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Performance analysis for airborne radar and clutter suppression

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Abstract
In airborne radar systems the returning echoes are taken by the antenna and passed through the detector circuits to obtain the envelope of the signal. To conquer the undesired clutter and interference constant false alarm rate algorithms are used these are well known for target identification in the clutter area. The aim of this work is to investigate the performance of different types of CFAR algorithms, and the effectiveness of the clutter suppression and target detection in radar systems. The comparative performance results show that the neural net- CFAR (NN-CFAR) detector has superior target detection in comparison with other types of CFAR detectors in clutter environments. Insights can be learned on issues like trespasser's motion, which are tougher to track due to complexity and hard terrains the adaptive learning helps it model the noise complexities thus decreasing false alarms and increasing probabilities of detection. In this work, the performance of NN-CFAR has been established and could prove to be a durable solution for improving radar target detection in scenarios where the environment is complex.

Keywords: Airborne radar systems, returning echoes, detector circuits, signal envelope

1. Introduction

Airborne radars outstanding performance upgrades their reliability in modern applications, such as aircraft, cruise missile, flying system, and target surveillance [1]. In the meanwhile, the clutter suppression methods have been the subject of radar research which can reduce the influence of strong ground clutter and enable the coherent radar signal to noise ratio (SNR) to estimate the true values of target scattering signals [2]. The airborne radar propagates and receives the electromagnetic wave by using the directional antenna, so the echo signal coming from the terrain surface can be strong significantly. The strong clutter causes the reduction of radar performance and target detection rate, and increases the false alarm rate. Therefore, the suppression of clutter echo is a significant issue for radar detection processing [3].

Ground clutter, which generally involves a mixture of fixed and moving components caused by man-made objects or natural phenomenon, leads to a serious performance degradation in target detection due to its high level of power and substantial fluctuation in radar returns. However, to the best of our knowledge, the clutter components with different values of Doppler frequency are all attenuated by filter banks or frequency discriminators in the same way. Clutter models are adopted to optimize the clutter suppression filter, even recently, ground clutter signals are hard to measure, predict, or model [4].

In the airborne radar receiver, the returning echoes are typically received by the antenna and then passed through detector circuitry that extracts the envelope of the signal, unwanted clutter and interference sources that detected can removed by used of CFAR detection as shown in figure [1].

In many cases the radar detection threshold is constantly adjusted as a function of the receiver noise level in order to maintain a constant false alarm rate. Radar works always in an environment with different sources of noise. It seeks for use of the adaptive threshold detector, which has a feature that adjusts automatically its level according to variety of the interference power in order to maintain a constant false alarm rate. Detector in radar receivers with this feature is known as the CFAR [5], that CFAR processors are utilized in order to keep the number of false alarms under control in a changing and unknown background of interference [6]. There different analytical methods to solve non homogeneous situations within the radar return the neural networks is possible to state that utilizing the proposed neural net with simple architecture led to reducing the impact of radar clutter when detecting radar targets on maps created from provided datasets [7]. Several authors have proposed fuzzy CFAR detector for the K distribution and nonhomogeneous background data for multiple-sensor distributed systems that simulation works show that the detection performance of the proposed fuzzy CFAR can almost be better than that of the CA-CFAR in homogeneous non-Rayleigh backgrounds and is better than that of the OS-CFAR in nonhomogeneous environments in both interfering targets and clutter edge conditions [8, 9].

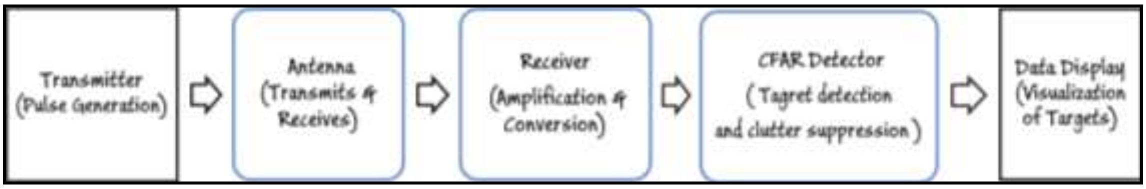

Fig 1: General block diagram of the airborne radar

2. Methodology

A detector in radar receivers has to be a detector with the adaptive threshold since radars always operate in an environment with a range of noise interference [10]. CFAR algorithms are a strong detection technique used in fields such as radar, communication systems and signal processing. Due to the disorderliness of clutter space it is often represented in terms of a statistical function of density of probability (P_{df}). In the last years, due to the introduction of high resolution radars it was realized that the clutter could not be always modeled by Gaussian distribution. The manner in which the high frequency increment in the amplitudes of the waves, starting from the peaks in the distribution, goes beyond the fixed threshold in the detection leads to numerous false alarms. Developments in recent investigation of sea clutter model, adaptive model is used with other distributions like Weibull, Rayleigh and K-distribution and which intern reduce the false alarm rate. However, sea clutter is not static but dynamic in nature and none of the earlier proposed distribution can represent the sea clutter completely [11]. Weibull clutter model has been employed for modeling of both land and sea clutter and it can be stated that the general form of Weibull distribution can be brought into correspondence with experimental data in a much wider range of conditions compared with other distributions [12, 13].

2.1 CA-CFAR detection

In a radar system, it is required to find out the level of power that any return that can be identified as a target. This threshold is set to ensure that required probability of false alarm rate is achieved by most radar detectors. In a natural environment, external interference and noise are often distributed in space and time. In this case, an adaptive threshold should be used, whereby the threshold level is adjusted to make the probability of false alarm constant. To achieve this, the following formula is used; This method is called CFAR detection [14]. The received signal x(t) in the cells is given by the following expressions, in cell averaging, a number of range and /or Doppler bins (cells) are processed Each pulse that is emitted results in an echo return and is measured using the square-law detector.

