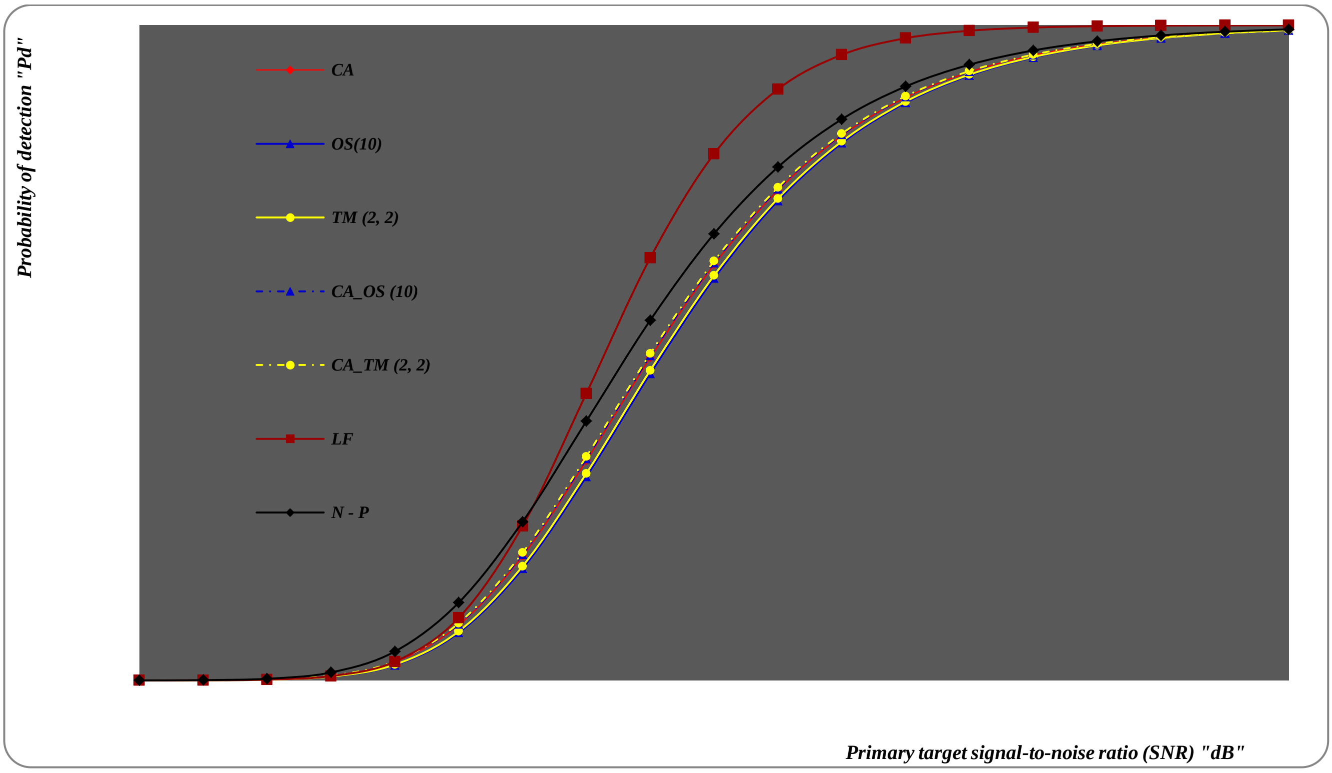

Fig.6. Multi-pulse homogeneous performance of the conventional as well as developed versions of adaptive schemes for partially-correlated χ^2 fluctuating targets when N=24, M=2, ρ=1.0, and $P_{fa}=10^{-6}$

The displayed curves of this plot show that the degree of regression of the developed version CA_TM(2, 2) augments to reach 15dB after which it precedes the N-P algorithm, while the new variant LP occupies the top position for SNR ≥ 7dB. The other detectors remain in their sequence as in the previous figures. At the end, Fig.6. repeats the same thing of the above sense for fully correlated (ρ_s=1.0) target returns. At this level of correlation, the modified model

CA_TM(2, 2) falls behind the N-P scheme whereas the novel version LP reserves its location of highest level of detection for signal strengths beyond 7dB. All the other schemes lie below CA_TM(2, 2) with respect to their positions from the detection level point of view.

To clearly demonstrate the superiority of the new technique of fusion, Fig.7. exhibits the needed signal strength, to satisfy a level of detection of 90%, for all the schemes under examination as a function of the correlation strength among the target returns. This plot visualizes the variation of curves, associated with the concerned processors, as the correlation coefficient increases. It is evident that the scenario of fusion needs always the lowest signal strength to attain a detection probability of 0.90. The new version CA_TM(2, 2) comes next till the correlation strength reaches 90%, nearly, after which it requires more signal strength than the N-P scheme to verify 90% probability of detection. As we have previously illustrated, the standard OS(10) technique demands the highest signal power to achieve a level of detection of 90%. The results of this figure demonstrate the observed notes about the behavior of the tested CFAR variants against the detection of partially-correlated target returns that are fluctuating following χ^2-distribution, of two-degrees of freedom, in their fluctuation.

