CFAR ALGORITHMS

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Introduction

Constant False Rate Alarm Algorithms or popularly known as CFAR Algorithm are crucial in the accurate detection of objects through the use of radars. It is essential to reduce false positive that may account due to unwanted noise, clutter, and interferences in the environment. An autonomous car requires accurate detection of obstacles in its path. It is quite undesirable if the car slows down or stops too frequently because of a false alarm rate. The false alarm rate may arise due to the reflection of radar signals from corners in the parking garage or benches on the side of the street. CFAR Algorithm is an adaptive algorithm that sets a threshold value for the cell under observation based on neighboring cells. Any value returned above the threshold is considered to be originated from a target. It is highly undesirable to set the threshold too low as it may lead to positive while upon setting a threshold too high, we may miss detecting many possible targets. Thus, CFAR algorithms vary the threshold upon a fixed probability of false alarm rate.

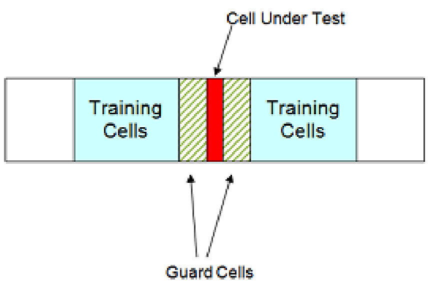
CFAR Algorithm is an exciting topic. It utilizes the beauty of statistics to get an adaptive threshold value for a constant false probability. To study the topic in-depth is very motivating as it has a crucial application, and it is used in every surveillance and radar system. It is fascinating to note that in a time when modern AI has replaced almost every traditional method, the algorithm still has not lost its importance. A new active field of research is to combine the power of both methods, the traditional CFAR and modern AI.

The start of the term paper highlights the basics of the CFAR Algorithm for the reader to understand it is working. We discuss two conventional CFAR Algorithms, *CA-CFAR* (Cell Averaging CFAR) and *OS-CFAR* (Ordered Statistics CFAR).

We then introduce the drawbacks of the algorithms and how recent developments have shown a possible way to tackle them. The term paper covers a Bilateral CFAR Algorithm that reduces the effect of noise and increases the detection probability of ships in SAR images. A breakthrough in SAR detection is the research at the University of Defence Technology, China, where the scientists have combined the robustness of CFAR with the efficiency of AI or Deep Neural Network Architecture. The research has opened another dimension for the application of CFAR Algorithms.

Conventional CFAR Algorithms

Any general CFAR Algorithm has a standard structure, a cell under test (CUT) where the possibility of a target is assessed, guard cells which are immediate neighbors of and training cells, which are the cells around CUT. As the target may be significant, its peak may even spread in guard cells. Thus we usually ignore their value in any analysis. The guard cells and CUT collectively form the sliding window. The length of the sliding window is a hyperparameter that is tuned based on the surrounding.



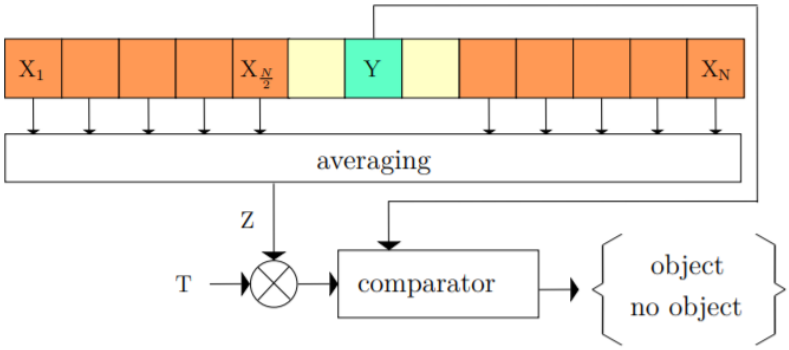
All CFAR algorithms are either linear or non–linear statistical operations on guard cells that give an optimum threshold value. It is important to note that noise is assumed to have gaussian distribution.