In analog implementation, these cells are obtained from a tapped delay line. The Cell under Test (CUT) is the central cell. The immediate neighbors of the CUT are excluded from the averaging process due to a possible spillover from the CUT [15, 16, 17]. When statistical variations occurs, meaning the clutter shape parameter is fluctuating, the operational false alarm probability deviates from the intended design value [18]. The output of M reference cells (M/2 on each side of the CUT) is averaged. The threshold value is obtained by multiplying the average estimate from all reference cells by a constant K_0 (used for scaling)

A detection is declared in the CUT if $Y_1 \geq K_0 Z$ CA-CFAR assumes that the target of interest is in the CUT and all reference cells contain zero-mean independent Gaussian noise of variance σ^2. Therefore, the output of the reference cells, Z, represents a random variable with gamma probability density function (pdf) with $2M$ degrees of freedom.

The CFAR averaging as shown in figure (2) [6] is often implemented after noncoherent integration, the output of each reference cell is the sum of n_p squared envelopes. It follows that the total number of summed reference samples is Mn_p. The output Y_1 is also the sum of n_p squared envelopes. When noise alone is present in the CUT, Y_1 is a random variable whose pdf is a gamma distribution with $2n_p$ degrees of freedom. Additionally, the summed output of the reference cells is the sum of Mn_p squared envelopes. Thus, Z is also a random variable which has a gamma pdf with $2Mn_p$ degrees of freedom.

The probability of false alarm (P_{fa})is then equal to the probability that the ratio Y_1/Z exceeds the threshold.

$$P_{fa} = \text{Prob}\left\{\frac{Y_1}{Z} > K_1\right\} \tag{1}$$

Equation (5) implies that one must first find the joint Pdf for the ratio Y_1/Z. However, this can be avoided if P_{fa} is first computed for a fixed threshold value V_T, then averaged over all possible values of the threshold. Therefore, let the conditional probability of false alarm when $y = v_T$ be $P_{fa}(v_T = y)$. The false alarm probability is:

$$P_{fa} = \int_0^\infty P_{fa}(v_T = y) f(y) dy \tag{2}$$

Where $f(y)$ is the probability density function (Pdf) of the threshold is given by [6]:

$$Pdf = f(y) = \frac{\left(\frac{y}{K_1}\right)^{Mn_p-1} e^{\left(-\frac{y}{2K_1\sigma^2}\right)}}{(2\sigma^2)^{Mn_p} K_1 \Gamma(Mn_p)} ; \quad y \geq 0 \tag{3}$$

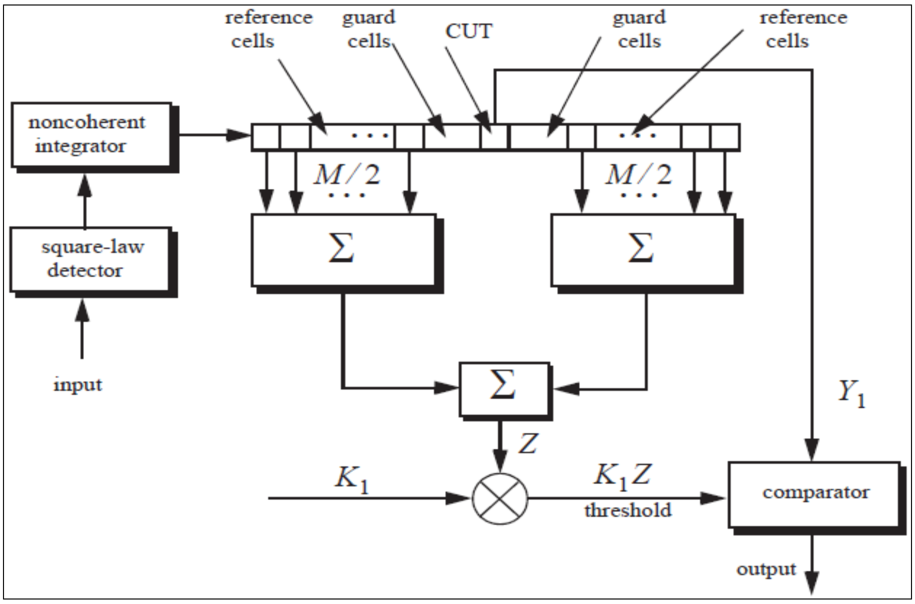

Fig 2: The typical CA-CFAR processor [REF [4, 6].

The typical CA-CFAR system is a very popular algorithm because of its very simple architecture and low computation effort. However, the performance of a CA-CFAR detector can degrade due to multiple targets and non- uniform clutter [12].

2.3. OS -CFAR Detector

The Ordered Statistics-CFAR (OS-CFAR) was proposed by Rohling [17] and consists of selecting an appropriate reference cell to estimate the background clutter power level [19].

