EFFICIENT NON HOMOGENEOUS CFAR PROCESSING

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***Abstract*— In this work a new radar detection method is proposed, the Cell Average Neural Network Constant false Alarm Rate (CANN CFAR), which can be used with Weibull distributed non homogeneous radar returns. This processor combines Maximum Likelihood estimation method with Neural Networks for the clutter parameter estimation, resolving homogeneity and determining clutter bank transition points and size. To characterize its performance, probability of detection is evaluated using Monte Carlo simulations and compared to other efficient CFAR schemes. As a result, CANN CFAR detection has better performance than conventional CFAR processors, especially when detecting targets located near clutter heterogeneities. An additional advantage of the proposed technique is its efficiency when determining clutter transition points, bank size and threshold setting. This efficiency translates in lower computation time than other CFAR algorithms, mostly considering real time processing.**

***Keywords*— Neural Networks, threshold, CFAR, clutter, detection, statistics.**

I. INTRODUCTION

In the case of naval medium range radars operating at S, C and X bands with pulse repetition frequencies (PRF) between 750 and 5000 Hz, available time between each radar return goes from 1 to 0.2 mseg. respectively. When working in real time, this is the available interval to carry out several processes such as signal capturing, filtering, detection, tracking, etc. It is well known that modern technologies like FPGA and digital signal processors (DSP) execute algorithms at very high speed. However, several radar processing tasks, as for example CFAR detection, require iterative algorithms that have slow convergence. Then, it is essential that these processing tasks be as efficient and fast as possible.

We are especially interested on the detection process carried out using constant false alarm rate (CFAR) in heterogeneous clutter. In a CFAR processor, the detection threshold is computed so that the radar receiver maintains a constant pre-determined probability of false alarm (P_{fa}) (Mahafza, 2000). In general, the radar return is completely unknown, and must be modeled in order to study its behavior and to find an appropriate CFAR detector. The herogeneous clutter is usually modeled as a sharp transition from one region to another, with a different distribution. In this work, the Weibull distribution is chosen to model heterogeneous radar returns. This distribution has been widely used to model both land and sea clutter and can generally be matched to experimental data over a wide range of conditions (Minkler and Minkler, 1990). Its probability density function (PDF) is known to represent sea and ground clutter at low grazing angles or at high resolution situations (Ravid and Levanon, 1992). It is characterized by two parameters: scale and shape.

Several detection schemes that are available take into account this two- parameter heterogeneous clutter model. The most notable is the Log-T (LT) detector proposed by Goldstein (Gandhi *et al.*, 1995; Goldstein, 1972; Weber and Haykin, 1985). For the two-parameter Weibull estimation problem, some authors assumed one parameter known and estimate the other. That is the case when this kind of distribution is used with the well known CFAR detection, as for example with cell average (CA) and order statistics (OS) CFAR processors (Gandhi and Kassam, 1988; Rohling, 1983).

A CFAR algorithm in which the parameters are estimated using Maximum Likelihood (ML CFAR), was developed by Ravid and Levanon (1992). The main objective was to reduce extensive CFAR loss exhibited by some conventional CFAR processors. However, this algorithm is more computational intensive than the other approaches.

Other specially interesting scheme is the *Range Heterogeneous* (RH) CFAR proposed by Doyuran and Tanik (2007). RH CFAR is suitable for non Rayleigh and range heterogeneous clutter. This algorithm estimates the homogeneity of the clutter and, if required, the transition point and threshold in the case of heterogeneity.

The main drawback of RH and ML CFAR is large computation time due to the number of iterations required for estimation in the CFAR window. An efficient alternative can be the CANN CFAR technique as is proposed in this work. This method combines both, ML for the clutter parameter estimation, and neural network (NN) for radar return homogeneity testing, and clutter bank transition points and size estimation.

Neural Networks have been employed by several authors in order to solve problems related to radar target detection. Haykin *et al.* (1991) and Haykin and Deng (1991), have proposed a clutter classification to distinguish between several mayor classes of radar returns including weather, birds and aircraft. This classifier incorporates both preprocessing and post processing procedures, as well as a multilayer feedforward network (based on back propagation algorithm) in its design. The superior performance of the NN classifier over the conventional classifier should be viewed as a practical demonstration of the potential value of NN as a tool for the classification of radar clutter and should establish confidence in the use of a multilayer feedforward NN as the basis for classifying primary radar returns in aid traffic control environment.