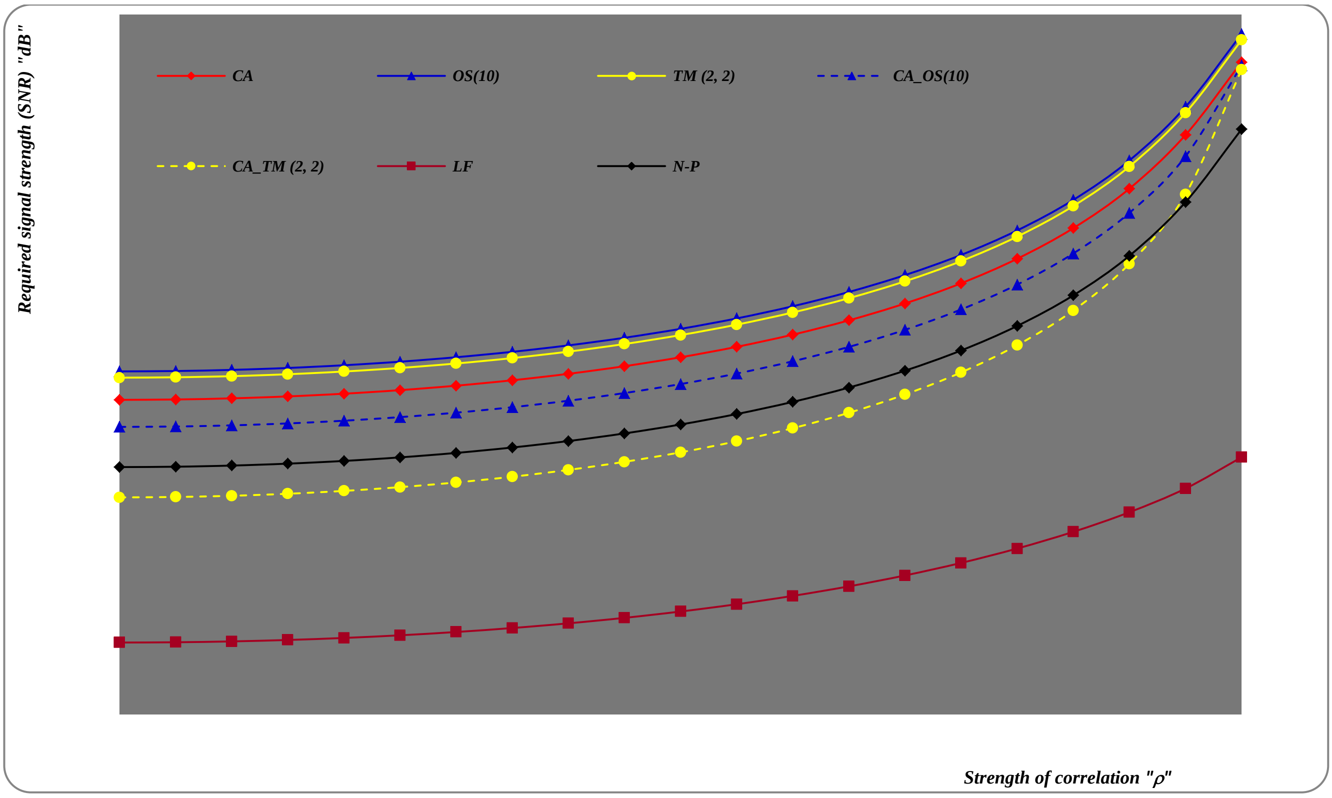

Fig.7. Multi-pulse signal strength requested to achieve a detection level of 90% of CFAR schemes as well as their derived versions for χ^2 fluctuation when N=24, M=2, and $P_{fa}=10^{-6}$

6.2 Heterogeneous (Multi-target) Background

The operating environment ideality of radar systems is extremely scarce whereas the need of these systems is growing at a rapid pace. In this vein, if the assumption of homogeneity is violated, the processor performance is significantly affected. In target multiplicity event, the inclusion of interfering signal power in the noise estimate yields to an unnecessary increase in overall threshold which in turn results in serious performance degradation. Therefore, technology of adaptation is of primary concern in the design of the future scenarios of radar systems. Here, we are interesting in displaying some numerical results that illustrate the reaction of the underlined detectors against the presence of outlying target returns amongst the estimating cells.

Fig.8. shows the detection performance of the tested schemes when one cell of each reference sub-window is contaminated with spurious target returns ($r_1=r_2=1$) of the same strength as that of the CUT and in the absence of post-detection integration (M=1). It is evident that the LF fusion model has the top performance which is the more closest to and coincides with that of N-P technique for stronger target returns.

