A CFAR ALGORITHM BASED ON SUMMATIONS PROCESSING

An Phan, Sandun Kodituwakku, Tri-Tan Van Cao

Defence Science and Technology Organisation (DSTO), Australia.

ABSTRACT

A new radar constant false-alarm rate (CFAR) algorithm, denoted as Sum-CFAR, based on the processing of the summations of reference cells is proposed. The new algorithm employs a censoring technique similar to the traditional censored cell-averaging (CCA) CFAR. The innovation is that instead of processing each individual reference sample, the summation of at least two reference samples are processed. Performance analysis with exponentially distributed interference shows a detection improvement of up to a few dBs compared with the traditional CCA-CFAR.

Index Terms— CFAR, Radar, Censored cell-averaging, Summations processing

1. INTRODUCTION

One problem in radar detection is to design a constant false-alarm rate (CFAR) detector that is resistant to clutter inhomogeneity such as step changes in clutter power and/or local peaks of high amplitudes known as outliers [1,2]. In practice, there are two common situations when clutter inhomogeneity is found: (i) there is a clutter edge (eg., at the border of land and sea), where the energy of interference changes; and (ii) there is an outlier (eg., a clutter spike, an impulsive interference, or another interfering target).

The most basic form of CFAR processing is the well-known cell-averaging (CA) CFAR [3]. The input to the processor is the output of either the envelope or squared-law detector, with samples in range (and Doppler if available). Each sample in the range/Doppler dimensions is called a cell. The test cell is the cell at which a detection decision has to be made. The interference power in the test cell is estimated using its surrounding cells which are termed reference cells. In the range-Doppler map, the reference cells form a reference window. The interference estimation is simply the sample mean of the power in the cells within a reference window. The detection threshold is then formed by multiplying the interference estimate with a constant, the value of which is determined by the required false-alarm rate. A few immediate neighbours (known as guard cells) on each side of the test cell are excluded from the estimation to prevent possible power spill-over from the test cell.

Under the condition that the sample in each reference cell is independent and identically distributed (i.i.d.) and is governed by the exponential distribution, the performance of the CA-CFAR processor is optimal (in the sense that the detection probability is maximised for a given false-alarm rate) when the number of reference cells is large. However, in the presence of clutter inhomogeneity, the i.i.d. assumption becomes invalid and the detection encounters the following problems: (i) masking of weaker targets near stronger targets, (ii) excessive false alarms at clutter transitions, and (iii) failure to detect targets near clutter edges.

Many CFAR detection algorithms that have certain robustness with respect to inhomogeneous clutter have been proposed, for instance, see [2, 4] for a comparative study. These algorithms can be classified into two groups.

In the first group, modifications to the original CA-CFAR algorithm were made to achieve a particular robustness. For instance, the smaller-of (SO) CFAR [5] is designed to be resistant to target masking by splitting the reference window into a leading part and a lagging part and then selecting the part with a smaller sample sum for threshold computation. To be resistant to false-alarm inflation at a clutter edge, the greater-of (GO) CFAR [6] is considered (by selecting the part with a greater sample sum). Other modifications that rely on rank ordering include the order-statistic (OS) CFAR [7], where the interference estimate is given by the amplitude of the k^{th} ordered reference sample; the censored cell-averaging (CCA) CFAR, where only the k smallest ranked samples are used for interference estimation via the cell averaging method [8].

In the second group a combination of multiple algorithms from the first group has been proposed, for instance, variable index (VI) CFAR (combining CA-CFAR, SO-CFAR, and GO-CFAR [9]), switching (S) CFAR (combining CA-CFAR with CCA-CFAR [10]), improved switching CFAR [11], robust ensemble CFAR (combining SO-CFAR, GO-CFAR, censored OS-CFAR, and geometric-mean (GM) CFAR [12]), etc.

In the design and assessment of these CFAR algorithms, the statistical distribution function known as the ϵ-contaminated model is assumed [13]. Recently, it has been shown that inhomogeneity observed in a variety of radar experimental data can be modelled as a finite mixture of Weibull densities, which is a generalization of the traditional ϵ-contaminated model [14] where an algorithm for identifying the parameters of each Weibull component in the mixture is presented. Based on the observation that inhomogeneous samples are usually localised in groups, the data are segmented into smaller sets, each of which is to be allocated to a different Weibull component. A distinctive feature of this modelling method is that it operates on the sum of at least two samples, but not on each individual sample as performed in other traditional CFAR processing techniques. Such summations processing improves the effectiveness of the truncation between the background noise and the inhomogeneous samples.