Ramamurti *et al.* (1993) trained a NN for the purpose of detecting a known signal corrupted by additive Gaussian as well as non-Gaussian noise of impulsive type. During the noise-only inputs, the network is trained to produce an output zero while, during signal-plus-noise inputs, it is trained to produce unit output. Once the network is trained and is employed as a detector, a signal is declared to be present if the network output exceeds 0.5. It was demonstrated that a NN can be trained to function as a detector in non-Gaussian noise, yielding considerable performance improvement over conventional detectors (based on statistical methods).

Kuck (1996) proposed the use of NN to implement two types of CFAR. The first one trained on target signal detection, this detector is trained to output directly a detection decision either target detection "1" or non-target detection "0". The second, trained on threshold estimation, this detector is trained to estimate an optimal threshold according to the current clutter distribution. Depending on the adaptation of statistical features, a multilayer NN detector can deliver better results for input distribution that cannot be modeled or only be modeled by some complex distribution functions. Gandhi and Ramamurti (1997) employed NN to detect known signals in additive non-Gaussian noise. Training of the NN for signal detection and its operation at some specified probability of false alarm are discussed. The NN, in this case, is employed not as a pre or a post processor (i.e.,one that simply assists the existing signal detector) but instead as an entity that completely determines the detection test statistic.

The CANN CFAR presents the benefit of being faster than the RH scheme while at the same time it maintains similar detection performance. The CANN CFAR method can be conceptually summarized as follows. In a first step, clutter parameter estimation is made by means of ML estimation method at the end of the complete radar return which is assumed to be homogeneous. Following, processing of radar returns are made by blocks. If the whole window is found to be homogeneous, a constant detection threshold is applied; otherwise, transition point and clutter bank length is calculated, using basic NN models, in order to determine a detection threshold capable of avoiding clutter banks.

In addition to the use of NN models to estimate clutter bank width and transition points, the main differences between RH and CANN CFAR are related to the block processing methodology used in the scheme proposed and the clutter parameter estimation made only once per complete radar return. As is discussed in the following, these differences lead to an efficient CFAR scheme, maintaining similar performance than RH or ML CFAR methods.

This work is organized as follows. In section II, some related basic detection models and notation are presented. The novel CANN CFAR method is introduced, with details, in section III. A complete performance analysis, including comparisons, is presented in Section IV. Finally, the conclusions are expressed in Section V.

II. BASIC CONCEPTS AND MODELS

Since our study considers homogeneous and non homogeneous radar returns, a brief description of the model used: Weibull radar return, is presented in this section. In addition, to describe CFAR concepts, the related threshold parameters: probability of false alarm P_{fa} and probability of detection P_d, are discussed. Also, basic tests to determine clutter homogeneity and NN used to implement them are included.

A. Radar return model

Let x_i be an observation at the input of the radar receiver taken within some resolution cell which represents a sampled radar return, observed over a time interval (window). The observation x_i may be composed by target plus clutter or clutter only,

$$x_i = \begin{cases} s_i + c_i & \text{Target signal plus clutter} \\ c_i & \text{Clutter only} \end{cases} \qquad (1)$$

x_i may be considered to be a sample from one of two random processes. One is the sample of x_i under the condition that no signal is present. The other is the sample of x_i under the condition that both signal and clutter are present (Minkler and Minkler, 1990). In this work, target signal is modelled as Rayleigh distributed random variable.

Clutter phenomena may be caused by a number of different sources. It may become necessary to identify clutter regions of differing clutter type and to describe their properties such as type, size and borders, power and spectral features rather than trying to suppress and ignore them at an early stage of signal processing. The assumption of a uniform clutter situation within the reference window is no longer maintained. Instead, provisions are made to handle transitions in clutter characteristics, clutter areas of small extensions, and interfering target echoes occurring within the reference window of the radar test cell (Rohling, 1983).

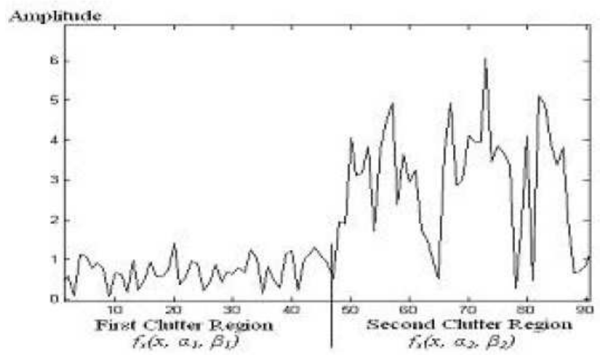

Figure 1: An illustration of non homogeneous return and clutter regions.