- **CA-CFAR**

The first algorithm is Cell Averaging CFAR, where we evaluate the threshold after taking the mean of the training cells around the cell under test (CUT).

$$Z = \frac{1}{N} \sum_{i=1}^{N} X_i,$$

The resultant mean from N neighboring cells forms the adaptive threshold. The mean after multiplication with a constant scaling factor T gives threshold value for that cell. Note that the threshold value varies with each cell under test as the reference window changes.



For a specified probability of a false alarm (P_{FA}) and a fixed window size N, the constant T is determined considering that noise is randomly distributed in each cell and follows a gaussian distribution. The resultant pdf of mean is given by $f_{z_n}(z)$.

$$f_{Z_N}(z) = \frac{\mu^N z^{N-1} e^{-z\mu}}{(N-1)!},$$

To get the expression of T in terms of P_{FA}, we calculate the probability

$$P_{FA} = E[Pr[Y \geq T \cdot Z | H_0]].$$

We define the hypothesis H_0 as the event that the training cells have noise only. In contrast, H_1 assumes the presence of an object. $Z|H_0$ depicts the value of the threshold, and Y is the value of CUT. The probability of a false alarm equals the possibility that the cell under test exceeds the threshold value under the condition H_0, which means only noise is present.

After calculating the probability, we get

$$P_{\mathrm{FA}} = \frac{1}{(1+\frac{T}{N})^N},$$

The expression can be further simplified to give the value of T in terms of window size N and the desired probability of false rate P_{FA}

$$T = N(P_{\mathrm{FA}}{}^{-\frac{1}{N}} - 1).$$

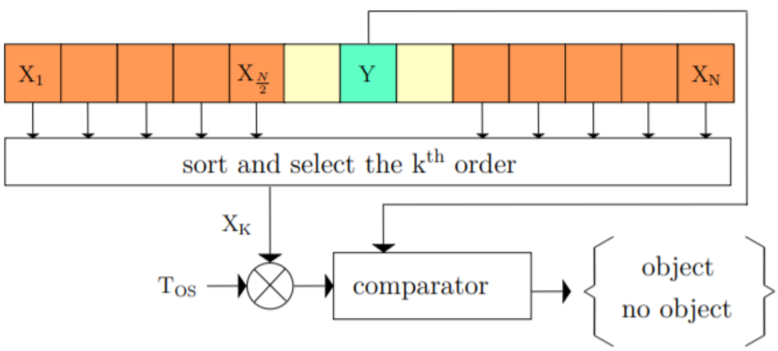
The benefit of using CA-CFAR is that it is relatively fast and gives satisfactory results in a homogenous environment. However, it fails to cater to multiple target detection, and in a non-homogenous environment, mean statistics for estimation of noise fails.

- **OS-CFAR**

In comparison to CA-CFAR, Ordered Statistics CFAR or (OS-CFAR) uses a particular value in the sliding window instead of all values in the window. The general idea of an ordered-statistic is that the noise estimation is based on the k^{th} values of reference values sorted in ascending order

$$X_1 \leq X_2 \leq ... \leq X_k \leq ... \leq X_{N-1} \leq X_N.$$

These statistics help in the detection of multiple targets as if there is another object present in the reference window; its value is not affecting the peak detection in the cell under test Y. The arithmetic mean used in CA-CFAR algorithms is replaced by a single rank of the ordered-statistic X_k.



This value is multiplied by a scaling factor T_{os} to get the value of the threshold. A value of $k = 3N/4$ has known to give good results. To get the value of the scaling factor *T*, we do sophisticated statistics modeling, and we get the following expression

$$P_{\mathrm{FA}} = k\binom{N}{k}\frac{(k-1)!(T_{\mathrm{OS}}+N-k)!}{(T_{\mathrm{OS}}+N)!},$$

For a given probability of false alarm PFA and the kth value of an ordered-statistic array of exponentially distributed values. We observe that we do not get a closed expression in the form of T as in CA-CFAR; thus, the value of k is found iteratively.