Based on this summations processing research theme, a modification of the CCA-CFAR, in which the summations of at least two reference samples are processed, is investigated in this paper. It is shown that a detection improvement of up to a few dBs compared with the traditional CCA-CFAR can be achieved in the case of exponentially distributed interference.

2. SUM-CFAR ALGORITHM

Consider a CFAR processor which receives input from the square-law detected samples in the range/Doppler cells. Assume that the amplitude of the sample in each cell can be modelled as an i.i.d. random variable X with an exponential probability density function (pdf) described by:

$$p_X(x) = \frac{1}{\lambda}\exp\left(\frac{-x}{\lambda}\right), \quad x \geq 0, \quad \lambda > 0 \tag{1}$$

where λ depends on the following two alternative hypothesis:

$$\begin{aligned} &\mathbf{H}_0 : \text{target absent}, \lambda = \mu \\ &\mathbf{H}_1 : \text{target present}, \lambda = \mu(1+\sigma), \end{aligned} \tag{2}$$

where $\mu > 0$ is the clutter-plus-noise power, and σ is the average signal-to-noise ratio (SNR) of the target. The model assumes a Swerling I target on exponentially distributed background [2].

The new Sum-CFAR algorithm is presented below. The algorithm is based on grouping reference cells, ordering summations of the groups, and censored averaging of the ordered sums in order to get the interference estimate for the cell under test.

Let x be the sample in the cell under test where target present/absent is to be verified, and $\mathbf{X} = \{x_i | i = 1, \ldots, N\}$ be the reference window of length N, comprising of samples in the neighboring cells around the cell under test, ignoring possible guard cells. These reference cells are grouped into groups of n, where $n < N$, as follows (without loss of generality, assume that $N/n = p$ is an integer):

$$\begin{aligned} &\mathbf{X}_1 = \{x_1,\ x_2, \ldots,\ x_n\} \\ &\ldots \\ &\mathbf{X}_p = \{x_{(p-1)n+1},\ x_{(p-1)n+2}, \ldots,\ x_{pn}\}. \end{aligned} \tag{3}$$

In each group $\mathbf{X}_j$, the n samples are summed to obtain $\{S_j | j = 1, \ldots, p\}$, where

$$S_j = \sum_{x_m \in \mathbf{X}_j} x_m. \tag{4}$$

The grouped sums $\{S_j\}$ are arranged in the ascending order to give the ordered sequence $\{S_{(j)} | j = 1, \ldots, p\}$ in which:

$$S_{(1)} \leq S_{(2)} \leq \cdots \leq S_{(p)} \tag{5}$$

The interference estimate η for the cell under test is then computed as the censored average of $\{S_{(j)}\}$.

$$\eta = \frac{1}{kn}\sum_{m=1}^{k} S_{(m)}, \tag{6}$$

where kn ($kn < N$) is the CFAR order comparable with OS-CFAR and CCA-CFAR previously described.

Target present/absent is then verified as follows:

$$x \underset{\mathbf{H}_0}{\overset{\mathbf{H}_1}{\gtrless}} \alpha \times \eta, \tag{7}$$

i.e., a target is declared present at the cell under test if x is greater than the detection threshold $T = \alpha \times \eta$; and absent otherwise, where α is a positive constant the value of which is determined by the required false alarm rate. From (7), the probability of detection (P_d) and the probability of false alarm (P_{fa}) are:

$$\begin{aligned} P_d &= \text{Prob}\left[x > \alpha \times \eta \mid \mathbf{H}_1\right] \\ P_{fa} &= \text{Prob}\left[x > \alpha \times \eta \mid \mathbf{H}_0\right]. \end{aligned} \tag{8}$$

From equations (4), (6), and (8), the detection threshold is computed as a constant multiplying with the summation of a subset S of the reference sample set. Under hypothesis $\mathbf{H}_0$, a sample x drawn from exponential distribution has the form $x = -\mu\ln(y)$, where y is a random number drawn from the uniform distribution over $[0, 1]$, and μ is the clutter-plus-noise power described in (2). Equation (8) is then equivalent to:

$$\begin{aligned} P_{fa} &= \text{Prob}\left[x > \text{const} \times \sum_{x_i \in S} x_i\right] \\ &= \text{Prob}\left[-\ln(y) > \text{const} \times \sum -\ln(y_i)\right] \end{aligned} \tag{9}$$

Equation (9) means that the proposed detector is CFAR since the false alarm rate is independent from the clutter-plus-noise power μ. The proposed Sum-CFAR algorithm generates a class of CFAR algorithms as group size n varies. In this paper, the notation Sum$_n$-CFAR is used to describe the proposed algorithm when group size of n is used. In Section 4, the performance of the Sum$_2$, Sum$_4$, and Sum$_8$-CFAR algorithms, corresponding to grouping of 2, 4, and 8 reference cells respectively, are compared with traditional CA, OS, and CCA-CFAR algorithms. Note that when $n = 1$, the Sum-CFAR algorithm simplifies to CCA-CFAR, thus proposed algorithm can be considered as a generalisation of the CCA-CFAR.

