# Fusion center with neural network for target detection in background clutter

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## Abstract

*Analysis of radar signals for target detection in background clutter involves the use of different algorithms. These algorithms provide different levels of detection probability and false alarms as a function of the clutter present. This paper provides a solution to the problem of selecting the appropriate algorithm for target detection in background clutter with high probability of detection and low false alarms. The approach is based in parallel execution of CA-CFAR (Cell Averaging Constant False Alarm Rate), GO-CFAR (Greatest Off) and SO-CFAR (Smallest Off) algorithms and a fusion center based on a neural network with different fusion rules. Results with simulated and real data are presented and discussed.*

## 1. Introduction

Radar returns for target detections are usually buried in thermal noise inherent to electronic equipment, and clutter caused mainly by reflection from wave tops on the sea. The clutter power is not known a priori; therefore the use of detection algorithms based on the comparison of noise levels versus a fixed threshold causes a considerable increment of false detections [1].

The target detection process in radar signal can be automated by means of a detection processor known as constant false alarm rate processor (CFAR processor). This detection processor is based on statistical models with unknown parameters that are proportional to the expected magnitude power of radar echoes. The detection processors calculate the threshold adaptively based on local noise power of a group of reference cells surrounding a cell under test.

Detection algorithms have been developed with adaptive threshold in order to maintain a low level constant false alarm rate and high probability of detection. Such is the case of the classical Cell Averaging (CA) CFAR processor, which sets adaptively the threshold estimating the mean level in a window of M range cells. CA-CFAR assumes a homogeneous, Gaussian noise environment [2]; these assumptions result in two major problems: clutter power transitions and multiple targets environment. The first case, clutter transitions (clutter edge), cause problems by generating an excessive number of false alarms. In the second case, one of the targets could be masked when multiple targets exist in the cells of the reference window [3].

To solve the problems associated to the CA-CFAR algorithms, several modifications have been proposed to improve their performance for different clutter conditions. Among the main variations of CA-CFAR algorithm are Greatest Of CFAR (GO-CFAR) and Smallest Of CFAR (SO-CFAR).

The modifications indicated above are based in splitting the reference window into leading and lagging parts around the cell under test, in the GO-CFAR algorithm the noise power is estimated by the greatest of the mean between leading and lagging windows. Using the GO-CFAR algorithm is possible solve the problem of the clutter transitions with an acceptable level of false alarms [4]. SO-CFAR algorithm is used to prevent the target mask caused by the presence of multiple targets in the window reference. The noise power noise is estimated by the smallest of the mean between leading and lagging windows with acceptable level of false alarms [4].

In all cases CA, GO and SO algorithms provide acceptable results in homogeneous clutter background. However, clutter background can not be modeled with a Gaussian distribution. In recent investigations on sea clutter modeling, adaptive models have been used with other distributions such as Weibull, Rayleigh and K [2]. These distributions diminish the number of false detections. However, the sea clutter constantly changes over time and none of the previous distributions can model it completely. Therefore it is necessary to use a different CFAR processor for each case of sea state.

Artificial neural networks (ANN) provide the possibility of solving the problem of choosing the adequate CFAR algorithm according to sea state to obtain the maximum detection probability and minimum probability of false alarms [5][6]. In this work we use ANN to implement a fusion center with different fusion rules. In the proposed approach only one sensor is used, the radar returns are processed with CA, GO and SO

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algorithms running in parallel, obtaining three signals to be fusioned.

The problem of fusing optimally the decisions from a number of sensors has been discussed in many papers. These are discussed in section two. This approach is based on a Neyman Pearson test and fusion center with **AND** and **OR** fusion rules, implemented on a single perceptron with back propagation training.

The content of this paper is as follows: Section 2 describes the related works in CFAR processors and the use of neural networks in target detection. Section 3 presents the proposed approach for target detection using CFAR variants and fusion center with neural network. Section 4 provides some results obtained with the proposed approach, which are discussed in section 5. Finally, some conclusions are presented in section 6.

## 2. Related Work

In this section we present previous work related to CFAR processors with both Neyman Pearson and neural network. Likewise related work in fusion sensors with neural network.

