Adaptive Thresholding in Marine RADARs

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Abstract: In order to detect targets upon sea surface or near it, marine radars should be capable of distinguishing signals of target reflections from the sea clutter. Our proposed method in this paper relates to detection of dissimilar marine targets in an inhomogeneous environment with clutter and non-stationary noises, and is based on adaptive thresholding determination methods. The variance and the mean values of the noise level have been estimated in this paper, based on non-stationary, statistical methods and thresholding has been carried out using the suggested two-pole recursive filter. Making the rate of false alarm constant, the concerned threshold resolves the hypothesis of existence or absence of the target signal. Performance of the mentioned algorithm has been compared with the well-known conventional method as CA-CFAR in terms of decreasing the losses and increasing calculation speed. The algorithm provided for detection of signal has been implemented as a part of signal-processing algorithms of some practical marine radar. The results obtained from the algorithm performance in a real environment indicate appropriate workability of this method in heterogeneous environment and non-stationary interference.

Keywords: adaptive thresholding; CFAR; detection; RADAR; two-pole filter.

1 Introduction

Detection is one of the most important subjects in communication receivers, including radar systems. An optimum detector determines either of the two assumptions of existence or absence of the target signals, with regard to the received observations and based on a given theorem. It is obvious that there is no receiver free from noises, thus such a decision to be made would not be free from errors. Usually, depending on the application, different optimization criteria such as Bays and Newman Pierson are used in designing detectors [1].

When radar reflected signal is contaminated with noise and clutter effect, fixed threshold cannot keep the false alarm ratio constant. Therefore, it would be necessary to use CFAR circuits in decision making for target detection in radar systems. Adaptive thresholding, non-parametric methods and clutter maps are the three major approaches ever have been introduced for thresholding, with constant false alarm [2]. Adaptive thresholding method assumes that the noise density function is known and there are only some unknown parameters in which should be estimated. Then, the unknown parameters would be estimated using the information of the neighbor points to the reference point. So, the threshold will be estimated. Parametric or non-parametric methods are based on the two hypothesis of existence or absence of a signal, assuming that the signal pdf and interference are known. For example, the GLRT detector has been known as both parametric and non-parametric detectors [3]. As the signal density function and interference are known in this detector, it is considered as parametric and as its statistical specifications vary with time and the environment variations, it is also considered as a non-parametric detector. When signal and interference pdfs are known, GLRT can be considered as the optimum detector.

Similarly, the clutter map method requires storage of the environment data in a number of different scans [4]. After these scans, the clutter map is prepared and thresholding is performed through comparison of signal and noise with the stored clutter map [5].

As the environments for marine radars are mainly inhomogeneous and non-static and assuming homogeneity may increase false alarm ratio in the system, performance of implementing maximum likelihood based method such as CA-CFAR, GO-CFAR etc. is not in a good condition. The radar which must detect targets upon the sea surface or near that should be capable of discriminating targets from the sea waves. Such reflections are also called sea clutters or echoes, which, compared to noises, can be even make more false alarms and may limit the radar detection

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capability. The most important issue in correct performance of a radar system is the detection algorithm of it which means announcement of the existence or absence of a target. Completely correct with real-time decision is something impossible, unless the radar is equipped with a rapid detection system with acceptable accuracy. In case we are going to use adaptive or non-parametric methods in thresholding and making decision in radars, it is necessary to be knowledgeable on the noise and clutter density functions and generally on interference in designing the detector. Designing optimum linear detectors follows with inverse calculation of the interference covariance matrix. As this calculation is practically difficult to implement as radar processor units with current technology, adaptive thresholding methods have been used in this paper for designing detectors.

The most important problem for CA-CFAR thresholder is its relatively high losses in heterogeneous conditions. This is why lots of papers have been prepared since long aiming to suggest a new method for decreasing the mentioned losses [6], [7], [8]. Our proposed algorithm aims to decrease the rate of CA-CFAR losses while increase its calculation speed. For more rapid implementation compared to the conventional CFAR methods, the obtained threshold has been implemented to the signal using a recursive filter with known coefficients. The comparison decision of this threshold, calculated on adaptive basis for radar different ranges, has been considered as detection criteria.

