

# Performance Analysis of a Modified Otsu-based Constant False Alarm Rate (CFAR) Algorithm under Varying Signal to Noise Ratio in Radar Systems

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**Abstract**— *The process of developing effective Radar target detection systems depends largely on the improved performance rate of the Constant False Alarm Rate (CFAR) technique deployed within the Radar system. These CFAR techniques typically estimate adaptive threshold values with the aim to maximize the probability of detection while maintaining the desired probability of false alarm. In this paper, we present a modified Otsu based CFAR algorithm that automatically estimates an effective adaptive threshold by processing each data sample within a given reference window for radar target detection. The performance of the proposed algorithm was evaluated using real-life acquired Radar return signals and the results obtained indicate that our algorithm performs similarly to the optimum (cell averaging) CA CFAR detector in a homogeneous environment, while typically outperforming other CFAR algorithms in similar conditions.*

**Keyword**— Adaptive, CFAR, Detection Probability, False alarm probability, Modified Otsu algorithm, Radar target, Threshold.

## 1. INTRODUCTION

A Radar system detects the presence or absence of targets by transmitting energy pulses into space [1]. The reflected pulses are then processed to determine the target presence or absence of targets within the scanning area [2]. In processing the received pulses, different algorithms use different methods to estimate the noise parameter within the signal, which is used to determine the power threshold also known as the detection threshold [3]. The accuracy of target detectors depends on how accurate the target processor is able to estimate this noise parameter. Different changing (Adaptive) threshold techniques have been proposed to estimate the noise power in order to maximize the probability of detection and to maintain a constant false alarm rate. Some of them include (mean level CFARs) such as CA CFAR processor which adaptively sets the threshold by estimating the mean level in a window of  $N$  range cells [4]. The CA-CFAR processor is the optimum CFAR processor that maximizes the probability of detection in a homogeneous background, but it experiences serious performance degradation at clutter edges and multiple target situations [3]. Some other mean level schemes were developed to alleviate the problems associated with the CA-CFAR like the greatest of CFAR (GO-CFAR) and the smallest of CFAR (SO-CFAR). The GO-CFAR has shown that in regions of clutter power transitions [5], only a minor increase can be expected in the false alarm rate; however the detector is incapable of resolving closely spaced targets. The SO-CFAR detector performs well in resolving two closely spaced targets but experiences performance degradation if interfering targets are located in both leading and lagging windows.

Furthermore, the SO CFAR processor also fails to maintain a constant false alarm rate at clutter edges [6].

Consequently, we consider the development of a new CFAR algorithm based on the Modified Otsu's algorithm [7]. The modified Otsu CFAR algorithm (MO-CFAR) unlike the mean level CFAR algorithms estimates the noise parameter by computing the specific index equivalent to the noise statistic from a computed between class variance in a window of  $N$  range cells. These  $N$  range cells surrounding the cell under test (CUT) are then used to set the adaptive threshold. The method has been shown to perform like the CA-CFAR in homogeneous background and experiences a lower false alarm rate than the other mentioned methods in heterogeneous background.

The rest of the paper is organized as follows: *Section 2* provides the basic assumptions description of the system model, *Section 3* provides an overview of the methodology, *Section 4* provides and discusses the results obtained, and the conclusion is provided in *Section 5*.

## 2. BASIC ASSUMPTIONS AND MODEL DESCRIPTION

In the CFAR detection scheme, the outputs from the square law detector device of the Radar system are sent serially into a shift register whose outputs are used by the modified Otsu algorithm to compute the test statistic,  $z$  (see Figure 1). In our model, the CFAR processor used by Gandhi in [3] has been replaced with the modified Otsu algorithm to compute the test statistic.