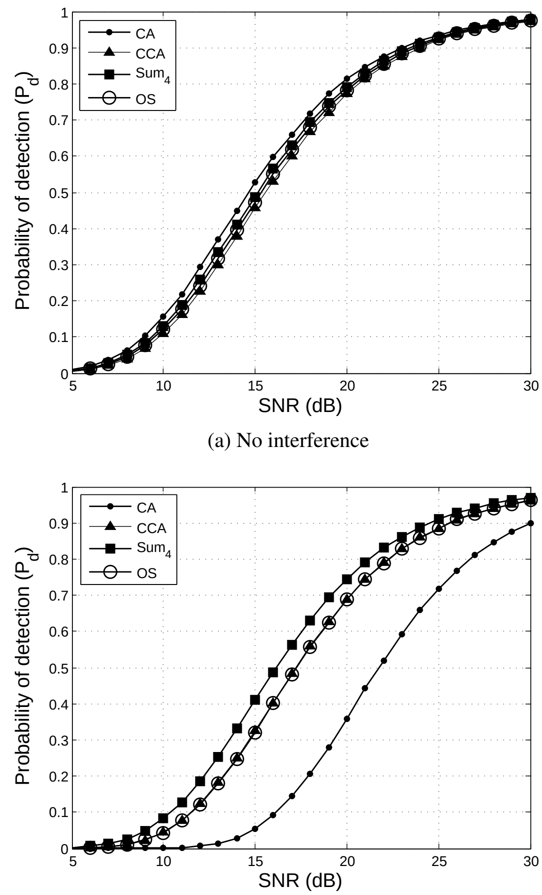
3. ANALYSIS

For a given reference window size N, the Sum-CFAR has two parameters to be designed: the group size n; and the number of reference cells kn employed in the interference estimation after censoring, which is referred to as the CFAR order. For CCA-CFAR, similarly, the CFAR order refers to the number of reference cells left after censoring. For OS-CFAR, the CFAR order refers to the index of the ordered reference cell which is used as the interference estimate. It is anticipated that higher CFAR order results in a smaller CFAR loss in a homogeneous background, but the detection performance is less robust in the nonhomogeneous situations. Here, the CFAR loss of a detector is defined as the additional SNR the detector requires in order to achieve the same detection probability of 0.5 compared to the CA-CFAR detector with no interference.

Several interference scenarios were analysed with varying interference power level. Both fixed and variable interference power cases were considered. In fixed power cases, the interference power was set fixed at 5, 10, 15, 20, and 25 dB above noise. In the variable power case, the interference power was set to be the same as the target power and varied as target power varied. The number of contaminated reference cells was set at 25% of the reference window length. The contaminated cells were grouped and then placed randomly in the reference window.

Three reference window lengths N = 16, 32, and 100 were examined. The small window lengths (16 and 32) are applicable in detecting point-like targets, while the large window size (100) can be used for detecting extended targets [14].

A closed-form false alarm computation for the CCA-CFAR (a special case of the Sum-CFAR) is feasible when only a few reference samples are censored [8]. Therefore, for a specified P_{fa}, the constant α is estimated using equation (8) via Monte-Carlo method with $100/P_{fa}$ trials, which is large enough so that the estimation error is within a 10% bound. The analysis was performed at $P_{fa} = 10^{-4}$.



(a) No interference

(b) 15 dB interference

Fig. 1. Detection performance comparison of different CFAR algorithms with and without interference at P_{fa} of 10^{-4} with 32 reference cells and CFAR order of 16.

4. RESULTS

Results for window length $N = 32$ are representatively shown in this Section. Detection performance of the new Sum_2, Sum_4, and Sum_8-CFAR algorithms are compared with those of CA, OS, and CCA-CFAR algorithms. The CFAR loss is used as the performance metric to compare six CFAR algorithms.

Figure 1 shows P_d curves of different detectors with and without interference. The CFAR order of 16 is used for Sum_4-CFAR, CCA-CFAR, and OS-CFAR. Figure 2 shows the CFAR loss of each detector as interference power varies for three different CFAR orders (16, 19, and 24). In the following sections, the results presented in the mentioned figures are discussed in detail under a number of sub-topics demonstrating the superiority of new Sum-CFAR detector over existing detectors.