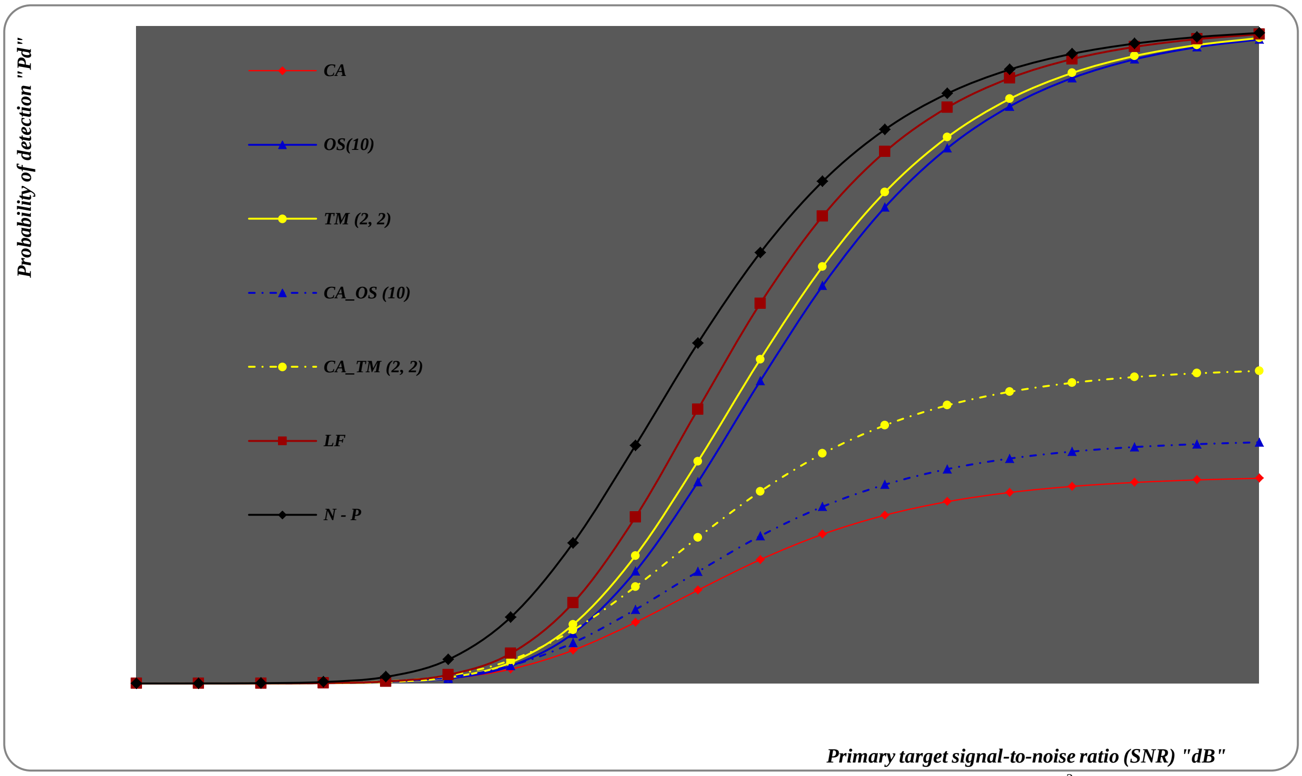

Fig.8. Single pulse multi-target performance of the conventional as well as developed versions of adaptive schemes for χ^2 fluctuating targets when N=24, r_1=r_2=1, INR=SNR, and P_{fa}=10^{-6}

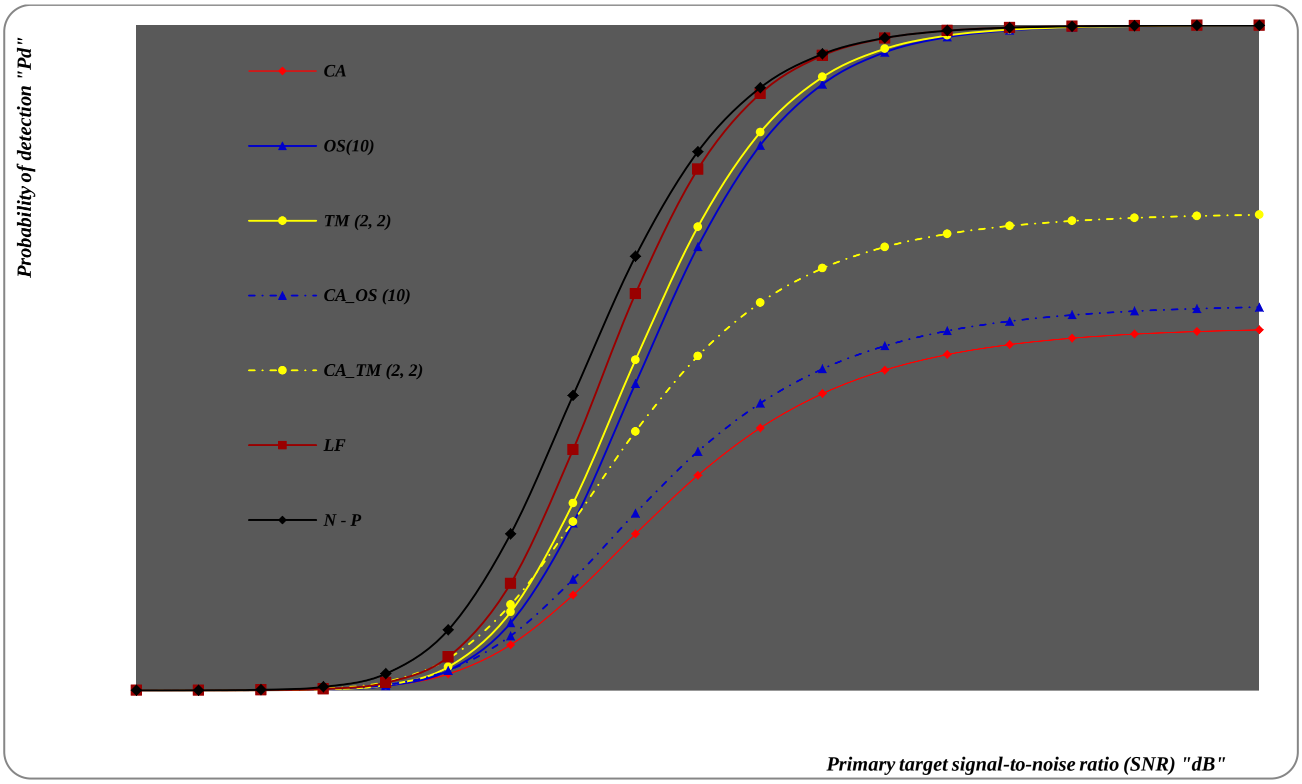

Fig.9. Multi-pulse multi-target performance of the conventional as well as developed versions of adaptive schemes for χ^2 fluctuating targets when N=24, M=2, ρ=0, r_1=r_2=1, INR=SNR, and P_{fa}=10^{-6}