OS-CFAR has a reasonable detection rate even in multiple target scenarios, and it outperforms CA-CFAR in the non-homogenous environment. However, calculation of T is iterative, and sorting for each CUT with a window of size n requires minimum $n\log(n)$ steps. Thus OS-CFAR is computationally expensive. Clutter problem by choosing a window size larger than clutter size.

Research Paper – 1

Problem- On extensive research, I found that while performing traditional CA-CFAR clutter noise hurt its efficiency as these noise increase false detection rate

Proposed Solution- Bilateral CFAR algorithm reduces the influence of SAR ambiguities and sea clutter through a combination of intensity distribution and spatial distribution.

The conventional CFAR algorithm takes the value of pixel or the intensity of cell as a parameter and searches for pixels that are unusually bright compared to those in the surrounding sea, and SAR ambiguities or sea clutter may meet this condition too. The sea clutter will lead to a false alarm, even if the statistical model fits the real data accurately. Therefore the bilateral CFAR also takes into account the spatial distribution of bright pixels.

To evaluate the spatial density, we define a kernel density function $f_h(x)$. The kernel density is obtained after choosing an appropriate Kernel function, which may be either square, sine, or gaussian. The critical property of the kernel is that its integral must sum up to the value of one.

$$f_h(x) = \frac{1}{n}\sum_{j=1}^{n}\frac{1}{h}K\left(\frac{x-x_j}{h}\right) \qquad \int_{-\infty}^{+\infty} K(u)du = 1$$

The kernel density of each pixel is estimated before the detection through the intensity domain by introducing a fixed-size sliding window $\Omega(w)$ in which w is the width of the window. w is determined by the size of ship targets and sea clutter. The paper highlights that w should be more significant than the size of the sea clutter pattern so that they can be ignored and smaller than half of the minimum size of the ship width so that what is contained by the sliding window will be able to reflect their spatial difference correctly. The paper has proposed $x_{spatial}$ with the below expression and with a gaussian kernel we get $f_{h=1}(x)$.

$$x_{spatial} = \frac{f_{h=1}(x) - \min\left(f_{h=1}(x)\right)}{\max\left(f_{h=1}(x)\right) - \min\left(f_{h=1}(x)\right)}. \quad f_{h=1}(x) = \sum_{j\in\Omega(w)} \exp\left(-\frac{1}{2}(x-x_j)^2\right).$$

Bright pixels of ship targets are often contiguous and concentrated in a small area, while bright pixels of the sea represent oppositely, i.e., the kernel density values of ship targets are often higher than that of the background.

A way to utilize both spatial and intensity distribution is to multiply both values at each cell.

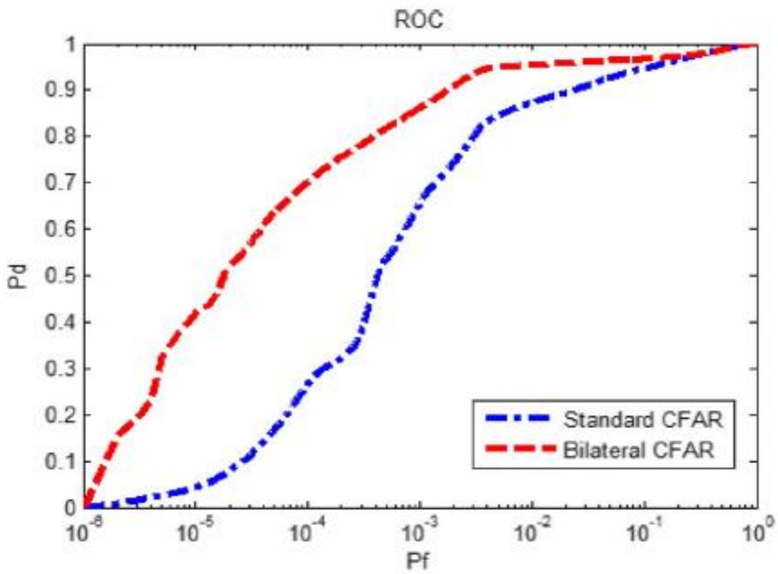
$$x_{combined_j} = x_{intensity_j} x_{spatial_j}.$$

Accordingly, four situations may arise- a bright set of pixels in a heterogeneous region, dark pixels in a heterogeneous region, homogeneous region, and ship targets. The table fig summarises values of $x_{spatial}$, $x_{intensity}$ and $x_{combined}$ in all cases.