4.1. Target detection with interference

As shown in Figure 1a, when there is no interference, CA-CFAR is the best detector. With respect to CA-CFAR, the performance of other detectors are ranked from high to low as follows: Sum_4-CFAR (0.5 dB loss), OS-CFAR (0.7 dB loss), and CCA-CFAR (0.9 dB loss). As shown in Figure 1b, when 15 dB interference is present in 8 reference cells, the best detector is Sum_4-CFAR, followed by OS-CFAR (1 dB loss), CCA-CFAR (1 dB loss), and CA-CFAR (5.6 dB loss).

4.2. Impact of interference power level

As shown in Figure 2, the CFAR loss increases as the interference power increases for all the CFAR algorithms. The CA-CFAR algorithm is significantly degraded by the increase in the interference power. At 15 dB interference and CFAR order 19, the best detector was found to be Sum_4-CFAR, followed by Sum_2-CFAR (0.2 dB loss), CCA-CFAR (0.7 dB loss), OS-CFAR (1 dB loss), Sum_8-CFAR (2.2 dB loss), and CA-CFAR (5.5 dB loss), as shown Figure 2b. When the interference power was set to be same as the target power and varies as target power varies, Sum_4-CFAR was still found to be the best detector.

4.3. Impact of CFAR order

Overall, the results suggest that a CFAR order of 16 (50% of the reference window length) performs well for all the interference scenarios. At 15 dB interference, the best detectors for CFAR orders 16, 19, and 24 were found to be Sum$_8$-CFAR, Sum$_4$-CFAR, and Sum$_2$-CFAR, respectively as shown in Figure 2. When the CFAR order is 24 (75% of the reference window length) as shown in Figure 2c, CCA-CFAR performed better than the Sum-CFAR if the interference power is higher than 17 dB.

For high CFAR order, the performance of the Sum-CFAR degrades more than CCA-CFAR due to a greater chance of having interfering samples in the sums. In the presence of the interference, the CFAR order of 50% of the reference window length is robust to most interference scenarios and gives a good detection performance.

4.4. Selection of group size n in Sum$_n$-CFAR

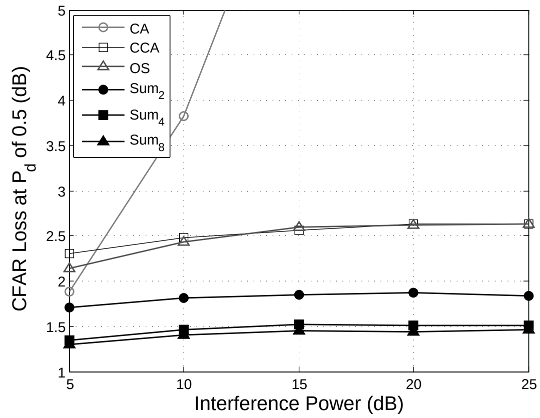
For all the interference scenarios and CFAR orders considered in the analysis, Sum$_2$-CFAR performed consistently well across all different scenarios. This is important as prior knowledge of the interference pattern might not be available. Sum$_4$-CFAR achieved a slightly better detection (0.3 dB) compared to Sum$_2$-CFAR when the CFAR order is 16 or 19. However, Sum$_2$-CFAR outperformed Sum$_4$-CFAR when the CFAR order is 24. Sum$_8$-CFAR performed well only when the CFAR order was low (16). Thus, Sum$_2$-CFAR was found to be the best detector, out of six CFAR detectors considered.

Although not shown here, it was found that for the other two window lengths (16 and 100) examined, the best Sum$_n$-CFAR combination is: group size $n = 2$, and CFAR order kn equivalent to 50% reference window length, giving a detection improvement of up to 1.5 dB compared with OS and CCA-CFAR.

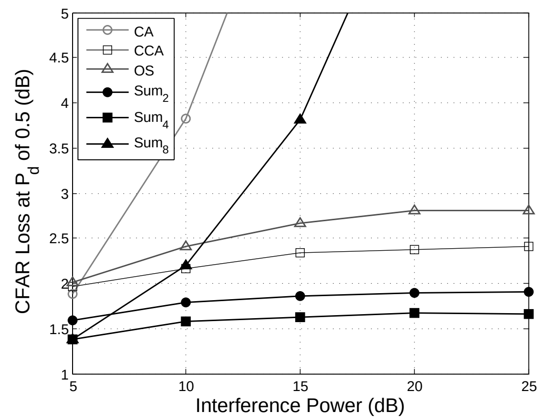
5. SUMMARY

The simulation results demonstrate that the new Sum-CFAR detector improves the probability of detection by up to 1.5 dB compared to traditional CCA-CFAR, OS-CFAR, and CA-CFAR in the presence of exponentially distributed interference. Below is a summary of the results obtained:

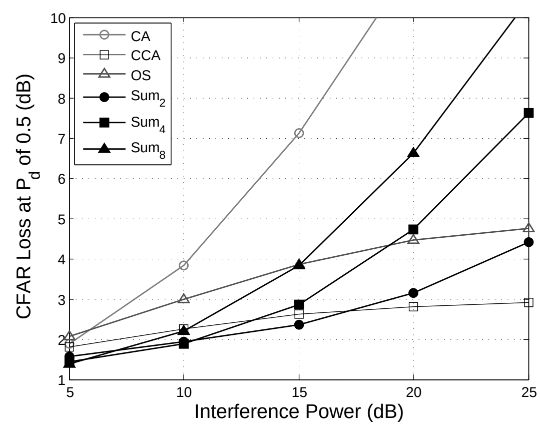
1. When there is no interference, the CA-CFAR is the best detector followed by the new Sum-CFAR algorithm, which is better than the OS and CCA-CFAR algorithms.
2. When the interference is present in 25% of the CFAR reference window, the Sum-CFAR is up to 1.5 dB better than OS and CCA-CFAR, and 5.8 dB better than CA-CFAR.
3. The CFAR loss increases as the interference power increases. However, detection performance of Sum-CFAR is still better than OS or CCA-CFAR for most cases.
4. A CFAR order of 50% of the reference window length is found to be most robust compared to CFAR orders of 60% and 75% of the reference window length.
5. The Sum$_2$-CFAR is the most robust detection algorithm performing consistently well across all the different interference scenarios.



(a) CFAR order = 16



(b) CFAR order = 19



(c) CFAR order = 24

Fig. 2. Comparing the performance of six CFAR algorithms in terms of the CFAR loss at P_d of 0.5 for a P_{fa} of 10^{-4} compared to CA-CFAR with no interference. Reference window length of 32 is used with 8 interference cells.

6. REFERENCES

[1] M. I. Skolnik, *Introduction to Radar Systems*, 3rd ed. McGraw-Hill Book Company, 2001.

[2] P. P. Gandhi, S. A. Kassam, *Analysis of CFAR processors in nonhomogeneous background*, IEEE Trans. Aerosp. Electron. Syst., 1988, 24(4), pp. 427-445.

[3] H. M. Finn, R. S. Johnson, *Adaptive detection mode with threshold control as a function of spatially sampled clutter level estimate*, RCA Rev., 1968, 29(3), pp. 414-464.

[4] P. Antonik, B. Bowies, G. Capraro, L. Hennington, *Intelligent Use of CFAR*, Kaman Sciences Corporation, 1991.

[5] G. V. Trunk, *Range resolution of targets using automatic detectors*, IEEE Trans. Aerosp. Electron. Syst., 1978, 14(5), pp. 750-755.

[6] G. V. Hansen, J. H. Sawyers, *Detectability loss due to greatest-of selection in a cell averaging CFAR*, IEEE Trans. Aerosp. Electron. Syst., 1980, 16, pp. 115-118.

[7] H. Rohling, *Radar CFAR thresholding in clutter and multiple target situations*, IEEE Trans. Aerosp. Electron. Syst., 1983, 19, pp. 608-621.

[8] J. T. Rickard, G. M. Dillard, *Adaptive detection algorithms for multiple target situations*, IEEE Trans. Aerosp. Electron. Syst., 1977, 13(4), pp. 338-343.

[9] M. E. Smith, P. K. Varshney, *Intelligent CFAR processor based on data variability*, IEEE Trans. Aerosp. Electron. Syst., 2000, 36(3), pp. 837-847.

[10] T. V. Cao, *Constant false-alarm rate algorithm based on test cell information*, IET Radar, Sonar Navig., 2008, 2(3), pp. 200-213.

[11] R. Zhang, W. Sheng, X. Ma, *Improved switching CFAR detector for non-homogeneous environments*, Signal Processing, 2013, 93, pp. 35-48.

[12] R. Srinivasan, *Robust Radar detection using ensemble CFAR processing*, IEE Radar Sonar Navig., 2000, 14(6), pp. 291-297.

[13] R. A. Maronna, R. D. Martin, V. J. Yohai, *Robust Statistics*, Wiley, 2006.

[14] T. V. Cao, *Modelling of inhomogeneity in radar clutter using Weibull mixture densities*, IET Radar, Sonar Navig., 2014, 8(3), pp. 180-194.