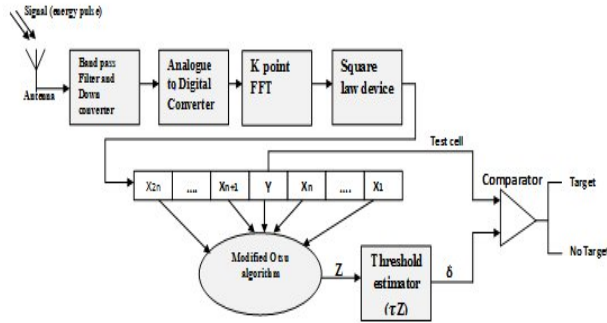


Figure 1: System model of the proposed MO-CFAR algorithm based on Modified Otsu algorithm.

Following Figure 1, a target is declared to be present  $H_1$  if  $Y$  (the signal from the cell under test) exceeds the threshold  $\tau z$  and a target is declared absent  $H_0$  if  $Y$  is less than  $\tau z$ . The (null hypothesis)  $H_0$  defines a noise only or (target absent) condition, while the (alternate hypothesis)  $H_1$  defines the signal plus noise or (target present) condition. Statistically, these hypotheses are defined as

$$H_0: Y(n) = W(n), \quad n = 1, 2, \dots, V \quad (1)$$

$$H_1: Y(n) = X(n) + W(n), \quad n = 1, 2, \dots, V \quad (2)$$

Where  $W(n)$  is the additive white Gaussian noise (AWGN),  $n$  is the time sample index,  $v$  is the number of measured samples,  $Y(n)$  is the received signal and  $X(n)$  is the transmitted signal. In addition, despite being complex valued, we note that the real spectrum component of the noise is used in this case, and not the phase components. The value of  $V$  is computed using

$$V = 2^{\lceil \log_2(Tf_s) - 1 \rceil} \quad (3)$$

Where  $T$  is total sensing period, and  $f_s$  is the sampling frequency. The signal's energy is computed using,

$$Y(k) = \left[ \sum_{n=1}^{V-k} y(n) \cdot \exp(-j(\frac{2\pi}{T})nk) \right]^2, \quad k = 1, 2, \dots, V \quad (4)$$

Where  $k$  is the sampling frequency index, also note that the performance of the detector is evaluated using the probability of detection and the probability of false alarm given as

$$P_d = P(Y(k) > \tau z | H_1), \quad k = 1, 2, \dots, V \quad (5)$$

$$P_{fa} = P(Y(k) > \tau z | H_0), \quad k = 1, 2, \dots, V \quad (6)$$

### 3. DESCRIPTION OF THE PROPOSED MODIFIED OTSU BASED CFAR ALGORITHM

In this section, we describe the modified Otsu algorithm according to [6], which serves as the basis CFAR technique

for use in our work. Each step of the algorithm including its use as a CFAR technique for Radar purpose is described as follows:

**Step 1:** Sense the input signal,  $y(n)$ ,  $n = 1, 2, \dots, V$ , and compute the energy of the signal as  $Y(k)$ ,  $k = 1, 2, \dots, V$ . Then set of signal samples,  $Y(k)$ ,  $k = 1, 2, \dots, V$ , representing a single spectral sweep,  $S=1$  is sufficient to start the algorithm. In applying this step to radar target detection, note that we will only need to sense the input signal within a given sliding window of size  $N$  and compute the energy for a single sample set, then continue the process until the total sample set  $V$  is processed. This modification ensures that a single threshold is not computed for the total sample set as in the case of Onumanyi et al [7], but computed for a single sample.

**Step 2:** Set the number of histogram bins as  $M = 256$ .

**Step 3:** Obtain the set of sample counts per bin  $C_i$ ,  $i = 1, 2, \dots, M$ , and the set of bin center values,  $B_i$ ,  $i = 1, 2, \dots, M$ , for the one dimensional data,  $Y(k)$ ,  $k = 1, 2, \dots, V$ , using,

$$(C_i, B_i) = F_D(Y(k), M), \quad D = 1 \quad (7)$$

Where the dimension,  $D$ , is now considered as  $D = 1$ , and  $F_D(\bullet)$  is a normal histogram function. The syntax for calling this histogram algorithm in MATLAB is given as " $[C_i, B_i] = hist(Y(k), M)$ ".