This paper has been developed in five sections. The next section provides a model for the receiver noise, for the received signal and the sea clutter. The third section provides the suggested algorithm for the thresholder along with design of the detector. Forth section shows the results of simulations and implementation of the suggested algorithm compared to CA-CFAR. Furthermore the conclusion comes as the last section.

2 Modeling of Signal and Received Interference

In fully coherent radars, the signals reflected from a target may have both modulations for the range and phase. As sea marine radars are confronted with slow-moving targets such as vessels or low-speed boats, there is generally no need in detection criteria to keep the phase and using coherency technology [9]. Thus, the reflected signal from a non-coherent radar target can be written as follows in marine radars:

$$S(t) = a_r(t)e^{j\,2\pi\,(f_o)t + j\,\varphi_0(t)} \tag{1}$$

where $a_r(t)$ is the range of reflected signal and $\varphi_0(t)$ is the initial phase of the transmitted frequency or f_o. $\mathrm{f_d}$, which shows the Doppler frequency due to movement of the target, is actually absent in this equation, as it is actually lost in a non-coherent radar receiver after passing by the envelop detector.

2.1 Signal Modeling

In radar processors, the reflection from the target would be as follows [9]:

$$\mathbf{X} = \mathbf{S} + \mathbf{I} \tag{2}$$

where "**S**" shows the signal with the equation provided in Eq. (1) and "**I**" shows the interference (sum of noise and clutter).

$$\mathbf{I} = \boldsymbol{C} + \boldsymbol{N} \tag{3}$$

In the above equation, "$\boldsymbol{C}$" shows the clutter and "$\boldsymbol{N}$" stands for the receiver noise. Followings are the vector of signal and interference samples:

$$\boldsymbol{X} = [x_0 \quad x_1 \quad \dots \quad x_{N-1}]^t \tag{4}$$

$$\mathbf{S} = [s_0 \quad s_1 \quad \dots \quad s_{N-1}]^t \tag{5}$$

$$\mathbf{I} = [i_0 \quad i_1 \quad \dots \quad i_{N-1}]^t \tag{6}$$

2.2 Noise Modeling

The noise received in reflected signal from the target is a combination of receiver noise or the inside noise of the radar system and the outside noise (from the environment). The sun noise, atmosphere noise and the combustion noise in different sources are samples of environment noise. Internal noise consists of noises produced by the noise temperature of the antenna; the phase noise resulted from oscillators and receiver thermal noise. In frequencies higher than UHF, the effects of outside noises are so decreased that the received noise can just be attributed to the internal noise of the receiver. Samples of noise are always present in receiver output and they can never be diminished down to zero. The receiver noise which mostly belongs to the thermal noise due to the movement of electrons in semi-conductors, are normally considered as complex white Gaussian noise. In compliance with the nyquist sampling rate, the consecutive samples of noise get uncorrelated from one another. Following is the vector of noise samples along with their spectrum specifications:

$$\boldsymbol{N} = [n(0) \quad n(T_s) \quad n(2T_s) \quad \dots \quad n\big((N-1)T_s\big)]^t \tag{7}$$

in which "T_s" is the sampling time. The receiver noise has a white spectrum and its distribution function is assumed as Gaussian. In the following relationship, σ_n^2 is equal to the noise power.

$$E\{n_i n_j\} = \begin{cases} \sigma_n^2 & i = j \\ 0 & i \neq j \end{cases} \tag{8}$$

Thus, the noise covariance matrix can be expresses as follows:

$$\boldsymbol{R}_n = \sigma_n^2\, \boldsymbol{I}_n \tag{9}$$

where "$\boldsymbol{I}_{\mathrm{n}}$" is the unit matrix of $N \times N$.