Rohling [17] defines an order statistics CFAR that is designed to suppress target masking. The OS-CFAR rank orders the N samples in the CFAR reference window and selects the k-th sample as the CFAR statistic. The CFAR is thus capable of rejecting $N-k$ interfering targets. In addition, an OS-CFAR is capable of suppressing clutter edge false alarms provided $k > N/2$. provide the following expressions for the average P_D and P_{FA} [20]:

$$P_D = \prod_{i=0}^{k-1} \frac{N-i}{N-i+\frac{\alpha_{os}}{1+SNR}} \tag{4}$$

$$P_{FA} = \prod_{i=0}^{k-1} \frac{N-i}{N-i+\alpha_{os}} \tag{5}$$

where α_{OS} is the OS-CFAR constant Rohling [17] examines the CFAR loss associated with an OS-CFAR and shows that it exhibits a relatively broad minimum as a function of k. To achieve a CFAR loss near the minimum, a reasonable value of k is $3N/4$ [20].

The OS-CFAR processor exhibits some loss of detection power in homogeneous noise background compared with the CA-CFAR processor but its performance in a multiple target environment is clearly superior, so its performance in a homogeneous environment is poorer than that of the CA-CFAR detector [16]. The OS-CFAR processor is unable to prevent excessive false alarm rate at clutter edges, unless the threshold estimate incorporates the ordered sample k near the maximum, that is unless k is very close to N; but in this case the processor suffers greater loss of detection performance [11].

2.4. Fuzzy-CFAR Detector

Proposed combined detection method using Fuzzy-CFAR detector is to improve the effectiveness of target detection in the radar systems especially in cluttered environments with non-homogeneous characteristics. The results show that the Fuzzy soft decision CFAR detector provides better probability of target detection in non-Rayleigh environments than the conventional schemes and thus is useful in case of radar systems performing in adverse scenarios [8].

The flow chart in figure (3) illustrate the processes used in the Fuzzy-CFAR combined detection methodology. The clutter characteristics of the real environment are lumped into fuzzy uncertain domain while a CA-CFAR framework which offers adaptive thresholding to sustain constant false alarm rate. These includes identification of fuzzy membership functions, the fuzzy inference system as well as the mean and threshold calculations, the detection decision process and the evaluation of the metrics of performane metrics.

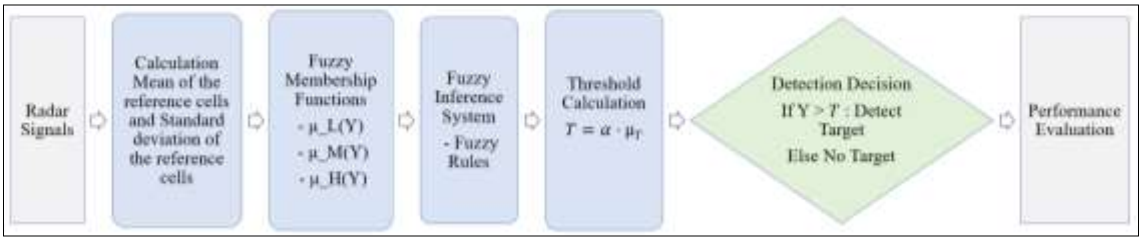

Fig 3: Processes of the Fuzzy-CFAR

This model incorporates Fuzzy logic to manage uncertainty and variability in clutter characteristics while leveraging the CA-CFAR approach for adaptive thresholding.

The fuzzy inference system combines the membership functions to determine the degree of target presence, that fuzzy rules are used to combine the membership values [21].

The mean of the reference cells (μ) and the standard deviation of the reference cells(σ) of the reference cells are calculated as:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} X_i \tag{6}$$

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(X_i - \mu)^2} \tag{7}$$

The Y represent the signal in the cell under test (CUT), Xi represent the values in the reference cells surrounding the CUT and N be the number of reference cells used for averaging. The Fuzzy membership functions [21] are defined to represent the degree of membership of the CUT signal in different categories (e.g., target, clutter): The value of k determines the width of the membership functions, the choice of k depends on the specific application and the desired level of overlap between the membership functions. A common value used is k = 1.

$$\text{Low Membership Function:}\quad \mu_L(Y) = \begin{cases} 1 & \text{if } Y \le \mu - k\sigma \\ \frac{\mu + k\sigma - Y}{2k\sigma} & \text{if } \mu - k\sigma < Y < \mu + k\sigma \\ 0 & \text{if } Y \ge \mu + k\sigma \end{cases} \tag{8}$$

$$\text{Medium Membership Function:}\quad \mu_M(Y) = \begin{cases} 0 & \text{if } Y \le \mu - k\sigma \text{ or } Y \ge \mu + k\sigma \\ \frac{Y - (\mu - k\sigma)}{2k\sigma} & \text{if } \mu - k\sigma < Y < \mu \\ \frac{(\mu + k\sigma) - Y}{2k\sigma} & \text{if } \mu \le Y < \mu + k\sigma \end{cases} \tag{9}$$

$$\text{High Membership Function:}\quad \mu_H(Y) = \begin{cases} 0 & \text{if } Y \le \mu - k\sigma \\ \frac{Y - (\mu - k\sigma)}{2k\sigma} & \text{if } \mu - k\sigma < Y < \mu + k\sigma \\ 1 & \text{if } Y \ge \mu + k\sigma \end{cases} \tag{10}$$

Fuzzy inference system combines the membership functions to determine the degree of target presence:

$$\mu_T(Y) = \max\big(\min(\mu_L(Y), \mu_M(Y)), \min(\mu_M(Y), \mu_H(Y))\big) \tag{11}$$

The threshold for detection is calculated as:

$$T = \alpha \cdot \mu_T(Y) \tag{12}$$

Where T is threshold level and α is the optimal threshold multiplier.

Probability of Detection (P_d):

$$P_d = P(Y > T \mid \text{Target Present}) = \int_T^{\infty} p(Y \mid H_1)\,dY \tag{13}$$

where H_1 indicates the hypothesis that a target is present.