Figs.9-12 are corresponding to Figs.3-6 for the case of multi-target environment and under the same correlation strength among interfering target as well as primary target returns. The displayed results show that the LF multi-target reaction tends to be coincident with that of N-P and may surpass it as the primary target echoes become stronger (SNR

≥ 15dB). On the other hand, the conventional TM(2, 2) scheme presents the more closest performance to that of N-P detector and the standard OS(10) procedure comes next. The modified versions CA_TM(2, 2) and CA_OS(10) have modest level of detection with CA_TM(2, 2) in the top, while the classical CA processor exhibits the worst detection performance.

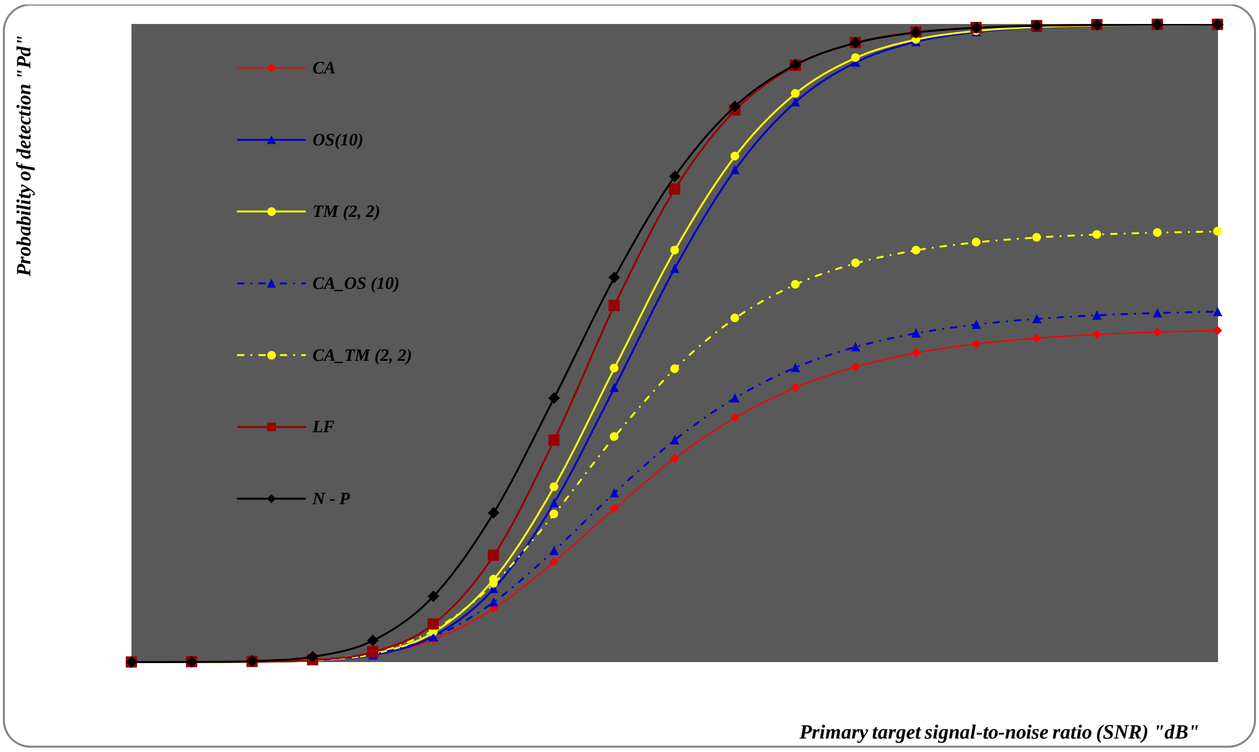

Fig.10. Multi-pulse multi-target performance of the conventional as well as developed versions of CFAR schemes for χ^2 fluctuating targets when N=24, M=2, ρ=0.65, $r_1=r_2=1$, INR=SNR, and $P_{fa}=10^{-6}$

