A New Fuzzy CFAR Processor for Radar MTD Systems

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Abstract—This paper proposes a new fuzzy constant false alarm processor (FCFAR) for radar MTD systems. The proposed amplitude processor decides the fixed threshold value for the CFAR using fuzzy logic controller according three input variables. First input is the fast threshold from fifty serially averaged range cells. The second is the slow threshold from concatenated 500 averaged range cells. The third input is the signal to noise ratio at the RF stage of the radar system. The proposed processor is simulated under Matlab program environment on 1 million range cells data in additive white Gaussian noise (AWGN) with non-homogeneous background clutter and from 5 to 30 dB signal to noise ratio (S/N). The results show the superiority of the proposed FCFAR than the traditional systems used during the last decade.

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1. INTRODUCTION

In surveillance radar, the signal returns from targets are usually buried in thermal noise and clutter, which refers to any undesired signal echo that is reflected back to the receiver by buildings, clouds, the sea, etc. The attractive scheme that can be used to overcome the problem of clutter are the Constant False Alarm Rate Processor (CFAR), which set the threshold adaptively based on local information of total noise power. This CFAR detectors estimate the characteristics of the noise by processing a window of reference cells surrounding the cell under test. The CA approach is such an adaptive procedure. However, the CA detector has a severely degraded performance in clutter edge and interfering targets echoes [1, 2]. Rohling modified the common CA-CFAR technique by replacing the arithmetic averaging estimator of the clutter power by a new module based on order statistics (OS) [3]. The OS-CFAR procedure protects against nonhomogeneous situations caused by clutter edges and interfering targets. Target detectability and robustness against interfering targets can also be enhanced using distributed detection [4, 5]. Zoubeida et. al. [6] assessed the performance of decentralized CFAR detectors in homogeneous positive alpha-stable operating environment and in the presence of interfering targets. The local sensors are assumed to be identical or different CFAR processors taking their own decisions about the presence of a target. Such binary information is subsequently sent to a fusion centre for the final decision which is taken according to “AND” or “OR” fusion logic. Long Cai,[7,8] proposed several kinds of new CFAR detector, analyzed the performance in multi-target and clutter-edge environment, when the background clutter follows Pearson distribution. Fuzzy CA/CAGO/CASO detectors offer detection superiority and better false-alarm-control capacity, but consider a distributed system consisting of two antennas and a fusion center. Each antenna computes the CFAR threshold value $T$ and then send it to fusion center to produce the global threshold value. Detector compares the global value to a decision threshold to decide whether a target is present. This paper introduce a new Fuzzy CFAR scheme uses the Fuzzy logic controller to decide the threshold of the processor $T$ based on a prior information from the received signal includes fast threshold from fifty serially averaged range cells, slow threshold from concatenated 500 averaged range cells, and signal to noise ratio at the RF stage of the radar system. This system tested with three common used CFAR schemes, CA-CFAR, GO-CFAR, and SO-CFAR, and improves its performance.

2. THEORETICAL DESCRIPTION

The detection threshold is computed so that the radar receiver maintains a constant pre-determined probability of false alarm. The relationship between the threshold value and the probability of false alarm then,

$$V_T = \sqrt{2\psi^2\ln\left(\frac{1}{P_{fa}}\right)} \quad (1)$$

If the noise power $\psi^2$ is assumed to be constant, then a fixed threshold can satisfy equation (1). However, due to many reasons this condition is rarely true. Thus, in order to maintain a constant probability of false alarm the threshold value must be continuously updated based on the estimates of the noise variance. The process of continuously changing the threshold value to maintain a constant probability of false alarm is known as Constant False Alarm Rate (CFAR).
Cell-Averaging CFAR (Single Pulse)

The CA-CFAR processor is shown in Figure 1. Cell averaging is performed on a series of range and/or Doppler bins (cells). The echo return for each pulse is detected by a square law detector. In analog implementation these cells are obtained from a tapped delay line. The Cell Under Test (CUT) is the central cell. The immediate neighbors of the CUT are excluded from the averaging process due to possible spillover from the CUT. The output of reference cells (on each side of the CUT) is averaged. The threshold value is obtained by multiplying the averaged estimate from all reference cells by a constant (used for scaling). A detection is declared in the CUT if

$$Y_1 \geq K_0 Z$$

where $Z_i$ is the average of the lagging reference window, that is,

$$Z_1 = \frac{2}{N} \sum_{i=1}^{N/2} X_i$$

and $Z_2$ is the average of the lagging reference window, that is,

$$Z_2 = \frac{2}{N} \sum_{i=N/2+1}^{N} X_i$$

It follows that the unconditional probability of false alarm is,

$$P_{fa} = \int_0^{\infty} P_{fa}(V_T = y) f(y) dy$$

where $f(y)$ is the threshold distribution.