2.3 Clutter Modeling

Nowadays, lots of measurements have been carried out by different researchers on the reflections from the sea surface. The measurements have been performed from HF frequency range up to millimeter to light waves and various data have been collected under different environment conditions. The data obtained from these measurements show high dispersal of the results, even in similar measurement conditions [6]. A reason for such high variations is difficulty of measurement or description of the sea state. Speed, period and direction of wind at the sea surface, oceanic flows, sea surface pollutions, the effects of storms in ocean surface in distant points and causing water waves and local climatic changes can all affect on the radar wave reflection from the sea surface. Thus, calibration of measurements at the sea surface is a difficult task, as this cannot be done under controlled conditions. Therefore, radar designers should take the above-mentioned changes into consideration in their designs and determine the radar performance under the effect of different conditions of sea reflections.

The Sea is one of the distributed targets which its echo range is depended on the dimensions of the area lighted by the radar beam width [7]. Parameters involved in the sea clutter can be divided into two sections; section one consists of the parameters relating to the radar such as carrier frequency, beam width of the antenna, polarization of the sent wave and pulse width and section two includes the environment-related parameters such as water undulations, height of the sea wave or sea force, speed and direction of the wind, etc.

So far, lots of models have been provided for describing the surface sea clutter density function, none of them in complete conformity with the actual conditions, with regard to the problems already mentioned with regard to the measurements. Rayleigh, Weibull, Log Normal, Gaussian mixture and K family models are of the most famous density functions provided in some papers for clutter distribution.

As in almost all sea marine radars, non-coherent integration is used to improve signal to noise ratio, decision is actually made based on pulse "N", where the "N" value is obtained with regard to rotation speed of the antenna, beam width and the pulse repletion frequency. Since clutter samples are not independent, and are highly correlated, joint distribution of "N" can be easily obtained by multiplying. Gaussian models resulted from central limit theorem (CLT) [1], can be taken into consideration for clutters when N different distributions are merged. Experience shows that Gaussian models are appropriate for radars rather than those with high range resolution and radars working in small beam width. When radar works in these conditions Rayleigh, Log Normal and K family distributions are introduced [10].

The particular radar in this paper is a commercial marine radar system in X band of frequency with almost 150-m range resolution cells and about 2-degree beam width at long ranges. As a wide area is seen as one cell, for this type of radar, water wave changes will have no considerable effect on the total area, against the radiated ray. Therefore, central limit theorem is applicable here and as the result, the Gaussian assumption can be applied to the sea clutter. However, when weak signal detection near a powerful clutter is considered, as the radar functions from a smaller pulse width with a range resolution of near 12 m, the Gaussian assumption of the clutter is not valid and the sea wave will show its non-stationary nature more considerably. We consider Weibull distribution for the sea clutter in the mentioned condition since we can obtain other introduced pdfs generally. For example we can reach to the Rayleigh distribution by setting 2 for the shape parameter in the Weibull distribution. This distribution is expressed by the following equation [4], [5]:

$$f_x(\mathrm{x}) = \frac{C}{\mathrm{B}}\left\{\frac{\mathrm{x}}{\mathrm{B}}\right\}^{\mathrm{C}-1} \exp\left\{-\left(\frac{\mathrm{x}}{\mathrm{B}}\right)^{\mathrm{C}}\right\} \tag{10}$$

where C and B are shape and scale parameters respectively. In order to obtain a constant false alarm ratio, our threshold based on C and B parameters is according to the following equation:

$$T = \{-\ln(P_{FA})\}^{\frac{1}{C}}B \tag{11}$$

where "P_{FA}" is the probability of false alarms. With regard to the correlation function of clutter samples, the clutter covariance matrix can be written as follows, which can be produced for each clutter model.

$$P_c = \begin{bmatrix} R_c(0) & \cdots & R_c((N-1)T_s) \\ \vdots & \ddots & \vdots \\ R_c((N-1)T_s) & \cdots & R_c(0) \end{bmatrix} \tag{12}$$

In the above equation, "T_s" is equal to time interval of the clutter consecutive samples. In Equation 12 $R_c(0)$ is equal to the clutter echo power received from the cell under test.

With regard to the above-mentioned equations, despite the noise covariance matrix, the clutter covariance matrix varies with changes in the environment conditions and the concerned cell spacing from the radar.