### 2.1. CFAR processors

To solve the problem of target detection in noise, different kinds of CFAR techniques have been proposed in the literature [3] [4]. The CA-CFAR is the most common detector used in adaptive signal processing for target detection. Figure 1 shows a block diagram of the CA-CFAR processor, in this processor a reference window of M/2 samples is taken to compute the average value of noise power in leading and lagging to cell under test (**$q_o$**). The noise power estimation is multiplied by a scaling factor T and compared to the value of the cell under test. If the value of the cell under test exceeds the computed value, then target detection is declared.

$$\text{Decision} \begin{cases} \text{Target present (1), if } q_0>QT \\ \text{Target absent (0), if } q_0<QT \end{cases}$$

The scaling factor T is used to set a desired false alarm probability, and is computed according to distribution probability of noise environment.

The problem of increased false alarm probability due to the presence of a discontinuity in the distributed clutter has been treated by Gandhi and Loizos [3] [4]. They present an analysis of performance of the *greatest of* selection logic in GO-CFAR, to control the increase in the false alarm probability. The figure 1 shows this logic of selection, basically it splits the reference window in leading and lagging windows (U,V) and compute the power noise level in each window to select the maximum value.

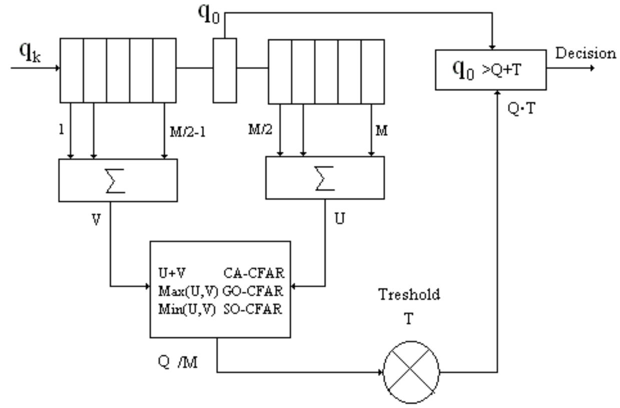


Figure 1. CFAR processor

In [7], Lombardo has shown that if two o more targets are present in the window cell reference, the use of logic SO-CFAR improves the detection probability respect to GO-CFAR. Figure 1 shows this logic, it computes the power noise level in each window to select the minimum value.

In [8] we proposed an approach to calculate the threshold for CFAR variants using the Neyman Pearson criterion and the Gaussian, Weibull and K probability distribution. In these work we showed that it is possible to process the radar signals using CA, GO and SO algorithms running in parallel, increasing detection probability with a low probability of false alarm.

On the other hand, Mirko proposed the use of artificial neural network (ANN) to implement two types of CFAR [5]. An ANN detector that is trained to output directly a detection decision estimating an optimal threshold according to the clutter distribution. He concluded that artificial neural networks can be trained on radar signal detection in mixed clutter environments and perform better than conventional radar detectors.

### 2.2 CFAR fusion approaches

Garvanov carried out a study of the efficiency of k-blocks CFAR processor fusion [9]. He selects *k* windows of M cells and computes a statistical test of each window. The fusion rule consist in adding the power level in each window and multiply them by a modified scaling factor, obtaining good results for one type of clutter. In [10] Liu shows the effectiveness of AND and OR fusion rules based in genetic algorithms to obtain the threshold to Order Statistics CFAR. He shows the effectiveness of fusion rules in homogeneous background and mentioned that the method should still be effective in nonhomogeneous situations with other fusion rules. In [11], Zhao also proposed an approach to use AND and

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OR rules to fusion CA-CFAR and OS-CFAR. In this case, a Gaussian model was used to calculate the threshold, obtaining good results in false alarm probability.

## 3. Fusion approach

Target detection in background noise involves appropriate filtering of sea clutter. This kind of filtering can be considered as a pattern recognition problem, which can be solved by means of an artificial neural network [6]. The results of different filters can be fusioned with a single neural network with an activation function according to the clutter model.

The proposed approach includes three CFAR processors running in parallel: CA-CFAR, GO-CFAR and SO-CFAR. Each one of these algorithms is combined with a clutter model to obtain the minimum probability of false alarms and the maximum probability of detection, adapting thresholds to the observed clutter. The combination of clutter models with CFAR algorithms is discussed in [8].

Figure 2 shows the block diagram of the proposed approach. The radar returns are sampled and processed with parallel CFAR algorithms at same time, obtaining a set of three results for each cell tested. Table 1 shows the inputs for the fusion center (CA, GO, SO) and the corresponding outputs for the two fusion rules ('1' represents target and '0' represents no target.