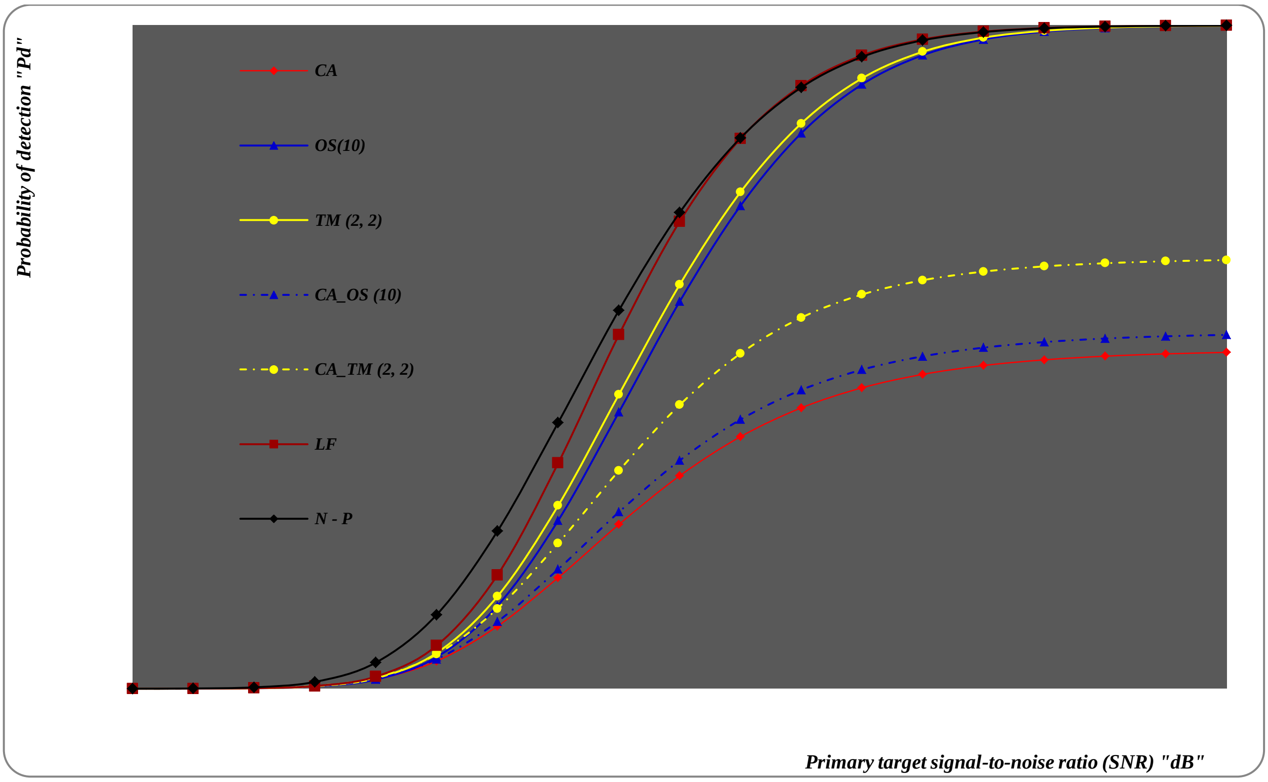

Fig.11. Multi-pulse multi-target performance of the conventional as well as developed versions of CFAR schemes for χ^2 fluctuating targets when N=24, M=2, ρ=0.85, $r_1=r_2=1$, INR=SNR, and $P_{fa}=10^{-6}$

The results of these figures confirm the utility of using post-detection integration in enhancing the performance of an adaptive processing mechanism, either the operating environment is free of or contaminated with interferers. Additionally, as the correlation among the target returns becomes strengthened, the processor performance deteriorates keeping the LF fusion version in the highest and the traditional CA procedure in the worst, whereas the remaining ones are in between with their positions as we previously stated.