Homogeneous clutter is assumed to have Weibull distribution (Doyuran and Tanik, 2007), that is described by the following expression:

$$p(x) = \begin{cases} \frac{\beta}{\alpha}\left(\frac{x}{\alpha}\right)^{\beta-1} e^{-\left(\frac{x}{\alpha}\right)^{\beta/2}} & x \geq 0 \\ 0 & otherwise \end{cases} \tag{2}$$

where α is the scale parameter that gives an indication of the energy level of the median, and β is the shape parameter (β), indicating the degree of distribution skewness (Minkler and Minkler, 1990).

In the case of non homogeneous returns, the clutter is assumed to have Weibull amplitude distribution and the distribution parameters change abruptly in range. A typical example of non homogeneous clutter return is illustrated in Fig. 1, where $f_x(x, \alpha_1, \beta_1)$ is the PDF of the first clutter region and $f_x(x, \alpha_2, \beta_2)$ is the PDF of the second one. Parameters α_1, β_1 and α_2, β_2 represent the distribution parameters of region 1 and 2, respectively (Doyuran and Tanik, 2007).

B. Probability of detection and false alarm

P_{fa} indicates the probability that a clutter sample x_i, is interpreted as a target echo during the threshold decision. We consider that x_i represents the sample in the cell under test (CUT), and it is a single sample of the clutter process (Rohling, 1983). For a specified value of P_{fa} and known clutter PDF the detector task is to decide H_1 (indicative of target signal present), or H_0 (indicative of no target signal present) according to the following detection rule (Davidson, 2000),

$$\begin{cases} x_i > T & H_1 \quad \text{declared} \\ x_i < T & H_0 \quad \text{declared} \end{cases} \tag{3}$$

where T represents the detection threshold. Then, formally, the P_{fa} is given by

$$P_{fa} \;=\; \Pr\left[x \geq T | H_0\right] = \int_{x>T} p(x; H_0)dx \tag{4}$$

where $p(x; H_0)$ is the PDF of the detection statistic under H_0 hypothesis. The probability of detection P_d is defined as

$$P_d \;=\; \Pr\left[x \geq T | H_1\right] = \int_{x>T} p(x; H_1)dx \tag{5}$$

where $p(x; H_1)$ is the PDF of the detection statistic under H_1 hypothesis (Minkler and Minkler, 1990).

C. Threshold

When the clutter distribution is modeled using a Weibull distribution, the detection threshold T can be obtained as a function of the clutter expectation $E\left[x\right]$ and a scalar function of P_{fa} given by

$$T = E\left[x\right] \delta\left(P_{fa}\right) \tag{6}$$

where

$$\delta\left(P_{fa}\right) = \frac{\left[\ln\left(P_{fa}^{-1}\right)\right]^{1/\beta}}{\Gamma\left(1 + \frac{1}{\beta}\right)} \tag{7}$$

and $\Gamma\left(.\right)$ is the Gamma function. It should be noted that when the shape parameter β undergoes significant change, the detection thresholds fail to maintain the desired P_{fa} (Minkler and Minkler, 1990).

Figure 2 illustrates P_{fa} variations when the β parameter of the Weibull distribution is modified from 0.5 to 3, for different values of $\delta\left(P_{fa}\right)$. In order to maintain the P_{fa} constant, the threshold multiplier $\delta\left(P_{fa}\right)$ must be decreased as the shape parameter β grows.

For a Weibull distributed random variable x the mean value is defined by $E\left[x\right] = \alpha\Gamma\left(1 + \frac{1}{\beta}\right)$ (Kuck, 1996). Then, the threshold can be written as

$$T = \alpha\left[\ln\left(P_{fa}^{-1}\right)\right]^{1/\beta} \tag{8}$$

In practice, the distribution parameters α and β are estimated using limited number of samples. That makes the actual false alarm rate different from the desired one. As the estimates are random variables, so is the P_{fa} (Doyuran and Tanik, 2007).

$$E\left[P_{fa}\right] = e^{\left[-\left(E[T]/\alpha\right)\right]^{\beta}} \tag{9}$$

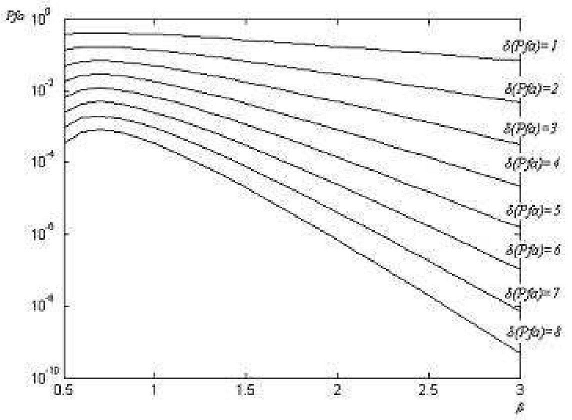

Figure 2: P_{fa} as a function of the shape parameter β variation.