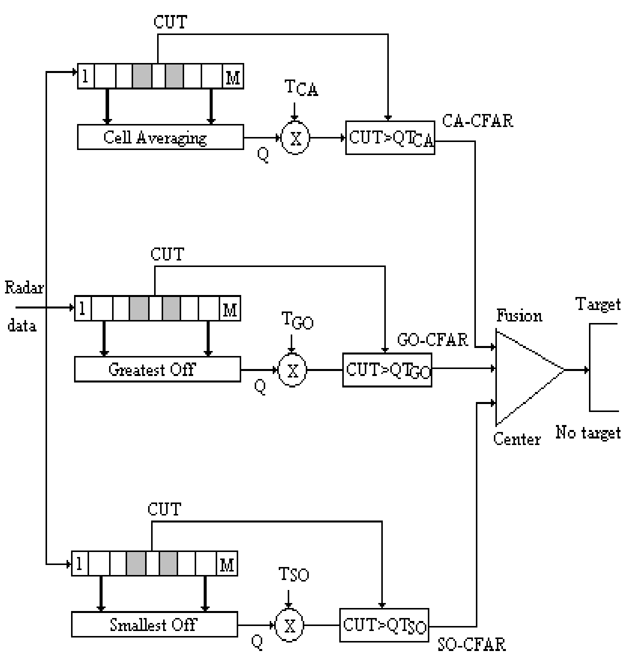


Figure 2. Proposed approach

Table 1. Possible CFAR outputs

| CA | GO | SO | AND-rule | OR-rule |
|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 1 | 0 | 1 |
| 0 | 1 | 0 | 0 | 1 |
| 0 | 1 | 1 | 1 | 1 |
| 1 | 0 | 0 | 0 | 0 |
| 1 | 0 | 1 | 1 | 1 |
| 1 | 1 | 0 | 1 | 1 |
| 1 | 1 | 1 | 1 | 1 |

### 3.1 AND rule

The CA-CFAR algorithm provides a low probability of false alarm and high detection probability. Therefore the output of CA-CFAR is taken as reference for the fusion center.

When CA-CFAR output is 1 (target present), there exists the possibility of a false alarm caused by clutter transition or multiple targets. To eliminate this false alarm, we can apply the **AND** fusion rule 1, shown in equation 1. This consists in applying the **and** logic between CA-CFAR and the output obtained of applying the **or** logic between GO-CFAR and SO-CFAR.

$$\text{ANDrule1}=\text{CA-CFAR}\left(\text{GO-CFAR}+\text{SO-CFAR}\right) \qquad (1)$$

When CA-CFAR output is 0 (target absent), there exists the possibility of a target lost caused by clutter interference. To eliminate this problem, we can apply the **AND** fusion rule 2, shown in the equation 2. This consists in applying the **and** logic between GO-CFAR and SO-CFAR.

$$\text{ANDrule2}=\text{GO-CFAR}\left(\text{SO-CFAR}\right) \qquad (2)$$

### 3.2 OR rule

The same as previous section, we take the output of CA as reference for the fusion center. The **OR** fusion rule consists in applying the **or** logic to outputs obtained for GO-CFAR and SO-CFAR. The equation 3 shows this rule.

$$\text{ORrule}=\text{GO-CFAR}+\text{SO-CFAR} \qquad (3)$$

The results of both, the **AND** rule and the **OR** rule fusions are shown in table 1. These results are the training vector for the neural network.


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### 3.3 Fusion center

To implement the fusion center, according to data nature shown in table 1, we select a single layer perceptron with bias and hardlims as a transfer function.

The figure 3 shows the neural network used on fusion center.

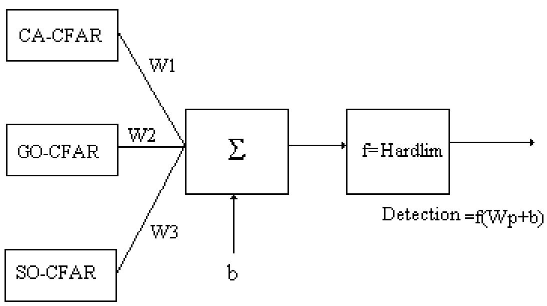


Figure 3. Fusion center with neural network

Equation 4 shows the output for the NN

$$\text{Detection} = \text{hardlims}\left(\sum_i W_i P_i + b\right) \qquad (4)$$

where $W_i$ is a vector containing the weights associated to inputs, $P_i$ is a vector containing the inputs to the fusion center (CA, GO and SO) and b is the bias.