The relationship between P_d and SNR:

$$P_d \approx Q\left(\frac{SNR - T}{\sigma}\right) \tag{14}$$

where $Q(x)$ is the Q-function, which represents the tail probability of the standard normal distribution.

Probability of False Alarm (P_{fa}):

$$P_{fa} = P(Y > T \mid \text{No Target}) = \int_T^{\infty} p(Y \mid H_0)\,dY \tag{15}$$

where H_0 indicates the hypothesis that no target is present.

Relation of P_{fa} to threshold level T:

$$P_{fa} = e^{-\lambda T} \tag{16}$$

The λ is a parameter related to the noise characteristics.

Signal-to-Clutter Ratio(SCR):

$$SCR = \frac{P_t}{P_c} \tag{17}$$

where P_t is the power of the target signal and P_c is the power of the clutter.
Clutter Attenuation (CA):

$$CA = \frac{P_{c_{\text{in}}}}{P_{c_{\text{out}}}} \tag{18}$$

where $P_{c_{in}}$ is the clutter power at the input and $P_{c_{out}}$ is the clutter power at the output.
Target-to-Clutter Ratio (TCR):

$$TCR = \frac{P_t}{P_{c_{\text{out}}}} \tag{19}$$

It should be noted here that Fuzzy-CFAR is less sensitive to clutter statistics and hence can be effectively implemented in a situation where the clutter characteristics are likely to exhibit a change in real-time. This makes it very robust since it adapts to current conditions to alter the detector's sensitivity threshold as opposed to adjusting it in accordance with historical precedents alone.

2.5. Neural Network CFAR Detection

Neural network model that learns from the radar signal characteristics and the surrounding noise. The model is then trained on radar signals that are synthesized out of real radar data. The adaptive mechanism is used to provide the network with the ability to change its parameters when the levels of clutter and noise are varying thus increasing the reliability of detection.
This model combines neural networks with CFAR, (NN-CFAR) detection to improve target detection in the radar systems especially when many clutters are present.
The neural network is trained with the obtained input features extracted from reference cells described by the statistical properties with the mean and standard deviation equations (6), (7). The experiments have shown that despite the fact that the NN homogeneity test is essentially a simplified version of the homogeneity test, it has a better performance when identifying non homogeneities within a radar return compared to the classical methods [11]. The processes that are employed in the NN-CFAR combined detection methodology is shown in a flowchart in fig (4).

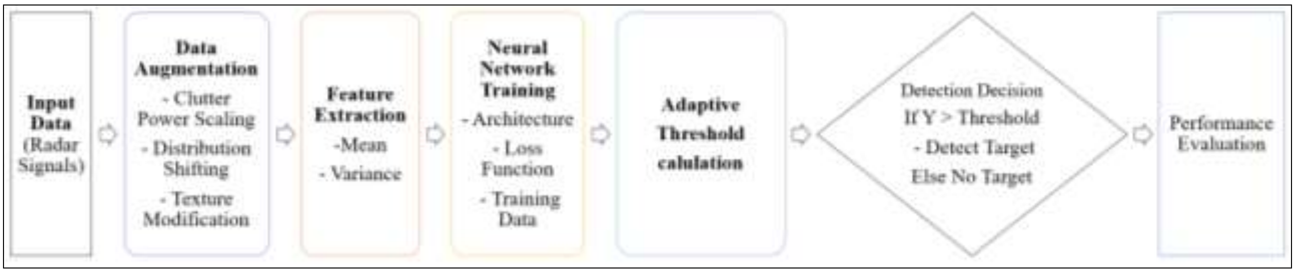

Fig 4: Process of Neural-CFAR detectors.

The training objective is to minimize the error in estimating the optimal threshold multiplier α.
The detection loss function is the mean squared error (MSE) between the predicted threshold multiplier (α_pred) and the true threshold multiplier (α_true), and it used in the neural network training for estimating the optimal threshold multiplier α.

$$\text{Detection Loss} = \frac{1}{M}\sum_{j=1}^{M}\left(\alpha_{\text{pred},j} - \alpha_{\text{true},j}\right)^2 \tag{20}$$

where M is the number of training samples.
Probability of Detection: The probability of detecting (Pd) a target in the presence of clutter.

$$P_d = P(Y > T \mid \text{Target Present}) - \int_{\tau}^{\infty} p(Y \mid H_1)dY \tag{21}$$

where H_1 indicates the hypothesis that a target is present.
The ratio of the power of the target signal to the power of the noise. can be approximated using the Q -function:

$$P_d \approx Q\left(\frac{SNR - T}{\sigma}\right) \tag{22}$$

where $Q(x)$ is the Q-function, representing the tail probability of the standard normal distribution.
The probability of falsely detecting a target when no target is present.

$$P_{fa} = P(Y > \tau \mid \text{No Target}) - \int_{T}^{\infty} p(Y \mid H_0)dY \tag{23}$$

where H_0 indicates the hypothesis that no target is present,
Threshold Level (T): The detection threshold above which a signal is considered a target. As threshold level τ increases, Pfa decreases in relation,

$$P_{fa} = e^{-\lambda T} \tag{24}$$

where λ is a parameter related to the noise characteristics.
The threshold level can vary with detection range due to changes in signal strength and noise characteristics. The relationship can be expressed as:

$$\tau(R) = T_0 + k \cdot R \quad (25)$$

where T_0 is the base threshold at a reference range, and k is a constant that represents the rate of change of the where (R) is detection range.