3 Design of Detector and Adaptive Thresholding

Here, based on the model provided for the signal reflected from the target, receiver noise and the clutter, a linear processor is provided. If a linear filter with "W" complex coefficient vector is used for detection, the most appropriate form for testing the linear detection is as follows [11]:

$$\left|\mathbf{W}_{opt}^{H}X\right| \underset{\mathrm{H}_0}{\overset{\mathrm{H}_1}{\gtrless}} \mathrm{T} \tag{13}$$

where "T" is the threshold which depends upon the appropriate P_{FA} and obtains from the Equation 11 and H_1 and H_0 are the existence and absence hypothesizes of the target, respectively. The "H" superscript in the above-mentioned equation stands for the Hermitian. Selecting "**W**" coefficients for optimization of detector depends on the clutter and noise distributions provided in the previous section. Optimum weighting coefficients are obtained from the following relationship.

$$\boldsymbol{W}_{opt} = \gamma \boldsymbol{Q}^{-1}\boldsymbol{S} \quad (14)$$

Such a filter is quite well known today in the field of detection area as the match filter. The linear detector is one of the most important and common detectors with known structure, which is used in showing existence of signals. Simplicity and acceptable performance of this detector has made it quite applicable.

Given the density functions provided in the previous section, the problem here follows with determination of "T" or threshold. For this purpose, it is necessary to estimate the unknown pdf parameters (such as the shape and the scale parameters). Up until now, different methods have been presented for estimation of the unknown parameters regarded to constant false alarm ratio; e.g. CA-CFAR, OC-CFAR, GO-CFAR, CMLD and TM-CFAR [3]. The suggested method which is based on the two-pole recursive filter has a faster implementation rate compared to the other provided methods. Meanwhile, its losses are considerably reduced with in longer time.

The most common type of spatial CFAR is CA-CFAR where use of adaptive CFAR is in the common range vector. Theoretically, the averaging CFARs (CA) perform a statistical estimation of un-biased minimum variance from the interference within the reference window.

A common disadvantage of the CA-CFAR method is its lack of resistance in coming to inhomogeneous environments [12]. When CA-CFAR is used along the range, it works well in a noisy environment but if there is a sea clutter with a fast variations, its performance will decrease. Also, if there are returns from a number of targets within the sampling cells (reference), its workability will considerably decrease, as these targets will automatically help the threshold to raise [13].

Different strategies have been put forward to improve the performance of CA-CFAR. For example, instead of using the average of windows at both sides of test cells, it is possible to compare average values of two cell groups and then multiply the larger or smaller value by a constant value and use it as the threshold level. In case of choosing the smaller average as the threshold, this technique is called SO-CFAR and in case of selecting the larger average, it is called GO-CFAR. The GO-CFAR method uses the window with larger average range as the criteria for determination of the threshold. Thus, the threshold level provided in this method is higher than the normal level and weaker targets may not be detected. On the other hand, if the data of a window with a smaller average range is used as the criteria for determining the threshold, a relatively lower threshold level is provided and it may result in higher probability of false alarm and saturation of the processor [12].

If a logarithmic detector is used before the CA-CFAR, this technique is called LOG-CA-CFAR (LCA-CFAR). This threshold selection method has been suggested for improvement of the CFAR performance against heterogeneous clutters. Output of the logarithmic detector is processed by a CA or an optimized type such as GOCA. Unfortunately, LCA has more losses than CA-CFAR [1].

For reducing the losses and improving decision making time, our proposed method uses the adaptive detection resulted from Two-Pole Filter, with the recursive coefficients calculated as the diagram block in Fig. 1, so that the variance and mean values of the noise have been calculated separately for each range cell and get closer to the actual values in the course of time. In Fig. 1 diagram block, "C" sits for the comparator whose task is to compare the input signal frequency with the estimated threshold.