D. CFAR

A simplified CFAR detector is illustrated in Fig. 3. The amplitude in the CUT is compared to the CFAR processor output, scaled by $\delta\left(P_{fa}\right)$, the threshold multiplier, which is a scalar factor. The CFAR processor applies an algorithm to the M range cell values at both sides of the CUT. The immediate neighbor cells are called buffer cells and are discarded to avoid contamination with the edge of the matched filter output from the target return (Rifkin, 1994). The detection threshold is computed so that the radar receiver maintains a constant pre-determined P_{fa} (Mahafza, 2000).

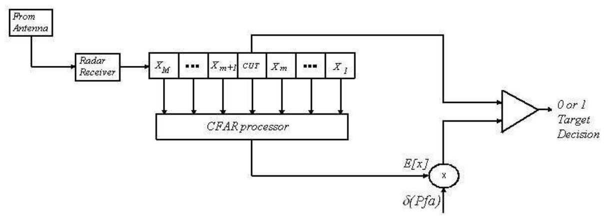

Figure 3: Simplified CFAR Scheme.

Several CFAR algorithms have been developed in order to find an adaptive threshold, which adapts itself to the clutter variations, maintaining a constant P_{fa}. An example of such processor is the CA CFAR processor which adaptively sets the threshold T (Eq. 6) by estimating the mean level, $\overline{x}$ in the window of M range cells (Gandhi and Kassam, 1988), where

$$\overline{x} = \frac{1}{M}\sum_{i=0}^{M} x_i \cong E\left[x\right]. \qquad (10)$$

This processor exhibits severe performance degradationin in presence of an interfering target in the reference window or in regions of abrupt change in the background cluter power (Gandhi and Kassam, 1988).

Another example is the OS CFAR processor proposed by Rohling, which has been considered to alleviate both of the above-cited problems (Gandhi and Kassam, 1988). In this algorithm the amplitude values taken from the reference window are first rank-ordered according to increasing magnitude, i.e., $x_1 \leq x_2 \leq ...x_M$. The central idea of an OS CFAR procedure is to select one value x_k, where $k \in \{1, 2, ..., M\}$ from the previous sequence, and to use it as an estimate for the average clutter power $E\left[x\right]$ as observed in the reference window (Rohling, 1983).

E. Homogeneity Test

A classic homogeneity test is the Anderson-Darling (AD) test (Stephens, 1974). It is used to test if a window of data comes from a specific distribution. The AD test makes use of the specific distribution in calculating critical values. Currently, tables of data support the AD test for the following distributions: normal, lognormal, exponential, Weibull, etc. (SED, 2003). Extensive tables of goodness of fit critical values A^2_{crit} for the two and three parameter Weibull distributions were developed through simulation for the Anderson-Darling statistic (Evans *et al.*, 1989). The test is defined as follows,

$$\begin{aligned} A^2 &= -M \\ &\quad -\frac{1}{M}\sum_{i=1}^{M}(2i-1)\left[\ln\left(w_i\right)+\ln\left(1-w_{m-i+1}\right)\right] \end{aligned} \qquad (11)$$

$$w_i = 1-\exp\left(-\left(\frac{q_i}{\hat{\alpha}}\right)^{\hat{\beta}}\right)$$

where, q_i are the ordered samples obtained by sorting x_i in increasing order, M is the number of samples to be analyzed, and $\hat{\alpha}$ and $\hat{\beta}$ are the estimated parameter values.

The test statistic A^2 in Eq. 11 is compared to the A^2_{crit} predetermined values, illustrated for example for the two-parameter Weibull distribution in Table I, at the 0.20, 0.15, 0.10, 0.05 and 0.02 levels of significance (defined as the probability of a false rejection of the null hypothesis in a statistical test). The critical values A^2_{crit} change with the number of samples used. The values in Table I are valid for $M = 40$ Weibull distributed samples. If the test statistic A^2 in Eq. 11 is lower than the critical value A^2_{Crit} in Table I, then it is decided that the distribution fits Weibull (Doyuran and Tanik, 2007).

Table 1: Critical values for various levels of significance for $M = 40$ Weibull distributed samples.