Smallest-of (CASO) CFAR

In the CASO-CFAR scheme, the clutter level estimate is the smallest of the sums of the leading and lagging sets of the reference cells. That is,

$$Z_{CASO} = \min (Z_1, Z_2)$$

where $Z_i$ is the average of the leading reference window, that is,

$$Z_1 = \frac{2}{N} \sum_{i=1}^{N/2} X_i$$

and $Z_2$ is the average of the lagging reference window, that is,

$$Z_2 = \frac{2}{N} \sum_{i=N/2+1}^{N} X_i$$

The block diagram of CAGO and CASO is shown in Figure 2.

Fuzzy Logic Controller (FLC)

Figure 3 shows the basic structure of a Fuzzy logic controller. The main building units of an FLC are a fuzzification unit, a Fuzzy logic reasoning unit, a knowledge base, and a defuzzification unit. Defuzzification is the process of converting inferred Fuzzy control actions into a crisp control action. The fuzzy knowledge-base has a rule-base that maps a Fuzzy inputs variable, $E$, into a Fuzzy output, $U$. 

Greatest-of (CAGO) CFAR

The clutter level is estimated by selecting the greatest of the leading and lagging sets of the reference cells. Therefore the statistic $Z_{CAGO}$ is given by,

$$Z_{CAGO} = \max (Z_1, Z_2)$$

where $Z_i$ is the average of the leading reference window, that is,

$$Z_1 = \frac{2}{N} \sum_{i=1}^{N/2} X_i$$

and $Z_2$ is the average of the lagging reference window, that is,

$$Z_2 = \frac{2}{N} \sum_{i=N/2+1}^{N} X_i$$
This can be expressed by a linguistic statement such as:
\[ E \rightarrow U \] (conditions \( E \) implies condition \( U \))
which may be written as:
\[ \text{IF } E \text{ THEN } U. \]
The Fuzzy knowledge-base also has a database defining the variables. A Fuzzy variable is defined by a Fuzzy set, which in turn is defined by a membership function. Fuzzy reasoning is used to infer the output contributed from each rule. The Fuzzy outputs reached from each rule are aggregated and defuzzified to generate a crisp output.

**Design**

In the design of an FLC system it is assumed that:
- A solution exists.
- The input and output variables can be observed and measured.
- An adequate solution (not necessarily an optimum one) is acceptable.
- A linguistic model can be created based on the knowledge of a human expert. In order to model a system linguistically, one needs to:
  - Identify the input and output variables of the process to be controlled (the plant). For example: speed, temperature, humidity, etc.
  - Define subsets that cover the universe of discourse of each variable and assign a linguistic label to each one. For example, the linguistic variable speed may be defined as three Fuzzy subsets: slow, medium, and fast as shown in Figure 4.
  - Form a rule-base by assigning relationships between inputs and outputs.
  - Determine a defuzzification method to be used to generate a crisp output from the Fuzzy outputs generated from the rule-base.

**Determination of Membership Functions**

Discrete and continuous membership functions of a Fuzzy set are intended to capture a person’s thinking. Fuzzy membership functions can still be determined subjectively in practical problems based on an expert’s opinion. In such a situation one can think of membership functions as a technique to formalize empirical problem solving that is based on experience rather than the knowledge of theory. The expert’s way of thinking can be captured either directly or through a special algorithm. Such determination could become more focused by physical measurements if the need arises. Available frequency histograms and other probability data can also help in constructing the membership function. It is important, however, to note that membership function values, or grades of membership, are not probabilities and they do not have to add to 1. Membership construction can be further simplified by selecting their form from the smaller family of the commonly used ones.

**Fuzzification**

Fuzzification is the process of making a crisp quantity Fuzzy. We do this by simply recognizing that many of the quantities that we consider to be crisp and deterministic are actually not deterministic at all; they carry considerable uncertainty. If the form of uncertainty happens to arise because of imprecision, ambiguity, or vagueness, then the variable is probably Fuzzy and can be represented by a membership function [11].