The threshold is estimated as follows:

$$\mathrm{T} = \mathrm{Y_b} \times B \quad (15)$$

The above equation is obtained from Equation 11 with this assumption:

$$\mathrm{Y_b} = \{-\ln(P_{FA})\}^{\frac{1}{C}} \quad (16)$$

To achieve the unknown parameter from the Weibull pdf we use maximum likelihood estimation [14]. So we would have:

$$\hat{B} = \left(\frac{1}{N}\sum_{j=1}^{N} x_j^C\right)^{\frac{1}{C}} \quad (17)$$

By setting C parameter equal to one in the above equation we will have:

$$\hat{B} = \frac{1}{N}\sum_{j=1}^{N} x_j \quad (18)$$

That in fact this parameter is the mean value of input information. Also by choosing $\mathrm{C} = 2$ in Equation 17.

$$\hat{B} = \left(\frac{1}{N}\sum_{j=1}^{N} x_j^2\right)^{\frac{1}{2}} \quad (19)$$

That in fact is the ML estimation of standard deviation for the Rayleigh distribution. Higher orders of C will result higher orders of Weibull distribution moments.

In order to increase the calculation velocity of estimating the unknown parameter $\widehat{\mathrm{B}}$ we used the following equations. In this equation, 1st moment and 2nd moment of the interference are calculated as follows:

$$\widehat{\mu_{\mathrm{n}}} = \mathrm{K_1} \times \mu_{\mathrm{n-1}} + \mathrm{K_2} \times \mathrm{input(i)} \quad (20)$$

$$\widehat{\sigma_{\mathrm{n}}^2} = \mathrm{K_1} \times \sigma_{\mathrm{n-1}}^2 + \mathrm{K_2} \times (\mathrm{input(i)} - \mu_{\mathrm{n}})^2 \quad (21)$$

And also $\mathrm{Y_b}$ is calculated using the following equation:

$$\mathrm{Y_b} = \mathrm{N} + \sqrt{\mathrm{N}} + \frac{-\ln(\mathrm{P_{FA}}) - 1 - \mathrm{x}}{(1.1\mathrm{N} - 0.1)^{0.51}} + x\sqrt{N} \quad (22)$$

where, "N" is the number of lines within the matrix of the radar data, whose threshold is determined collectively. Meanwhile, we have the following relationship:

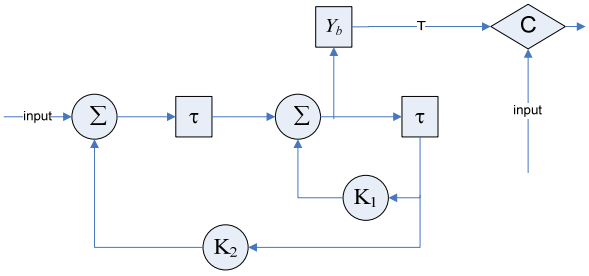

Fig. 1 Proposed detector diagram.

$$x = g - \frac{2.515517 + 0.802853 * g + 0.010328 * g^2}{1 + 1.432788 * g + 0.189269 * g^2 + 0.001308 * g^3} \quad (23)$$

where g is equal to:

$$g = \sqrt{-2 \ln P_{FA}} \quad (24)$$

Therefore, the threshold will have different values in different P_{FA}s and is sensitive to it. Meanwhile, one threshold is determined for each range cell. With regard to the recursive relationship in Equation 20 and Equation 21, estimation of the mean will result in a closer value to the actual value of the noise average with elapse of longer time and the new inputs being added, as despite CA-CFAR, the length of the averaging window here is not limited to the "M" cell already determined and it is extended to the length of the signal. Parameters K_1 and K_2 in Equation 20 allow for calibration of the system under different environment conditions for the designer. It is noteworthy that the sum of parameters K_1 and K_2 in this equation is equal to 1 and in the simplest case, when $K_1 = K_2 = 0.5$, it can be observed that the recursive average tends after some time to the actual average. Our suggested values are 0.91 for K_1 and 0.09 for K_2. Also $\hat{B} = \hat{\mu} + \widehat{\sigma^2}$ represent a better performance in comparison of a single moment for B.

Meanwhile, for a better performance of the suggested algorithm, it is possible to use a limiting factor which is related to our natural information on the system. This limiting factor may be designed and used on hardware or software basis. For instance, if determined values are $P_d = 0.9$ and $P_{FA} = 10^{-6}$, the required signal to noise ratio is 13.5 dB according to tables [5], for detection announcement. Therefore, if the input signal in the i^{th} moment is higher than the obtained threshold by more than 13.5 dB, it may not be entered into calculation of the average and the previously-calculated value can be entered into the algorithm as the new input.