Signif. %	0.20	0.15	0.10	0.05	0.02
A^2_{crit}	0.511	0.561	0.632	0.755	1.036

F. Neural Networks

The perceptron is the simplest model of a neuron. The weights ($w_i, i = 1, ..., M$) scale the input signals. A bias factor w_0 is also contemplated. Figure 4 depicts the perceptron.

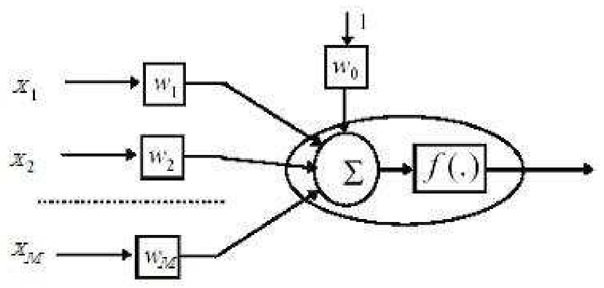

Figure 4: Computational model of a single neuron.

The usual activation functions $f(.)$ are: the sigmoid and the hyperbolic tangent (tanh). In this work the hyperbolic tangent (tanh) is used (Galvez *et al.*, 2004), which has a wider operating range.

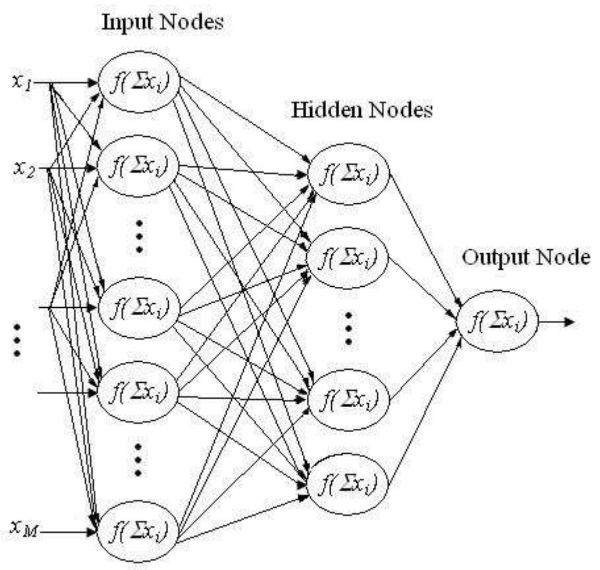

Figure 5: Multilayer perceptron architecture.

Neural Networks are realizations based on input patterns mapped onto output patterns. An usual realization is the multilayer architecture. A multilayer NN consists of an input layer, one or more hidden layers, and an output layer. Each layer (except for the input layer) is formed by a number of *neurons* or processing units, each one consisting of a linear combiner and a nonlinear device as is shown in Fig. 5. The linear combiner uses *synapses* of adjustable weights (Haykin *et al.*, 1991).

There are several reasons for the use of NN approach: (1) a NN has the intrinsic ability to learn from the input data and to generalize; (2) it is non parametric and makes weaker assumptions about the input data distributions than traditional statistical (Bayesian) methods; and (3) NN are capable of forming highly non linear decision boundaries in the feature space (Haykin and Deng, 1991).

In order to recognize patterns, the network needs to be trained. The backpropagation is a well-known and largely successful learning algorithm for supervised learning networks where input and domain are known a priori, as described in Galvez *et al.* (2004). Solving a problem with NN generally involves the following steps: (1) select a network topology, which fits to the nature of the problem. (2) choose the activation functions, which are appropriate for the nature of the problem. (3) training the NN with a training procedure. (4) generalizing the network over a set of samples different from those used for the training (Galvez *et al.*, 2004).

Lopez Estrada and Cumplido (2005) provide a solution to the problem of selecting the appropriate algorithm for target detection in background clutter with high probability of detection and low false alarm. The approach is based in parallel execution of CA CFAR, GO CFAR and SO CFAR algorithms and a fusion center based on a NN with different fusion rules. The use of CFAR variants on parallel allows to detect targets in different clutter types by fusioning the results into a single decision. The NN is a good solution to solve the problem of target detection using three or more variants of CFAR algorithm and fusioning their results.

In this work the CFAR processor combines ML estimation method with NN for the clutter parameter estimation, resolving homogeneity and determining clutter bank transition points and size, obtaining then, a quite efficient operation when working in Weibull homogeneous and non homogeneous radar environments.