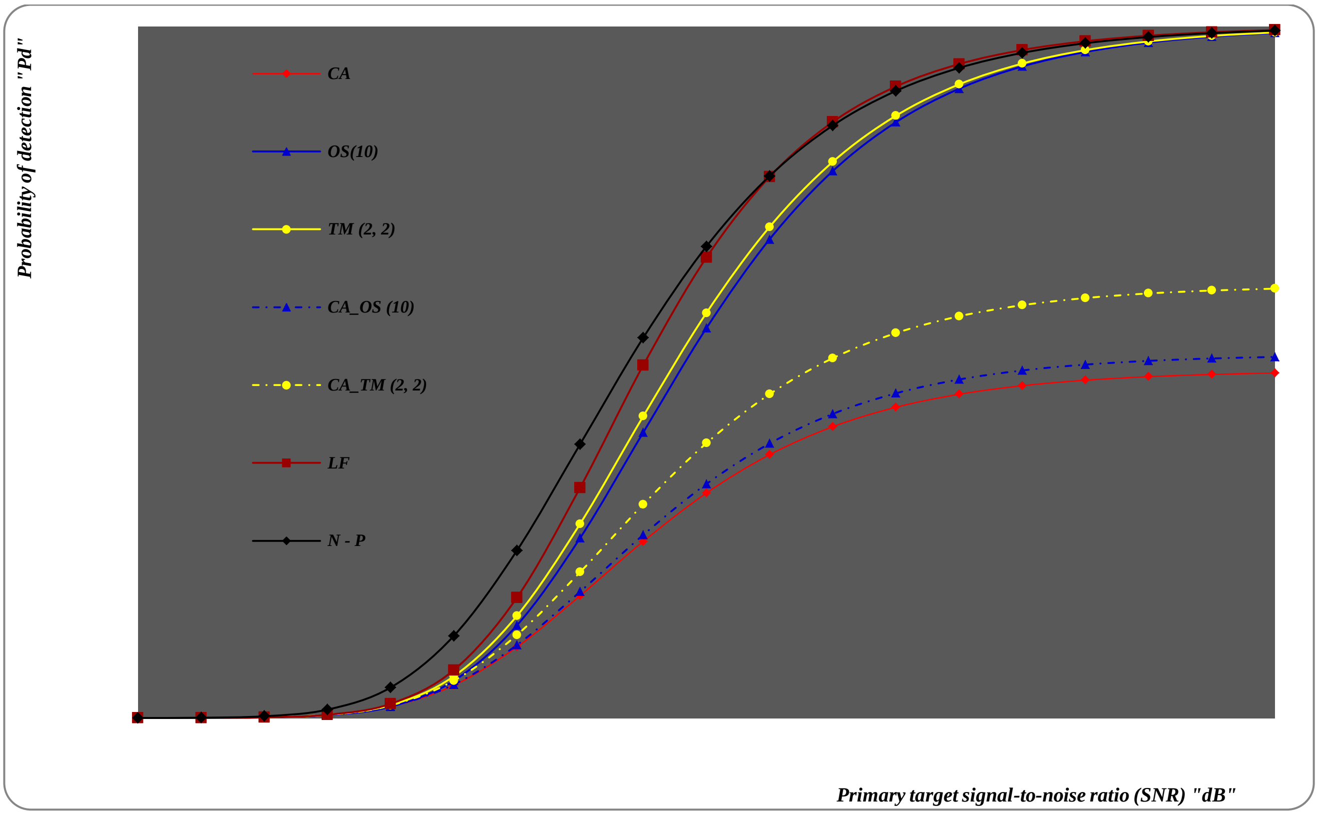

Fig.12. Multi-pulse multi-target performance of the conventional as well as developed versions of CFAR schemes for χ^2 fluctuating targets when N=24, M=2, ρ=1.0, r_1=r_2=1, INR=SNR, and P_{fa}=10^{-6}

The second category of curves includes Figs.13-14. The candidates of this group have the characteristics of required signal strength to satisfy a specified level of detection when the target returns are either fully-correlated, Fig.13., or fully de-correlated, Fig.14., given that the CFAR circuit based its processing on integrating two pulses (M=2). As a reference of comparison, the same N-P characteristic is incorporated with the elements of these figures. To clearly discuss the behavior of the tested detectors, let us define the dynamic range as the range in which the CFAR processor has the capability of replying the demanded probability of detection. The figures under investigation show that the procedures CA, CA_OS(10), and CA_TM(2, 2) have limited dynamic ranges; the narrowest is for CA while the CA_TM(2, 2) has the widest. On the other hand, the LP, TM(2, 2) and OS(10) mechanisms possess full ranges, which means that they are capable of attaining any level of detection. For a given P_d, the LF fusion category requires the minimum signal strength to verify such value of P_d. In addition, the required signal puissance of LF model coincides with, and may lowered than, that needed by N-P scheme to reply a detection level greater that 80% (P_d=0.80). Moreover, as the correlation coefficient increases, the CFAR strategy demanded more strengthened signal to satisfy the same level of detection, as Fig.13. demonstrates. Furthermore, the dynamic range of CA along with its modified versions becomes narrower, relative to the case of zero correlation.