The training algorithm for fusion center is described below.

- The vector weights and bias are initialized with random values.
- The first pattern (ouputs of CA,GO and SO) and the output expected (AND and OR rule) are presented. The patterns and outputs expected are shown in the table 1.
- The output is calculated with equation 4.
- If the output is incorrect the weights and bias are recalculated with equations 5 and 6 respectively.

$$W_{\text{next}} = W_{\text{previous}} + (\text{Detectionexpected - Detection}) * P \qquad (5)$$

$$b_{\text{next}} = b_{\text{previous}} + (\text{Detectionexpected - Detection}) \qquad (6)$$

where *Detection expected* are the values shown in table 1 for the AND rule and OR rule.

The CFAR algorithms and the NN for the fusion center in the proposed approach have been implemented in Matlab. For visualizing purposes we take the power amplitude of CFAR algorithms and the NN outputs.

## 4. Results

### 4.1 Radar data

Two sets of data have been used in this work: the first set was generated by a simulation that contains targets and clutter with Gaussian, Weibull and K distributions [8][12], while the second set was obtained from a X band radar and containing targets and clutter with Gaussian distribution.

Input data are grouped in vectors named range profile. This data vector is procesed by the CFAR algorithms. Figure 4 shows one range profile from each set of data.

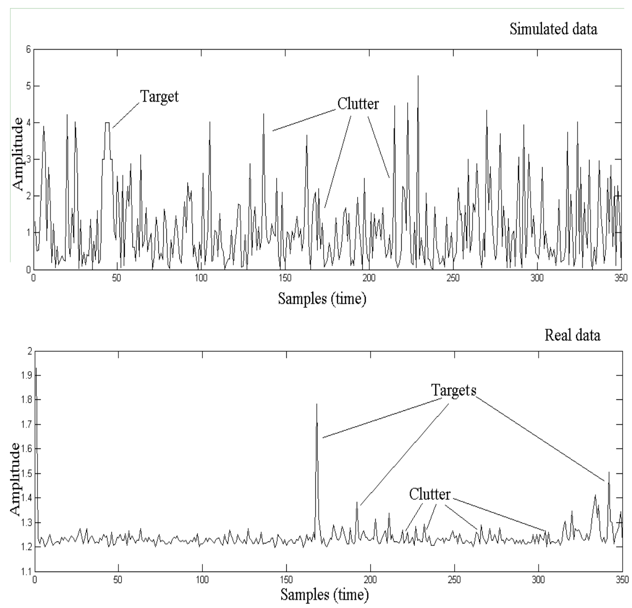


Figure 4. Range profiles

### 4.2 CFAR processor

Results shown in figure 5 were obtained using the CA-CFAR, GO-CFAR and SO-CFAR algorithms. The figure shows simulated and real range profiles and the corresponding threshold computed by CFAR algorithms. The difference of levels in threshold calculated by each one of the algorithms, produce false alarms in some cases or false detections in others. However, by having the targets detected by the three algorithms simultaneously we can obtain fusioned results for target detection with high detection probability and low level of false alarms.