III. CANN CFAR PROCESSOR

In this section a detailed description of the novel *cell average neural network constant false alarm* (CANN CFAR) processor is presented. Figure 6 depicts the CANN CFAR block diagram. The radar return is the input to the ML Parameter Estimation block where clutter parameters are estimated. A portion of the radar return (at the end of range) and higher than the CFAR window size, is chosen for this estimation; the estimation is performed assuming homogeneity. The threshold multiplier $\delta(P_{fa})$ (Eq. 7) is found and used in the thresholding blocks, for a large number of reference cells (M) and relatively high P_{fa}. The CANN CFAR estimates the clutter parameters only once within each radar return; note that the ML and RH CFAR processors make such estimation for each CFAR window, making the process more computational intensive.

The radar return enters NN1, NN2 and NN3 Neural Network blocks in groups of samples, these blocks follow the structure shown in Fig. 5 for the multilayer perceptron architecture and were trained by means of the backpropagation learning algorithm.

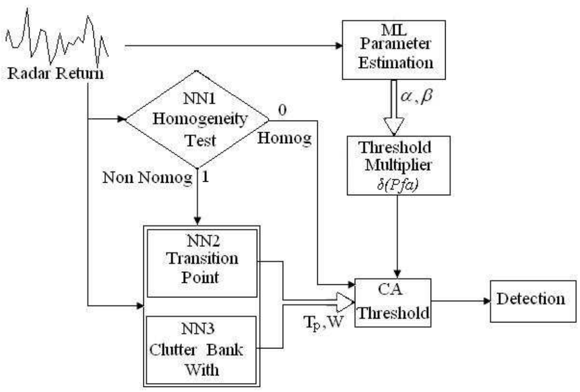

Figure 6: The CANN CFAR.

The processor performance is significantly affected when the assumption of homogeneous reference window is violated (Gandhi and Kassam, 1988). By this reason Homogeneity Test block (NN1) analyzes each portion of the radar return signal by means of NN1 in order to determine whether that portion of signal is homogeneous or not.

If the homogeneity test is positive, the CA CFAR threshold is applied. This is justified since the CA CFAR processor is the optimum CFAR processor (maximizes probability of detection) in a homogeneous background for certain well defined conditions[1] (Gandhi and Kassam, 1988). As the size of the reference window increases, the probability of detection approaches that of the optimum detector which is based on a fixed threshold (Gandhi and Kassam, 1988). Then, T is obtained according to Eq. 8.

On the other hand, if the homogeneity test is negative, that is a clutter bank is detected within the CFAR window, the transition point is estimated by means of the Transition Point block (NN2) and the clutter bank size is estimated using the Clutter Bank Width block (NN3). Making use of these two data, the threshold is then set by dividing the window into three groups of cells: the set that is situated previos to the transition point, the group that contains the clutter bank itself and those cells that follow the clutter bank. Each region is averaged separately and multiplied by $\delta\left(P_{fa}\right)$ (Eq. 7) in order set a different threshold for each mentioned group of cells, resulting then, a threshold that avoids clutter banks. Finally, the detection is carried out, a target is declared if the signal amplitude in the CUT is greater than the threshold.

A study of the performance of the proposed scheme is presented in the following section.

[1]Optimality can be shown when the reference cells contain independent and identically distributed (IID) observations governed by an exponential distribution.

IV. PERFORMANCE ANALYSIS

In this section, CANN CFAR simulation results are shown to illustrate and discuss its performance. Also, the examples included are used to perform comparisons with other CFAR processors, as for example, RH CFAR and OS CFAR.

A. System Simulation

The parameters used to define the estimation are described in the following. The ML Parameter Estimation block takes 80 samples at the end of each Weibull distributed radar return in order to estimate scale α and shape β parameters with the purpose of obtaining the threshold multiplier $\delta\left(P_{fa}\right)$.

NN training, using the backpropagation algorithm, is performed using Weibull distributed radar return contains 40 samples, coincident with the width of the CFAR window size.

In the case of NN1 Homogeneity Test block, a network composed by 40 input, 40 neurons in its hidden layer and only one output, was trained for 20000 epochs by means of 6160 radar returns; 400 homogeneous with diverse parameters ($\alpha = 1$; $\beta = 2$, 1.6 , 1.4, 1.33), and 5760 non homogeneous containing different size and parameter clutter banks situated at several positions. The NN2 Transition Point block has 40 input, 100 neurons in its hidden layer and one output. This network was trained for 3000 epochs using 3200 radar return each containing clutter banks situated at several positions.

The NN3 Clutter Bank Width block is composed by 40 input, 140 neurons in the hidden layer and one output. It was trained for 3000 epochs using 20480 radar returns which contain different size and parameter clutter banks situated at several positions.