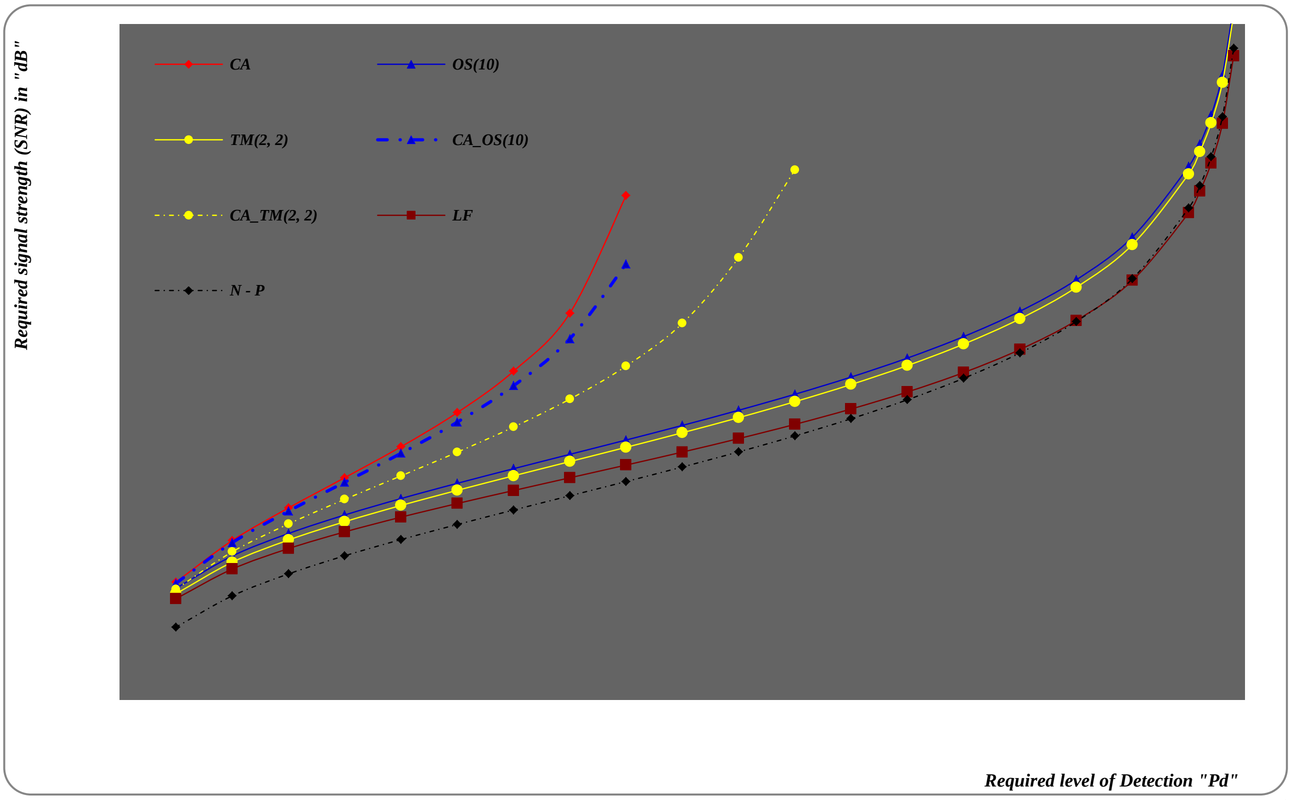

Fig.13. Multi-target required SNR to reply a given detection level for CFAR detection schemes when N=24, M=2, ρ=1.0, $r_1=r_2=1$, INR=SNR, $P_{fa}=10^{-6}$

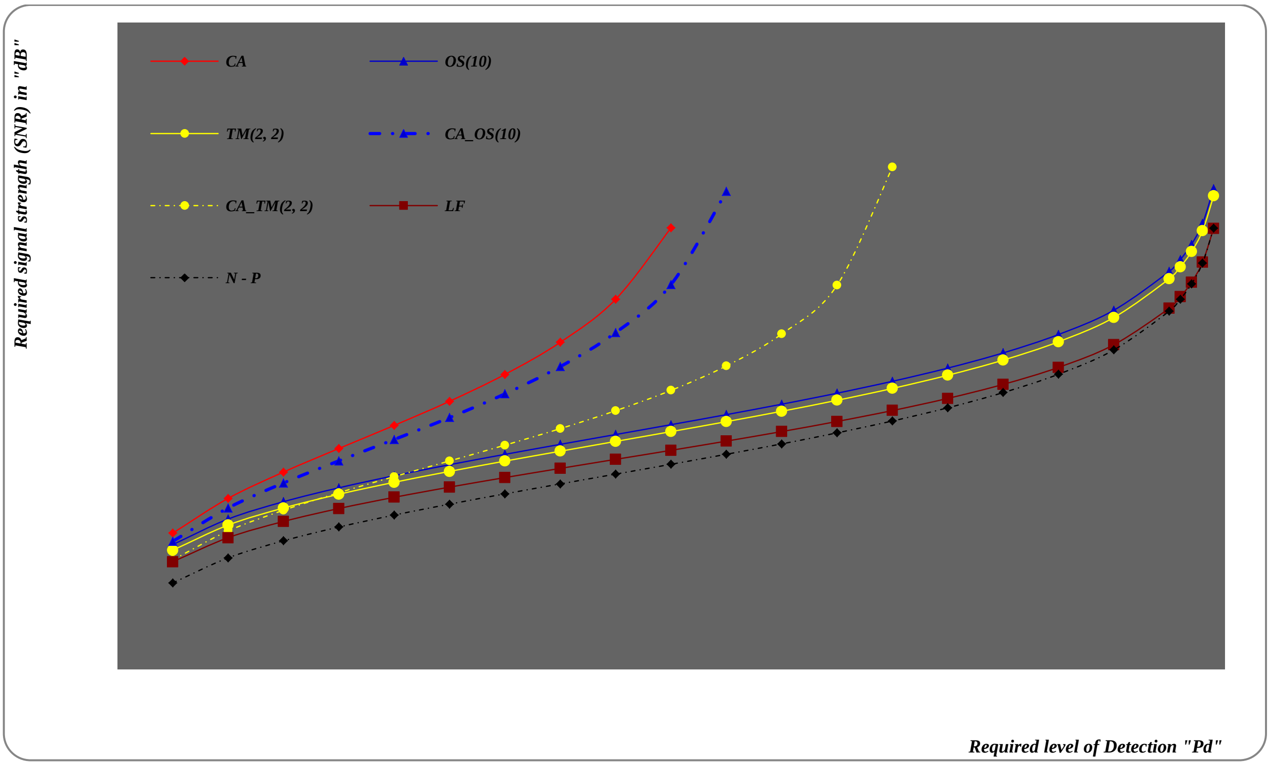

Fig.14. Multi-target required SNR to reply a given detection level for CFAR detection schemes when N=24, M=2, ρ=0.0, $r_1=r_2=1$, INR=SNR, $P_{fa}=10^{-6}$

Finally, let us go to examine the effects of spurious target returns on the ability of the tested scenarios to maintain the pre-assigned rate of false alarm. In Fig.15., we draw some numerical results that depict the false alarm performance of the examined variants when some candidates of the sample set are contaminated with interfering target returns of equal strength. This scene illustrates the variation of the false alarm rate as a function of the strength of correlation among the target returns that have a signal strength of 10dB when only one sample in each reference subset is doped with fallacious target return (r_1=r_2=1) and the CFAR circuit is provided by a post-detection integrator that integrates two consecutive sweeps (M=2). The displayed results demonstrate that the LF strategy, the conventional OS scheme, and traditional TM detector are the only ones that have the ability to keep the rate of false alarm fixed near its designed value; irrespective to the correlation of the interferer's returns, whilst the CA processor along with its modified versions fails to attain such requirement.