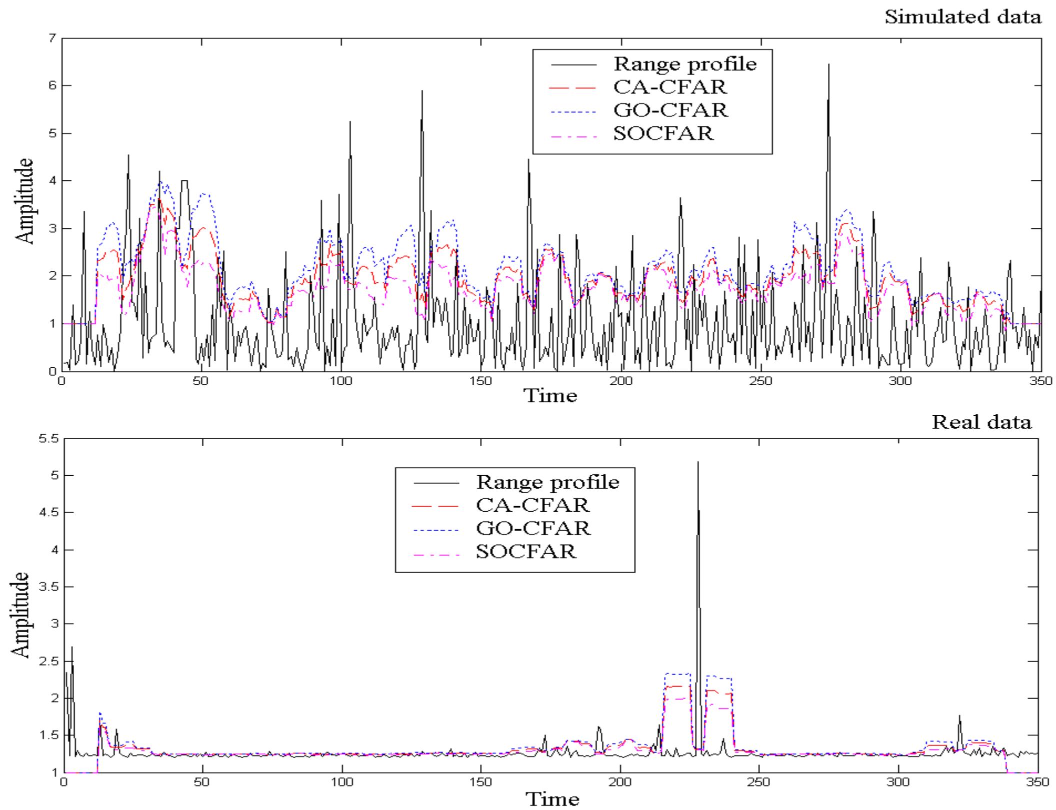


Figure 5 CFAR processor outputs

### 4.3 Fusion center

The first step for the experiments involved the neural network training. The inputs shown in Table 1 were presented to neural network proposed in Section 3.3, together with the desired outputs for both, AND and OR fusion rules. Figure 6 shows the short time for training the single layer perceptron, since the input patterns are lineally detachable.

Having trained the network we obtained the results shown in the figure 7. These results were obtained using range profile with both real and simulated data.

Figure 7a shows a range profile obtained for simulated data and clutter with weibull distribution. In the same figure we observe the outputs obtained with CFAR algorithms and fusion rules. The differences obtained for each CFAR algorithm are shown inside a rectangle. In some cases a target is detected by some CFAR variant, in other cases the target is lost. In the low part of the figure we show the outputs obtained fusioning the CFAR outputs It can be observed that lost targets are recovered. Additional to fusion results, the output level is enhanced resulting in increased signal to noise ratio.

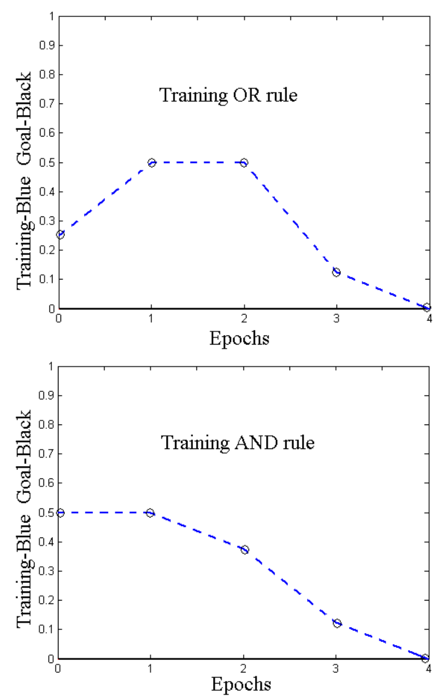


Figure 6 Epoch for training network.