The CA Threshold blocks obtain a constant threshold in the case of homogeneous clutter by means of Cell Averaging the 40 samples in the shift register and multiplying them by $\delta\left(Pfa\right)$ according to Fig. 3.

B. Homogeneity Test

A group of 1000 homogeneous different parameter Weibull radar returns are used with the NN1 Homogeneity Test and the AD test, for comparison purposes. The percentage of homogeneity error resulting of the use of both tests, for the radar returns used, are included in Table 2. When using NN homogeneity method the error is higher than with the AD test.

Table 2: Homogeneity test in percentages implemented with the NN Homogeneity Test and with the AD test.

	Homog. error	Non Homog. error
NN	17.62 %	1.88 %
AD	5.50 %	39.86 %

On the other hand, when testing homogeneity on a group of 1000 non homogeneous Weibull radar returns, the NN homogeneity test gives better results, a 2 %, error only, that is to say a 37.98 %, less than the AD test. This is a great advantage in detection since if a non homogeneous radar return is confused by homogeneous, it could produce a large number of false alarms.

With the AD test the homogeneity error is approximately constant for any shape parameter (β). In the case of the NN homogeneity test, the error increases when the Weibull shape parameter (β) goes beyond $\beta = 2$ (Rayleigh PDF). Thus, for $\beta = 2$, the error is 7.8 % , for $\beta = 1.6$ the error is 14.6 % and for $\beta = 1.3$ the error is 27.2 %. When a homogeneous radar return is confused by non homogeneous, in block NN1, the following blocks NN2 and NN3 act as if it were a non homogeneous radar return, trying to detect a clutter bank within the window. As a consequence, this result in a variable threshold that is high in the area of the erroneous clutter bank detected, affecting in consequence, the P_d performance.

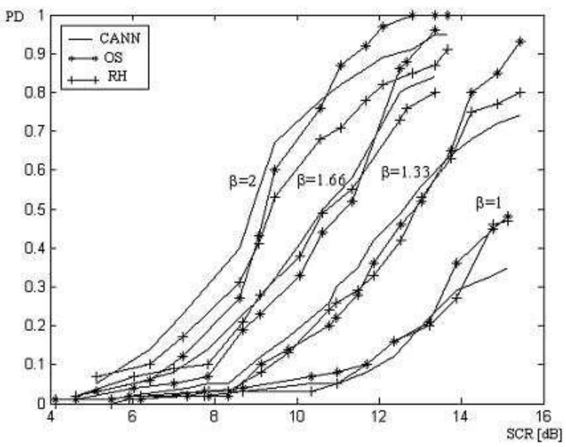

Figure 7: P_d against the Signal to Clutter Ratio (SCR) for different shape parameter values with homogeneous Weibull clutter.

C. Probabililty of Detection

The P_d (Eq. 5) evaluation was performed using MonteCarlo simulations for 100000 homogeneous Weibull radar return samples with distribution parameters ($\alpha = 1$; $\beta = 2$, 1.6 , 1.4, 1.33).

Figure 7 illustrates typical results obtained for P_d vs signal-to-clutter ratio (SCR)[2], for different shape parameter, with homogeneous Weibull clutter. CANN, RH and OS CFAR performance is evaluated and compared. It can be appreciated from the curves that the performance of the CANN CFAR is slightly above the other processes, denoting an improvement in the P_d especially for higher shape parameter β (less spiky Weibull distributions) and small SCR.

An study was made in order to evaluate P_d loss in the NN1 block when homogeneity test fails and a possible propagation of the error occurs through the NN1, NN2 and NN3 cascade. The results are summarized in Table 3. 100 homogeneous radar returns of 1200 samples each were processed by NN1 Test block and compared to an ideal behaviour of this block. From the results, it can be concluded that P_d loss increases as the shape parameter goes beyond the Rayleigh case ($\beta = 2$). This is an expected result, considering that the homogeneity error increases when the Weibull shape parameter is higher than $\beta = 2$.

Table 3: P_d loss obtained for homogeneity test error for 100 homogeneous radar returns of 1200 samples each with a SNR of 12 dB and a $P_{fa} = 10^{-3}$.

β	P_d NN1	P_d NN1 ideal	P_d loss
2.0	0.80	0.83	3%
1.6	0.64	0.68	4%
1.4	0.51	0.56	5%
1.3	0.44	0.51	7%

D. Thresholding

Figure 8 depicts a comparison between the three CFAR methods of thresholding. The detection threshold is applied over a Weibull non homogeneous radar return containing a target near a clutter bank. In the case of the OS CFAR it can be observed that clutter bank picks overcome the threshold resulting in an increment in the number of false alarms. In this case the clutter bank masks the target, missing the detection. In the case of RH CFAR processor, the threshold avoids the clutter bank and detects the target correctly, but has the disadvantage of requiring much more processing time than the other two algorithms.