3. Simulation Results

As for the performance assessment, analytical models are given along with MATLAB codes to simulate the proposed CFAR techniques for different scenarios with respect to SNR and clutter environment. Start by generating the clutter regions by following these steps; Generate a radar Data Generator and Noise and clutter are produced by using Gaussian random variables in MATLAB. In figure (5) shows detected targets signals by implements a NN-CFAR detector by using MATLAB cods. The noise and clutter are implemented as random variables with Gaussian distribution. A signal is generated similarly. The average noise estimate is calculated from the combined noise and clutter. A detection threshold is set based on this estimate, where Number of cells in the reference window N = 32, Guard cells G = 4%, Probability of false alarm P_{fa} = 1e^{-6}, SNR = 10_{dB}.

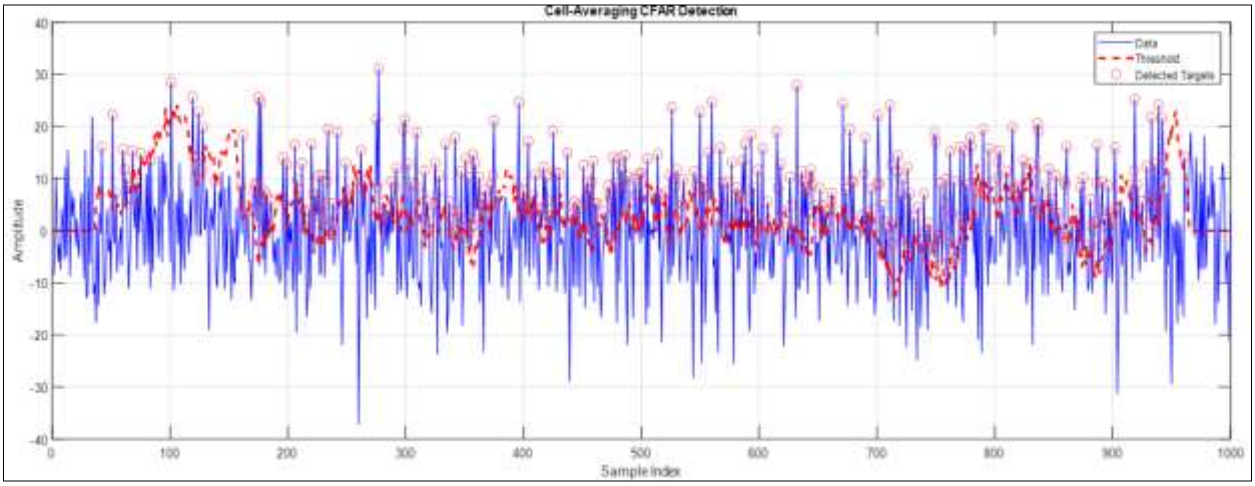

Fig 5: Signal received and detected targets signals at some of range cells.

The figure (6) demonstrates that used NN-CFAR processing it is possible to detect signals (targets) in noisy surroundings successfully. Depending on the conditions of the detection, some factors can be changed: reference cells size, threshold factors, the number of samples N = 1000 of the dataset, the number of used reference cells =20 to estimate noise, parameters of guard cells=5 and the detection threshold equals to 1.5 based on the noise level.

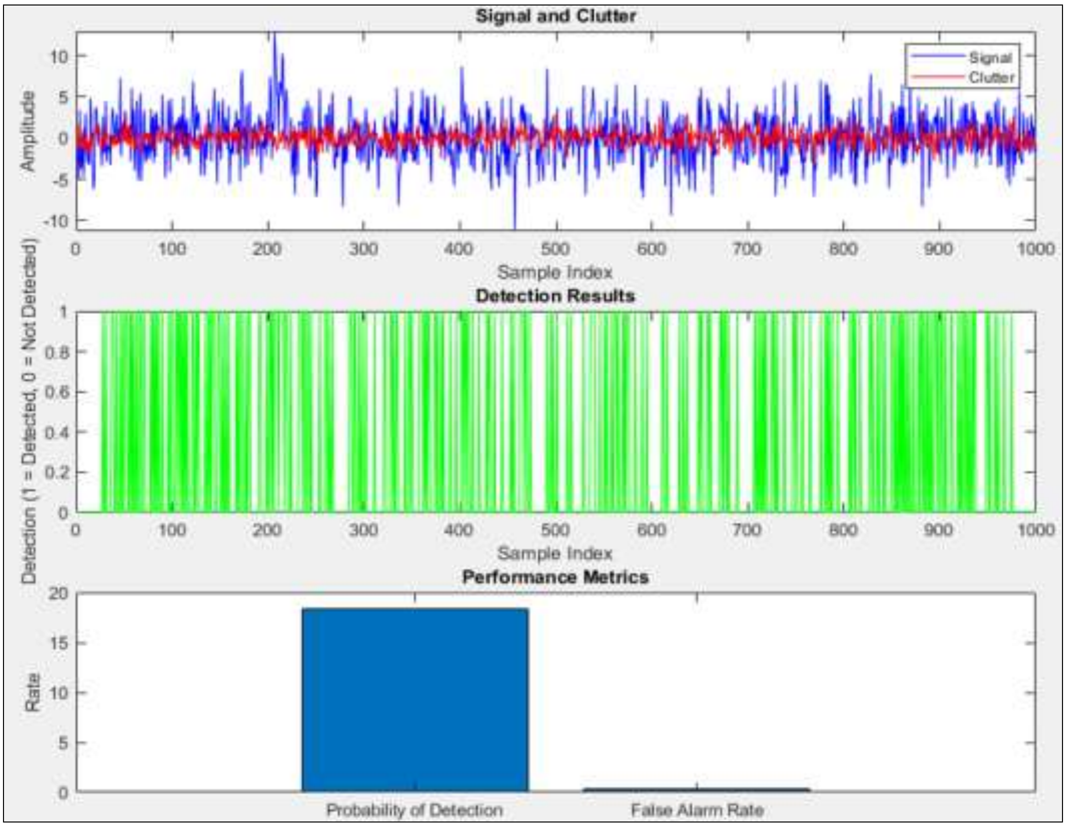

Fig 6: Detect signals amidst clutters.