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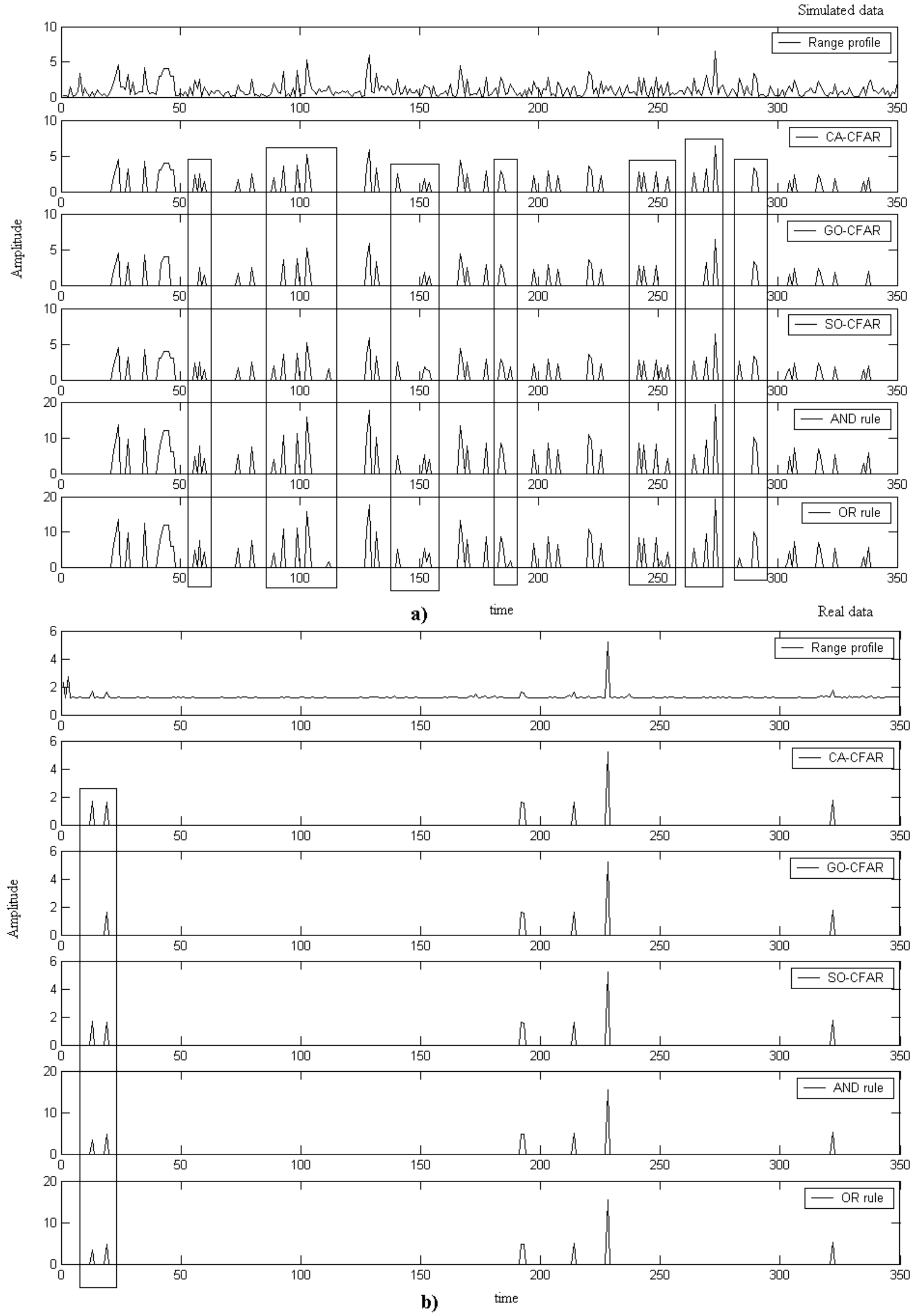


Figure 7 Target detections with fusion center

Figure 7b shows a range profile of real data, this data vector have Gaussian noise and targets. For this example there exists one lost target in the output of GO-CFAR but it is recovered in the fusion, enhancing the signal power level in both cases AND and OR rule fusion.

Finally, figure 8 shows a performance comparative between the proposed approach and the traditional variants of CFAR proposed in the literature.