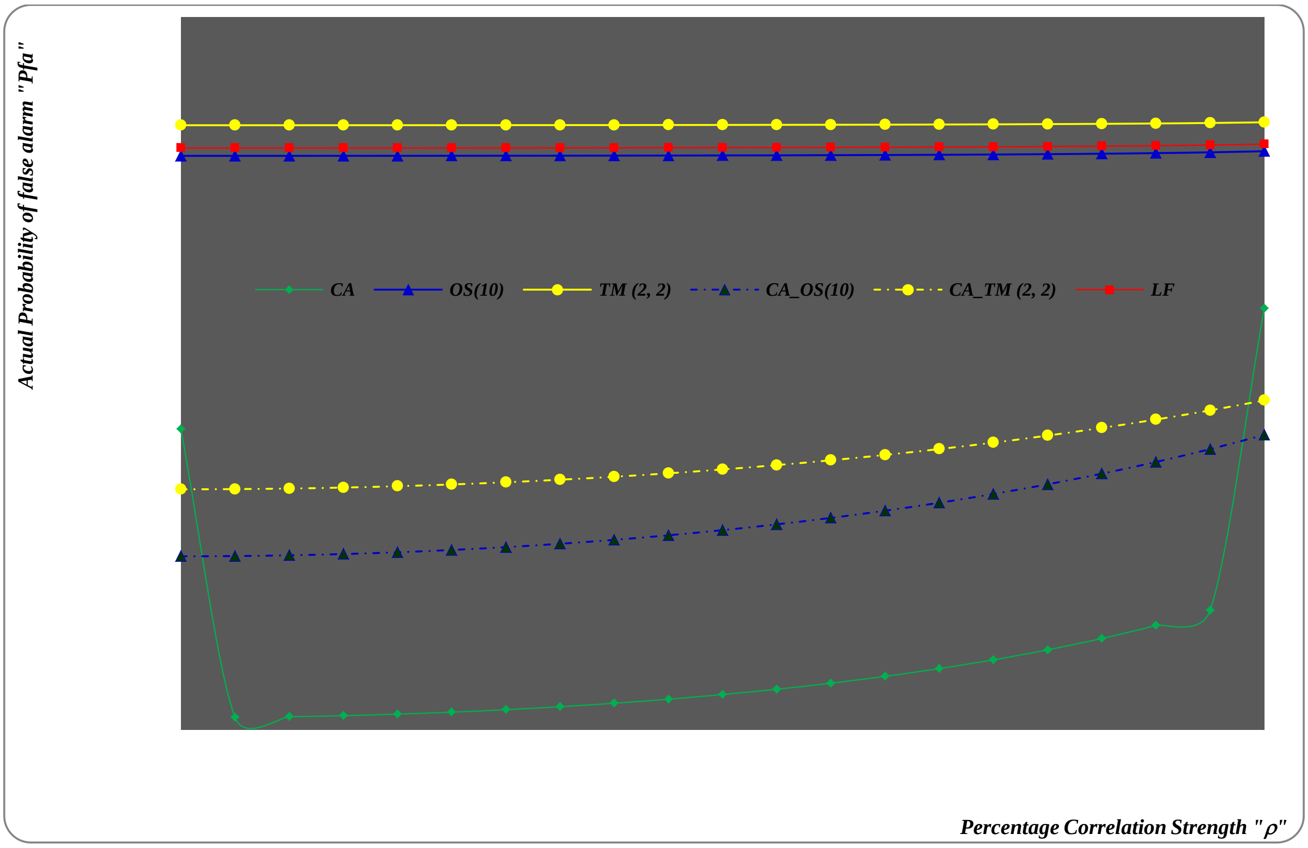

Fig.15. Multi-target actual false alarm probability of CFAR detectors for χ^2 fluctuating targets with 2-degrees of freedom when N=24, M=2, r_1=r_2=1, INR=10dB, and design P_{fas}=10^{-6}

7. Conclusions

The performance of the linear fusion procedure of adaptive detection in homogeneous as well as in heterogeneous backgrounds, when the target of interest along with the spurious ones follow χ^2-distribution with two-degrees of freedom in their fluctuation, with the special curiosity to the partially-correlated target returns, have been analyzed in this paper. Closed form formulas for the detection and false alarm probabilities were analytically investigated and the performance of the underlined methodology along with its fundamental variants was evaluated and numerically simulated. The simulation results exhibited that the new technology possesses a satisfactory performance and robustly reacts against non-ideal conditions. A comparative study, associated with the detection of partially-correlated targets by the LF scenario, against CA, OS, and TM mechanisms along with their developed versions was done. The obtained numerical results revealed that the LF strategy outweighs, in its detection performance, the standard N-P processor which is taken as a yardstick in any new contribution in the CFAR world. Additionally, the displayed results demonstrated that there is an evident amelioration in the processor performance when the radar receiver is supplied with a post-detection integrator. Moreover, the LF fusion type can detect radar targets that cannot be detected by the CA algorithm which is considered as the king of the CFAR alternatives. More specifically, the LF mechanism presents unique merits in terms of detection performance enhancement in comparison with the state-of-the-art CFAR techniques. In target multiplicity situation, on the other hand, the novel model has a detection behavior which is closed to that of the N-P scheme and may surpass it if the target returns were strengthened.

In summary, through extensive simulations, the superiority and robustness of the proposal were clearly demonstrated by outperforming the conventional processors of CA, OS, and TM-CFAR in scenarios with different correlation strengths among target returns, and false alarm probabilities. The cost is that LF-CFAR suffers from more computational burden and elapsed time than other processors. Finally, the results of the study allow drawing conclusions about which architecture is more suitable to be applied for improving the current radar systems.

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