It can be observed in figure (7) that NN-CFAR has the least detection loss for all threshold level. This suggests that the method is less sensitive to noise and clutters and will produce better detection performance even if set at lower thresholds. OS-CFAR results in a higher detection loss at lower threshold but decreases sharply at higher thresholds.

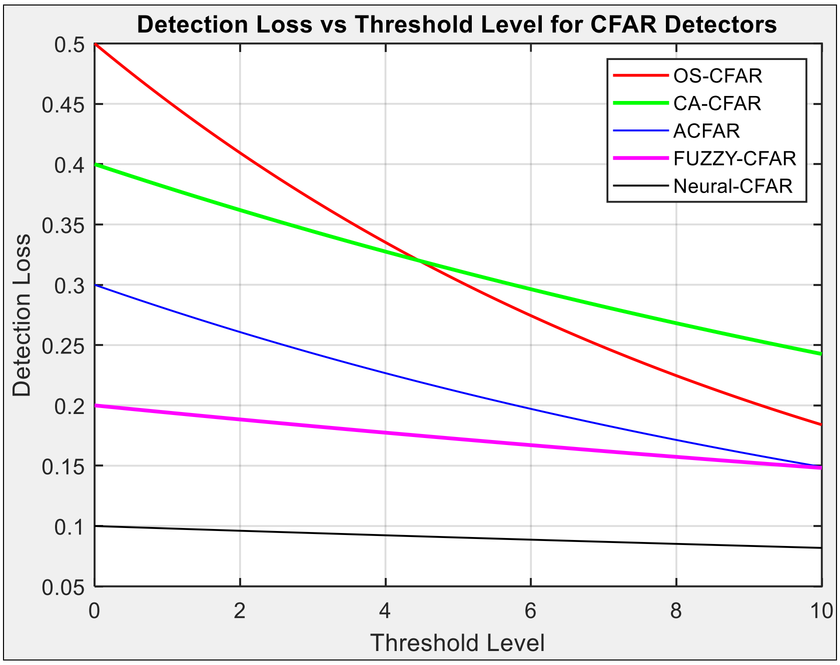

Fig 7: Detection loss vs threshold level

In figure(8)shows the Probability of False Alarm with respect to threshold levels illustrates that compared with other methods NN-CFAR has achieved the lowest Pfa level at any specific threshold.

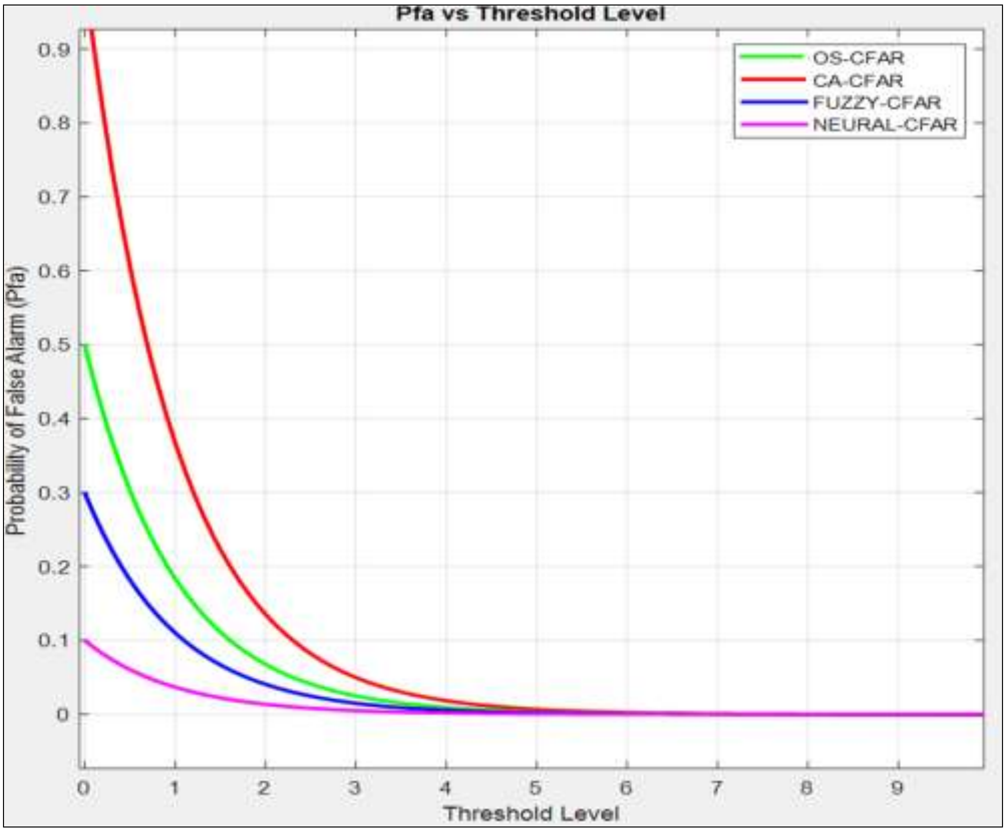

Fig 8: The Probability of False Alarm versus threshold levels

Figure(9) shows the Neural-CFAR consistently exhibits lower detection loss across all SNR levels compared to other methods. This indicates its robustness in identifying targets even in low SNR conditions. The adaptive nature of NN-CFAR allows it to effectively learn and adjust to varying noise environments, contributing to its superior performance. Num. of samples = 1000; SNR_{dB} = -10:1:20 and the clutter level = 0.5.