In the case of the CANN CFAR, it should be noted that the threshold is set just over the clutter bank without touching it, and also correctly detects the target. The CANN and the OS CFAR processes take approximately the 3 %, of the time that the RH takes. This is due to the fact the RH CFAR window displacement is made by sample, but in the CANN CFAR the displacement is carried out by groups of samples (40 for this case). As a consequence, the parameter estimation in the RH algorithm is made every window, i.e, if the radar return is composed by 512 samples, the parameter estimation will be done at least 472 (512-40) times for a 40 sample CFAR. In the CANN CFAR the parameter estimation is carried out only once for each 512 sample return, at the beginning of the process, taking the last 80 samples for this case. On the contrary, in the case of the OS CFAR the displacement is made by sample, without any parameter estimation within the CFAR window in this case.

[2]The ratio between clutter and signal level is called signal to clutter ratio (SCR) and can be calculated as SCR=Average Signal Power/Average Clutter Power=$E[s^2]/E[c^2]$, where the average power is equal to the mean square value of signal or clutter distribution respectively.

Taking into account previous results and exhaustive simulations, the following remarks are important. The CANN CFAR estimates the Weibull distribution parameters only once at the beginning of the process, taking the last radar return samples for the task. This has the advantage of speeding up the system, but the disadvantage of running the risk of taking a non representative group of samples for the parameter estimate, resulting in an inaccurate threshold multiplier $\delta(P_{fa})$. In the case of the OS CFAR, since one clutter parameter is assumed known and the other estimated, that can result in a threshold multiplier far from the optimum. The RH CFAR, on the other hand, estimates the Weibull radar return parameters each CFAR window, even up to three times within the window in the cases of non homogeneous sample groups, resulting then, a more exact $\delta(P_{fa})$ calculus, but a very time consuming process.

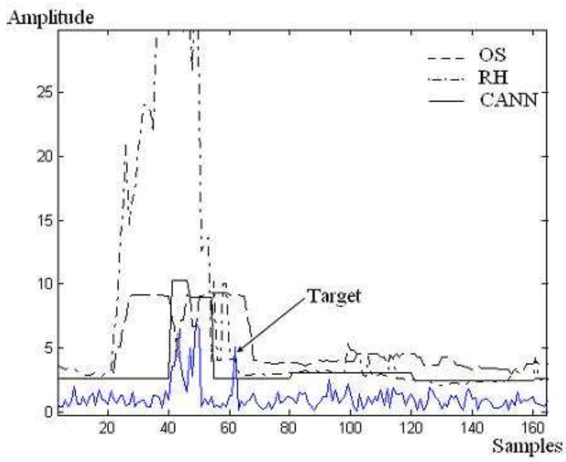

Figure 8: Weibull non homogeneous radar return containing a target near a clutter bank. $P_{fa} = 10^{-3}$, $\alpha = 1$, $\beta = 2$. Clutter Bank: $\alpha = 4$, $\beta = 2$.

V. CONCLUSIONS

The CANN CFAR is quite efficient when working in Weibull homogeneous and non homogeneous radar environments with the great advantage of having a faster operation than the RH CFAR, due to the conceptual different way in which the samples are processed.

An analysis in section IV showed that a P_d loss occurs when the NN1 homogeneity test fails, especially when the the shape parameter goes beyond the Rayleigh case ($\beta = 2$). As a future work it should be convenient to investigate a CFAR structure capable of avoiding error propagation through the NN1, NN2 and NN3 cascade.

When estimating the Weibull parameters by means of the ML Parameter Estimation block (fig. 6), homogeneity is assumed for that portion of signal, in a future work it should be convenient to test homogeneity in order to assure approximation to the radar return parameters due to the direct influence of them over the threshold calculation (eq. 6 and 7), and in consequense over the P_d. On the other hand, it could be useful to try another less time consuming method than the ML estimation with the purpose of obtaining the radar return parameters each CFAR window.

The CANN CFAR acts as a shift register, but the data displacement is made by groups of samples and not by sample as is the case of the conventional processors. That is useful to save processing time. A possible disadvantage of CANN CFAR technique is that it could increment the false alarm probability in the cases of sharp edge clutter bank discontinuities very near the end of the CFAR window. A future work in order to overcome this problem could be to implement an edge clutter bank detector.

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