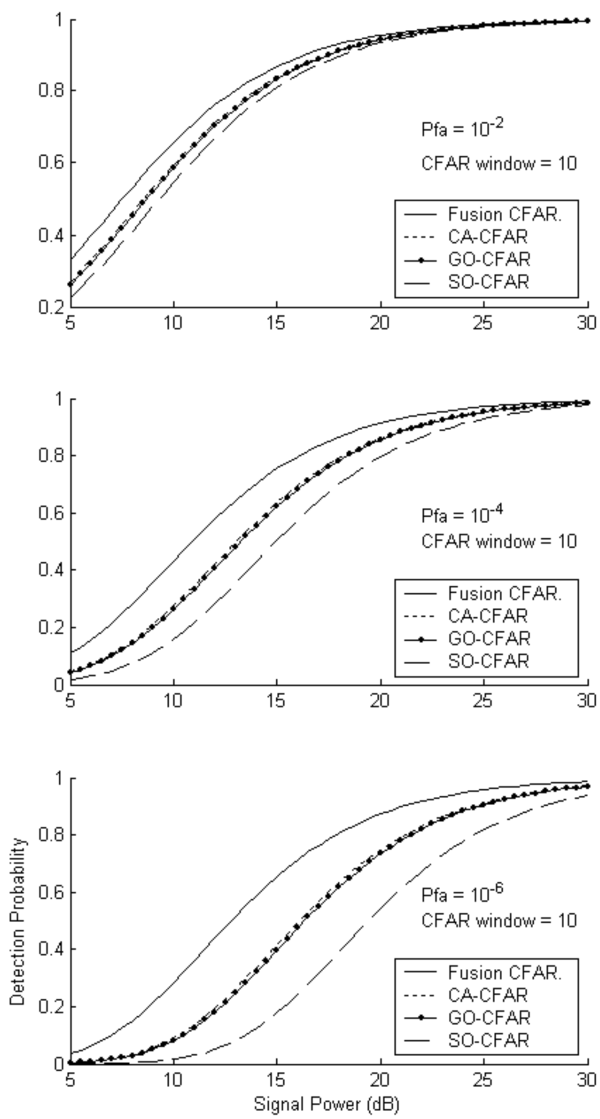


Figure 8 Performance of proposed approach

## 5. Discussion

The CA-CFAR is optimum for one type of clutter distribution, obtaining variations of false alarms for different clutter types. The variants GO-CFAR and SO-CFAR can solve the problems associated by the CA-CFAR algorithm. The CFAR algorithm has demonstrated to generate good results when the appropriate variant for some clutter background type. However it is necessary to select the appropriate variant of CFAR according to noise existent.

According to results obtained in the section 4, the problem discussed above can be solved by fusioning results obtained by CFAR variants. This was done by means of a single perceptron to carry out a fusion center obtaining good results. It is also possible to use a multilayer neural network, extending the use of neural network to CFAR algorithms.

## 6. Conclusions and future work

The use of CFAR variants in parallel allows detecting targets in different clutter types by fusioning the results into a single decision. The neural network is a good solution to solve the problem of target detection using three o more variants of CFAR algorithm and fusioning their results.

According to results obtained, it is possible to extend the use of neural networks to CFAR algorithm. A hybrid approach would include the use of neural networks with statistical algorithms. Neural networks could also be trained to perform the CFAR algorithm for different clutter environments.

## 7. References


[1]. Skolnik M. “Introduction to radar system”. Mc Graw Hill. New York. 2001.

[2]. Farina, Gini, Greco. "High Resolution Sea Clutter Data: A Statistical Analysis of Recorded Live Data" IEE Proceedings Radar, Sonar & Navigation. Vol. 144 No. 3. 1997. pp 121-130

[3]. Loizos A. “On Adaptive Censored CFAR Detection” Ph. D. Dissertation New Jersey Institute of technology.

[4]. Gandhi P, Kassam S.”analysis of CFAR Processors in Nonhomogeneous Background” IEEE Transactions on Aerospace and electronics Systems. Vol 24 No. 4 1988.

[5]. Mirko Kuck. “Constant False Alarm Detection of Radar Signal with Artificial Neural Network”. Master Thesis Skovde University 1996.

[6]. Serhat M, Yardimci Y.”Target selection using neural networks” Signal and Data Processing of small targets Conference USA 2002.

[7]. P. Lombardo. M. Sciotti. “Segmentation-based technique for ship detection in SAR images”. IEE. Proc. Radar, Sonar, Nav. Vol 148. No. 3. June 2001.
[8]. Lopez S, Cumplido R “A Hybrid Approach for Target Detection Using CFAR Algorithm and Image Processing” Fifth Mexican International Conference on Computer Science. 2004.
[9]. Garvanov I. “K- stage CFAR Detection in Binomial Distribution Pulse Jamming” Proc. of the International Radar Symposium, Dresden, Germany, pp. 369-375, 2003.
[10]. Liu W, Lu Y. “A Novel Threshold Optimization for Distributed OS-CFAR of Multistatic Radar Systems By Using the Genetic Algorithm” IEEE Radar Conference 2001.
[11]. L. Zhao, W. Liu. “A Novel Approach for CFAR Processor Design”. IEEE Radar Conference. 2001.
[12]. Mahafza B. R.“Radar Systems Analysis and Design using Matlab” Ed. Chapman & Hall/CRC. Alabama. 2000.


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