**Step 4:** Compute the sample probability  $P_i$  for the  $j^{th}$  bin using

$$P_i = C_i / \sum_{i=1}^M(C_i), \quad i, j = 1, 2, \dots, M \quad (8)$$

**Step 5:** Compute the set of sample cumulative probabilities,  $d_i$  for the  $j^{th}$  bin using

$$d_i = \sum_{i=1}^M P_i, \quad j = 1, 2, \dots, M \quad (9)$$

**Step 6:** Obtain the sample mean,  $\mu_j$  for the  $j^{th}$  bin using

$$\mu_j = \sum_{i=1}^M (P_i B_i), \quad j = 1, 2, \dots, M \quad (10)$$

**Step 7:** Calculate the total mean,  $\epsilon$  using

$$\epsilon = \sum_{j=1}^M \mu_j \quad (11)$$

**Step 8:** Compute the set of between-class variance  $\sigma_j$  for the  $j^{th}$  bin using

$$\sigma_j = [(\epsilon \cdot d_j - \mu_j)^2 / d_j (1 - d_j)], \quad j = 1, 2, \dots, M \quad (12)$$

**Step 9:** Find the subset of the maximum between-class variance  $\sigma_2$  using

$$\sigma_2 = \arg \max\{\sigma_j\}, \quad j \in M \quad (13)$$

This step ensures that the algorithm achieves an estimate of the noise floor by searching for the threshold at the

maximum between-class variance, by doing this, a form of noise variance estimation is done.

**Step 10:** Determine the specific index  $z$  of the subset with the condition

$$Z = R \text{ if } R \geq M/2 \text{ and} \tag{14A}$$

$$Z = E \text{ if } R < M/2 \tag{14B}$$

The condition specifies that when the measurement contains only noise samples (that is, if  $R \geq M/2$ ) then the algorithm returns the upper bound,  $R$ , of the subset. However, if otherwise, the algorithm selects the lower bound index,  $E$ .

**Step 11:** Compute the detection threshold  $\Delta$  using,

$$\Delta = \tau z \tag{15}$$

Where  $\tau$  is a constant threshold factor. This value was defined according to Gandhi [4].

$$\tau = (NP_{fa}^{-1/s} - 1) / (1 + S) \tag{16}$$

Where  $s$  is the signal to noise ratio.

#### 4. RESULTS AND DISCUSSIONS

To evaluate the performance of the CFAR technique, the values of  $P_d$  and  $P_{fa}$  are computed according to Fawcett [8]. We computed the probability of detection  $P_d$  using

$$P_d = T_P / A_P \tag{17}$$

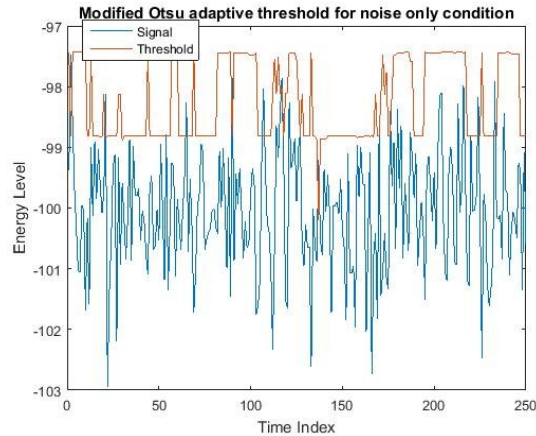
Where  $T_P$  is the number of truly detected signal samples and  $A_P$  is the total number of actual true signal samples. The probability of false alarm was computed using

$$P_{fa} = F_P / A_N \tag{18}$$

Where  $F_P$  denotes the falsely detected signal samples and  $A_N$  is the total number of actual noise samples.