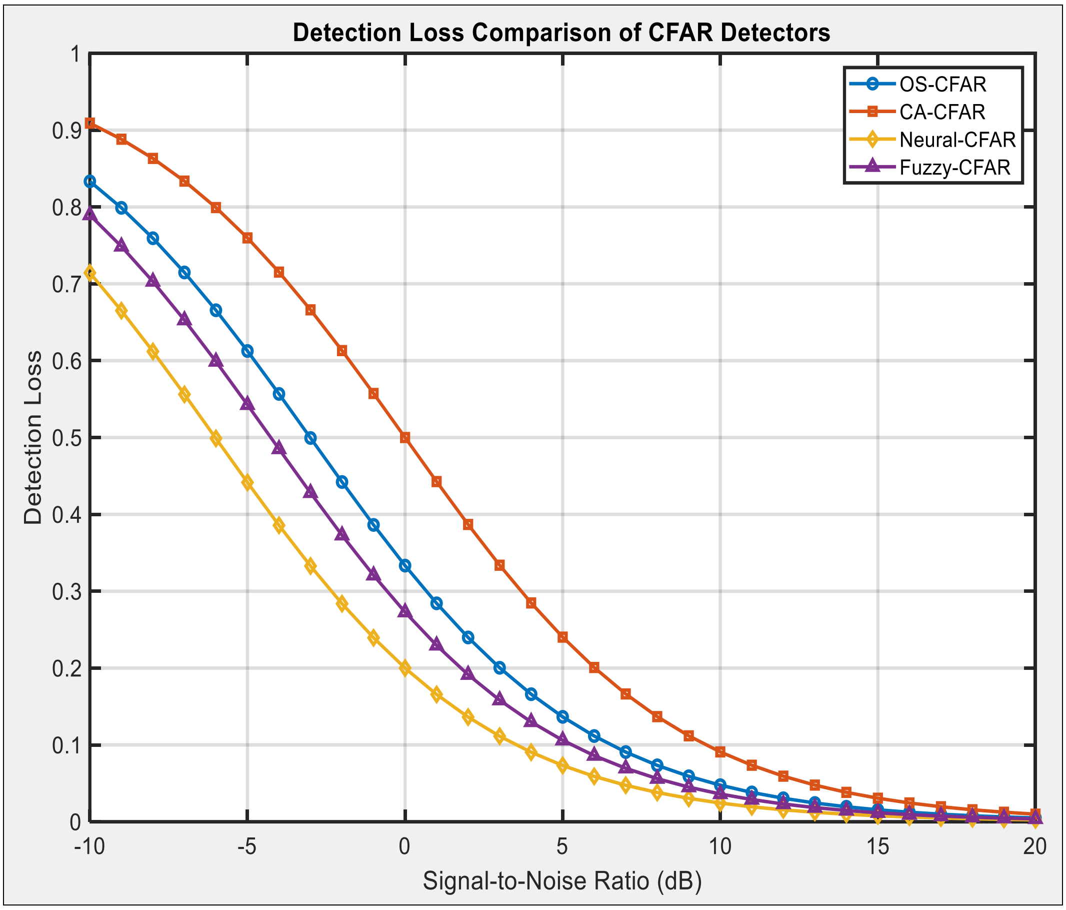

Fig 9: Detection Loss vs SNR:

From the figure (10) shows that the probability of false alarm rate is directly proportional to the amount of noise variance in received signal for radar target detection, that slight increase in total noise power will increase the probability of false alarm to larger factor. Noise Variance are set from 0 to 5 with the interval of 0.1 which denotes various levels of noise. Turn threshold to T=1 for checking of false alarms. From the graph it is observed that the variation of Pfa with noise variance is least for the NN-CFAR detector out of all the detectors.