Another point which should be considered in the use of the suggested algorithm is determination of the initial values for the noise variance and mean values. As the provided algorithm is highly depended on its previous values, determining wrong values for the initial values may its intensive divergence. However, in designing radars, as some parameters such as the receiver bandwidth, environment temperature and the number of ADC bits are previously determined, the noise initial variance and mean values can be easily estimated.

In our suggested method, it is possible to use statistical parameters within the cell for which the threshold is being calculated (average, standard deviation, etc.) or use a non-parametric method (such as classification based on the order statistics) in determining the threshold. Meanwhile, it is possible to separate the concerned from other cells by means of time lag (range), angle or a combination of such components. Finally, as already mentioned, it is possible to implement a series of non-linear processes (such as limiting factor or large samples correction) on the cell under test before estimating the statistical parameters.

4 Simulation Results on Real Data

Standard deviation of the adaptive thresholding suggested here is larger than the optimum detector by almost 15 percent and this forces some losses in the system. However, the calculating method is very simple and workable for real time applications. This is while implementation of the optimum detector and calculation of inversed covariance matrix in real time is very time consuming with the existing processors. In terms of the effect and the amount of losses, the suggested thresholding can be compared with Cell-Averaging CFAR method.

Fig. 2 shows the diagram of Cell-Averaging CFAR losses for different false alarm probabilities. As it can be seen, length of "M" should be equal about 150 cells in $P_{FA} = 10^{-6}$ to reach 0.2 dB losses compared to the optimum detector. We assumed that we had already 10 pulses integrated for this chart. If the pulses were lower, the losses would have been more [5]. This type of averaging can be very time-consuming in radar applications.

In the proposed thresholding algorithm, in order to estimate actual loss from actual values, we simulated the Weibull interference and noise for 1000 times, with the mean of 0.73 and the variance of 0.09. It aimed to investigate on the values estimated for the average and the variance and compare it with the values already determined. Then, we estimate the threshold using equation 15 for both cases and calculate the pre-assumed values from the estimation results. As the result the standard deviation from actual values of the mean and the variance will decrease when the samples are being added. Meanwhile, in the worst case out of the mentioned simulations, the thresholding losses have also been calculated, which is almost 0.27 dB in the tenth sample to 0.09 dB in the 70 th sample. These simulations have been carried out in the false alarm ratio of 10^{-6} so that the detector losses can be compared with those provided for CA-CFAR.

Fig. 3 illustrates the losses diagram based on the input data in the suggested detector for different false alarm rates. It refers to this important note in using our suggested thresholding system that in case the number of the investigated samples is sufficiently high, the false ratio is considerably decreased, so that in longer time, the suggested detector acts similar to the optimum

detector. For example, in the 150 th sample, the rate of losses has been decreased down to 0.07 dB. This is while in CA-CFAR, selection of a larger window is inevitable (see Fig. 2).

Diagrams of Fig. 4 and Fig. 5 shows the threshold obtained from CA-CFAR and the proposed threshold on a real radar signature. Meanwhile, we show in Fig. 5 that the adaptive threshold is shifted appropriate to the P_{FA} changes. In these figures, the horizontal axis shows the time or just discrete samples entered into the thresholding system. The vertical axis shows the received signal amplitude after ADC and other conventional algorithms of signal processing in marine radars (such as STC and FTC). As delineated samples are taken from real radar signatures, their range have been shown without normalization for investigation on what occurs in reality.