**Table 1:** Performance analysis of the Modified Otsu (MO-CFAR) algorithm in varying snr conditions.

	Probability of Detection	Probability of False alarm
Noise Only	-	0.05
Signal plus Noise (2dB snr)	0.5	0.05
Signal plus Noise (5dB snr)	0.75	0.03
Signal plus Noise (10dB snr)	0.80	0.04



**Figure 2:** Detection thresholds for MO-CFAR algorithm in noise only condition.

#### 4.1 Performance in the Noise only (target absent) condition $H_0$

To evaluate the noise only or target absent condition, a spectrum containing only noise was constructed by simulating an AWGN (Additive White Gaussian Noise) with zero mean and unit variance. The spectrum was computed for 250 samples using the detector in fig 1. In this condition we are most concerned with the probability of false alarm since a noise only spectrum is not expected to contain any radar target for detection. The figure 2 above is a graph that shows the estimated thresholds in this condition. It was seen in the table 1, that the modified Otsu based CFAR algorithm experienced a false alarm rate of 5% in this condition.

Note that, in all figures, the red lines signifies the detection thresholds while the blue ones corresponds to the signal amplitudes in decibels within a given time.

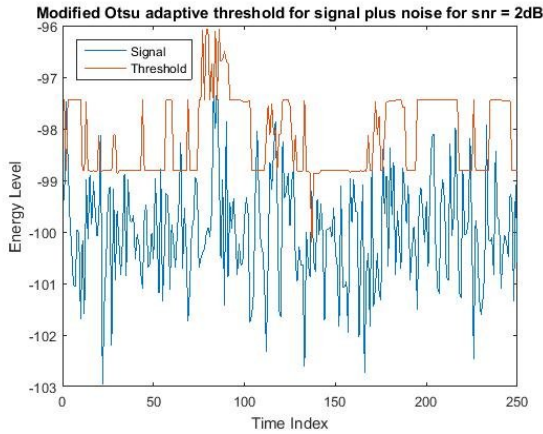


Figure 3: Detection thresholds for MO-CFAR algorithm for signal to noise ratio of 2dB.

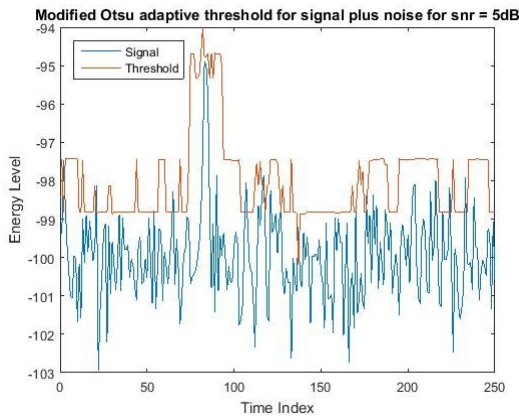


Figure 4: Detection thresholds for MO-CFAR algorithm for signal to noise ratio of 5dB.

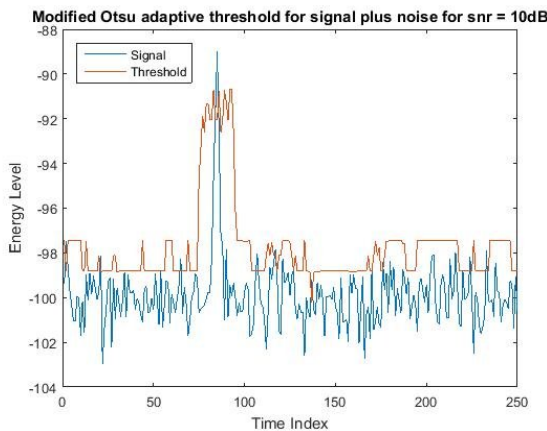


Figure 5: Detection thresholds for MO-CFAR algorithm for signal to noise ratio of 10dB.