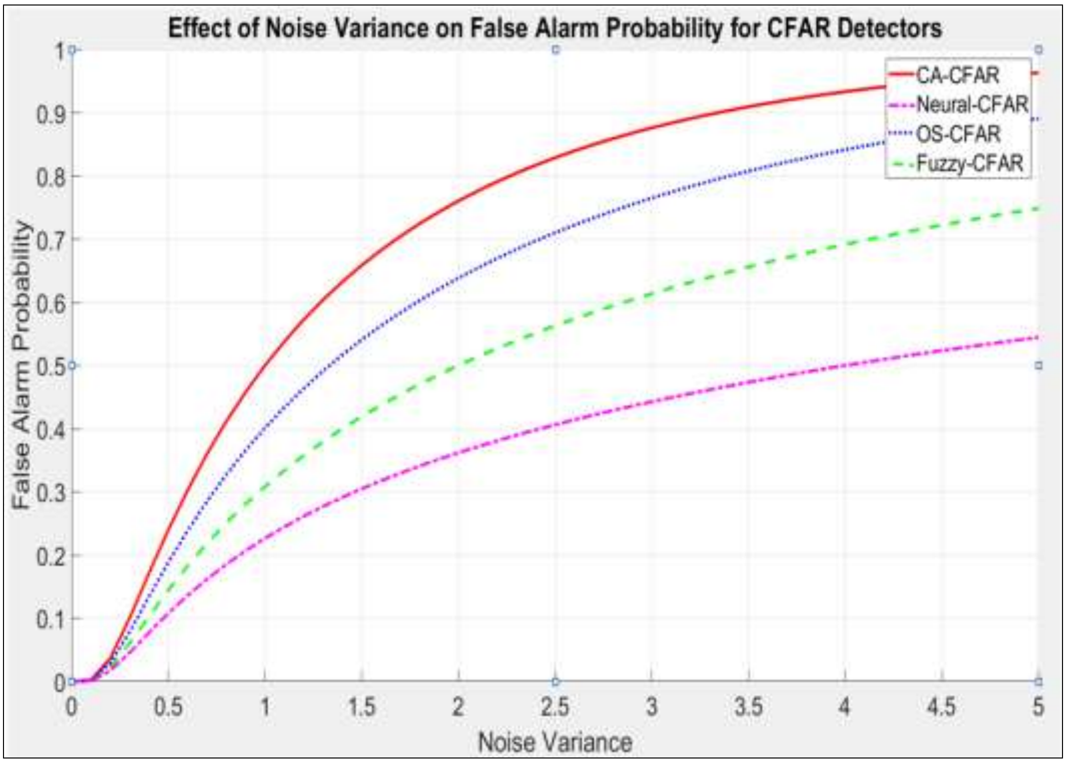

Fig 10: The false alarm probabilities based on noise variance for the different CFAR detectors.

The figure (11) also indicates that at a certain level of SNR, the NN-CFAR has a higher probability of detection as compared to the Fuzzy-CFAR.

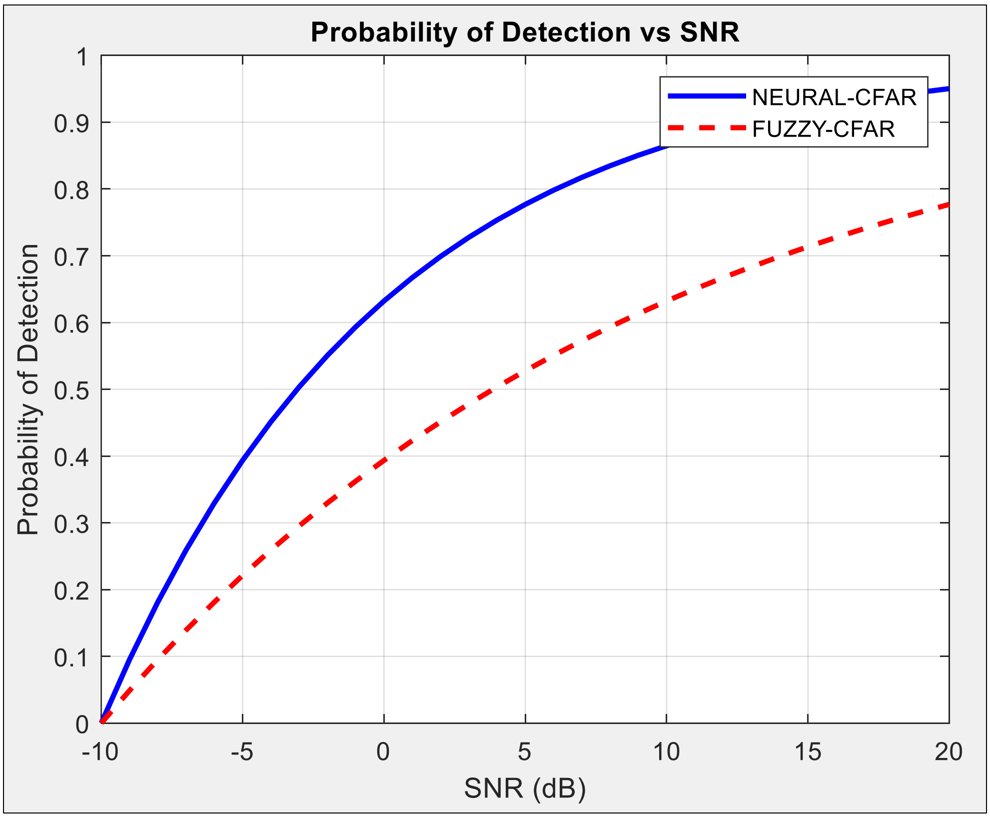

Fig 11: Probability of Detection vs SNR

Conculation

Comparing different type of CFAR algorithms, it is found out that flexibility and high performance are two major criteria of the target detection systems. These conclusions can be employed in further research aimed at the improvement of the methodologies in the framework of airbone radar systems which enhance their complicated operating modes and ensure the required level of target detection probability coupled with the minimal false alarm rate.

That is why the choice of the best CFAR detector is directly linked to given characteristics of an environment. In this paper, we have covered NN-CFAR, Fuzzy-CFAR, OS-CFAR and CA-CFAR techniques for high complexity situations as additional processing is needed. In this estimative, the neural network CFAR detector is presented and analyzed with conditions relating to benchmark of conventional methods and optimal theory. By simulation it seems that generalized NN-CFAR attains more suitable performance than other CFAR algorithms, is good in terms of detection especially when there is variation in noise level, has higher probability of detection for given SNR value, less decision threshold average and it seems to have low probability of false alarm as low as possible to the desired rate.

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