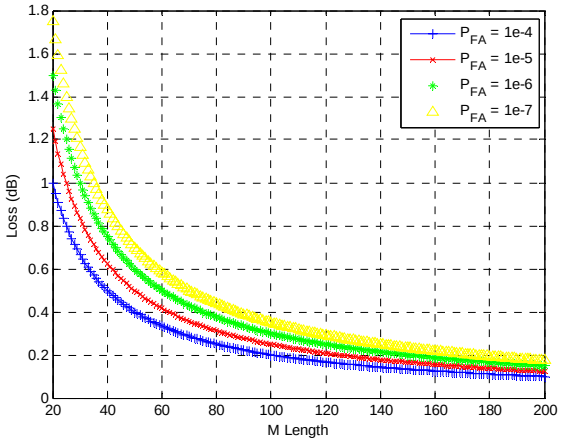

Fig. 2 Loss diagram based on the widow length in CA-CFAR.

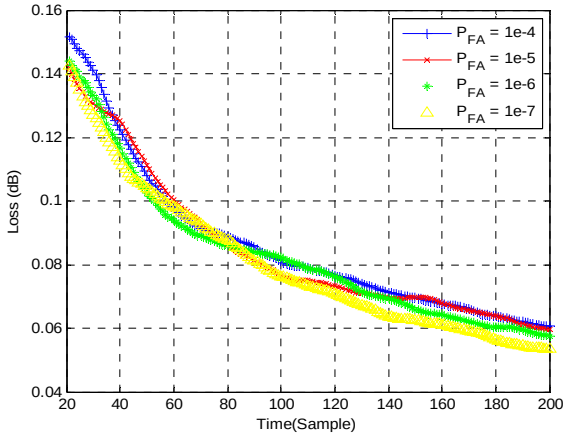

Fig. 3 Loss diagram based on input data in the proposed detector.

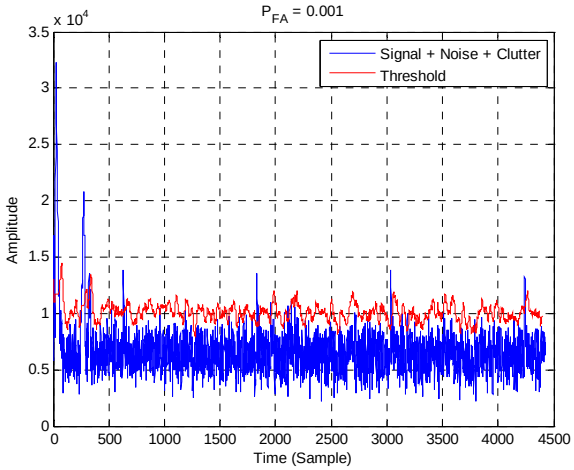

Fig. 4 Thresholding in CA-CFAR method on real radar signature.

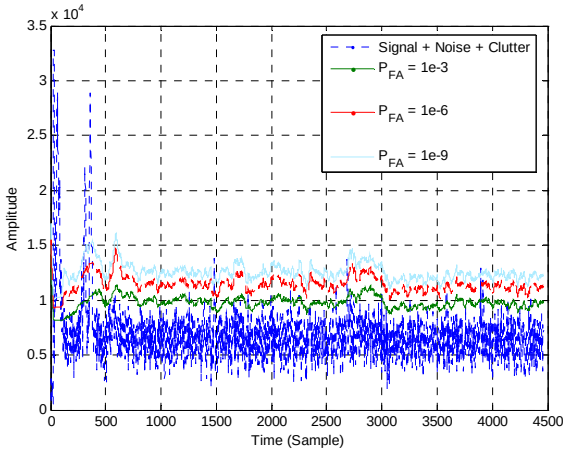

Fig. 5 Threshold sensitivity in P_{FA} in the suggested detector on real interference.

5 Conclusion

At the time being, different algorithms have been suggested for detection and thresholding according to a constant false alarm rate. In this paper, we aim to suggest a fast implementing algorithm for thresholding and making decision in sea marine radar systems. In this paper, we have introduced statistical models for signal, noise and clutter in sea marine radars and then we have obtained optimum detector using a suggested recursive two-pole filter with known parameters. Based on the assumed density functions, we suggested a semi-optimum detector, that beside very good calculation speed, it shows very small amounts of losses with the past of time. The proposed algorithm has been tested on real radar signatures and has been implemented on a sea marine radar system. The results indicate good performance of the algorithm in non-stationary sea interference.

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