4.2 Performance analysis in signal plus noise background  $H_1$  of varying signal to noise ratio

To evaluate the algorithm’s performance under varying signal to noise ratio, we also simulated the condition by computing 250 samples of IID (independent and

identically distributed) RVs (random variables) and varied the signal strength relative to a fixed noise level. The signal to noise ratio was varied from 2dB in figure 3 to 5dB in figure 4 and to 10dB in figure 5. The table 1, shows the detection probabilities, false alarm probabilities and the varying signal to noise ratio conditions. We observed that as the signal to noise ratio improved, there was a gradual improvement in the probability of detection as it experienced a detection probability of 50% at 2dB in (figure 3), 75% at 5dB in (figure 4) and 80% at 10dB in (figure 5). The algorithm also kept a false alarm rate of less than 6% in the entire varying signal to noise ratio conditions. The performance degradations at lower signal to noise ratio conditions is supported by similar results obtained by Datla in [9], suggesting that energy detectors often fail to distinguish signals from noise because of the noise uncertainty effect.

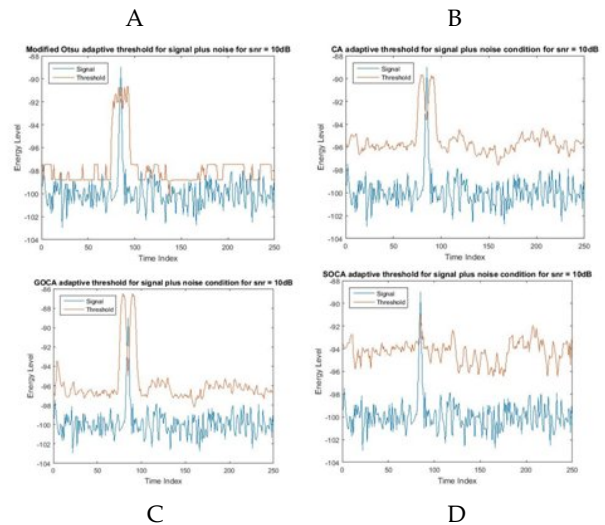


Figure 6: Detection thresholds for MO-CFAR, CA-CFAR, GO-CFAR and SOCFAR in a homogeneous signal plus noise  $H_1$  or (target present) environment for SNR of 10dB

To evaluate the performance of the algorithm relative to other well known CFAR detectors, we simulated the signal plus noise homogeneous condition at a signal to noise ratio of 10dB, and computed the detection thresholds and their corresponding detection probabilities and false alarm probabilities. The techniques simulated and compared were, MO-CFAR, CA-CFAR, GO-CFAR and SO-CFAR. It was seen that the MO-CFAR in (figure 6A) had the highest detection probability of 80% with a corresponding false alarm probability of 0.04, exceeding the detection probabilities of CA-CFAR (figure 6B) and GO-CFAR (figure 6C) which had a detection probabilities of 60% respectively, with false alarm probabilities of 0.00 while the SO-CFAR (figure 6D) had a detection probability of 40% and a false alarm probability of 0.00 recording the lowest probability of detection.

**Table 2:** shows the detection probabilities and false alarm probabilities of the MO-CFAR, CA-CFAR, GO-CFAR and SO-CFAR in a homogeneous  $H_1$  or (target present) environment.

	Probability of Detection	Probability of False alarm
MO-CFAR	0.80	0.04
CA-CFAR	0.60	0.00
GO-CFAR	0.60	0.00
SO-CFAR	0.40	0.00

**5. CONCLUSION.**

In this paper, we have presented a modified Otsu based CFAR algorithm for radar target detection and evaluated its performance in noise only and signal plus noise environment under varying signal to noise ratio conditions. The detection thresholds for the proposed CFAR were computed along with the detection probabilities and false alarm probabilities. Its performance in these environments showed that the modified Otsu based CFAR performance improved as signal to noise ratio increased.

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