**Defuzzification**

For a given input, several IF/THEN rules could be launched at the same time. Each rule would have a different strength, because a given input may belong to more than one Fuzzy set, but with different membership values. In general, the output of the Fuzzy reasoning would involve more than two Fuzzy sets; therefore, one can write:

\[ F = \bigcup_{i=1}^{k} F_i \] (11)

Assuming the support of \( F \) is \( X = \{x_1, x_2, x_3, \ldots \} \) then for \( x_i \in X \), \( F(x_i) = w_i \) indicates the degree to which each is suggested by the rule-base as a good output for the given input. The defuzzification operation is applied on \( F \) to determine the best crisp output. Numerous defuzzification methods have been suggested in the literature; however, sometimes different authors name the same method differently. No method has proved to be always more advantageous than the others. The selection of which method to use depends primarily on the experience of the designer [12].

**Centroid method**

This method is also known as the center of mass, or center of gravity method. It is probably the most commonly used defuzzification method. The defuzzified output, \( x^* \) is defined by,
\[ x' = \int \frac{\mu_F(x)}{\mu_T(x)} dx \]  

(12)

where the symbol \( \int \) denotes algebraic integration. Figure 5. Represent this method graphically [13].

Center of largest area method
This method is applicable when the output consists of at least two convex Fuzzy subsets which do not overlap. The result is biased towards a side of one membership function.

First maxima method
This method is applicable when the output is peaked; the smallest value of the domain with maximum membership is selected.

Center of sums method
This method uses the algebraic sum of the individual Fuzzy subsets instead of their union. Although the calculations become faster, this method leads to adding the intersecting areas twice.

3. THE PROPOSED METHOD

The block diagram of the proposed Fuzzy CFAR is demonstrated in Figure 6. The Fuzzy controller receives three inputs, the first from fast running average processor, the second from slow running average processor, and RF signal to noise ratio and gives the threshold voltage required for the comparator. The membership function of each input and output signals is divided into four membership functions, very low, low, high, and very high as shown in Figure 7. The surface transfer characteristic between fast, slow threshold and the output is demonstrated in Figure 8. The transfer characteristics between RF noise figure and fast, slow threshold inputs are illustrated in figs (9,10).

4. SIMULATION RESULTS

The simulation is performed using Matlab program environment on 100 million range cell data assuming target fluctuates a Swerling 1 target in under nonhomogeneous Gaussian clutter. It utilize Monte-Carlo simulation method to illustrate the performance of fuzzy CA/GO/SO CFAR detectors with length N of reference window is 8, 16, and 32, and desired false alarm rate constrained for each S/N. Figure 11. shows the detection probability of CA-CFAR scheme with 8, 16, and 32 neighboring cells with respect to the proposed Fuzzy CFAR. It is clear from the figure that the proposed system enhances the detection probability at low signal to noise ratio from 5 to 30 %. Figure 12, 13 demonstrate the same comparison for GO-CFAR and SO-CFAR and gives conclusion denotes that Fuzzy CFAR scheme has superior improvement over the normal types of CFAR. Figs. 14 to 16 introduce a comparison between the three Fuzzy CFAR schemes with 8, 16, and 32 cells. The results show that Fuzzy CA-CFAR performs the other two types during all these simulations. The probability of false alarm rate varied with signal to noise ratio from Fuzzy CFAR type to another type as shown in Figure 17.
Figure 8. The transfer characteristic of the fast and slow threshold input

Figure 9. The transfer characteristic of the fast threshold input and RF noise figure.

Figure 10. The transfer characteristic of the slow threshold input and RF noise figure.

Figure 11. The detection probability comparison between CA-CFAR and Fuzzy CA-CFAR

Figure 12. The detection probability comparison between GO-CFAR and Fuzzy GO-CFAR

Figure 13. The detection probability comparison between SO-CFAR and Fuzzy SO-CFAR
Figure 14. The detection probability comparison between Fuzzy CA, GO, and SO-CFAR at N=8

Figure 15. The detection probability comparison between Fuzzy CA, GO, and SO-CFAR at N=16

Figure 16. The detection probability comparison between Fuzzy CA, GO, and SO-CFAR at N=32

Figure 17. The probability of false alarms comparison between Fuzzy CA, GO, and SO-CFAR

5. CONCLUSION

The paper introduce a new Fuzzy CFAR scheme uses the Fuzzy logic controller to decide the threshold of the processor T based on a prior information from the received signal includes fast threshold from fifty serially averaged range cells, slow threshold from concatenated 500 averaged range cells, and signal to noise ratio at the RF stage of the radar system. This system tested with three common used CFAR schemes, CA-CFAR, GO-CFAR, and SO-CFAR, and improves its performance. The results show the superiority of the proposed FCFAR than the tradition systems used during the last decade.

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