VALUES FOR REGIONS OF DIFFERENT TYPE IN SAR IMAGES

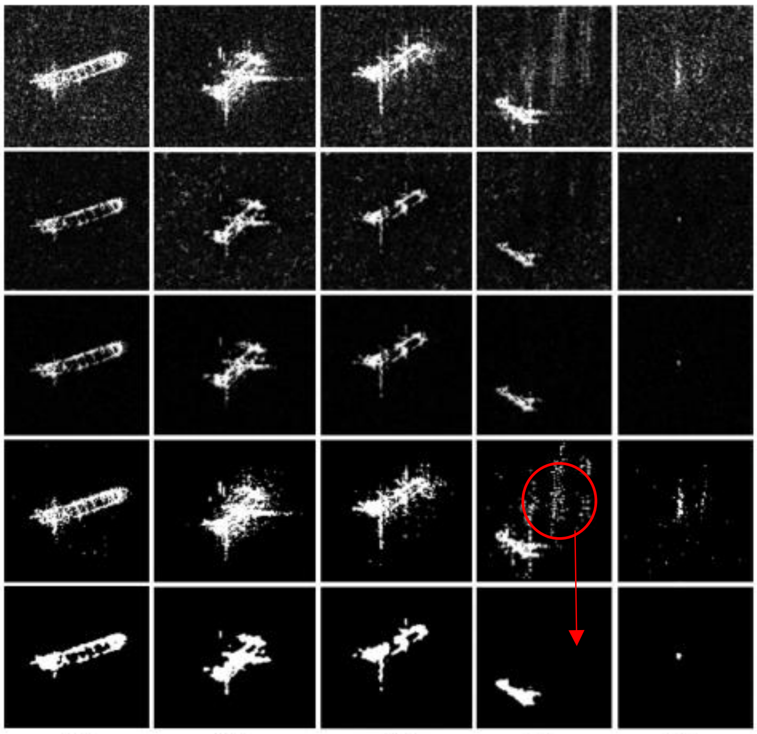
Type / Value	Ship targets	Background		
		Heterogeneous region		Homogeneous region
		Bright pixels	Dark pixels	
$x_{intensity}$	High	High	Low	Low
$x_{spatial}$	High	Low	Low	High
$x_{combined}$	High	Low	Low	Low

Once the combined distribution is figured out, a standard CFAR detection is employed to get the value of threshold T. Thus, if $x_{combined}$ of a pixel lies above T, this pixel is declared to be a ship target point; otherwise, it is considered to be a clutter point. The target detection is completed by comparing all pixels in the SAR image with T.



The Bilateral Algorithm, when applied to data, gave astonishing results. It had a high rate of P_d with lower P_f as compared to general CFAR.When P_f is as high as 10^{-1}, P_d of the bilateral CFAR is about 0.3% higher than that of the standard CFAR. With P_f decreasing to 5×10^{-3}, P_d of the bilateral CFAR decreases very slowly and keeps above 0.9. This is because most of the overlap is eliminated in the bilateral CFAR. Thus, P_d will not be strongly affected by the change of P_f in this particular stage.

The figure in the right depicts the image after performing traditional and Boilateral CFAR on five specimens. The handling of noise is better in bilateral CFAR. The fourth row shows the image after analysis by normal CFAR, while the last row shows the image after Bilateral CFAR. The red marker shows the difference in a normal CFAR and Bilateral CFAR, the bright spots are scattered so they have low value in spatial analysis and so they are removed in bilateral CFAR.



(a) (b) (c) (d) (e)

Fig. 5. Comparison of standard CFAR and bilateral CFAR in the TerraSAR-X image. The top row shows the original SAR image subsets. The second row shows the spatial image (pixel values are multiplied by 255). The third row shows the combined image. The fourth row shows the result of the standard CFAR. The bottom shows the result of the bilateral CFAR.

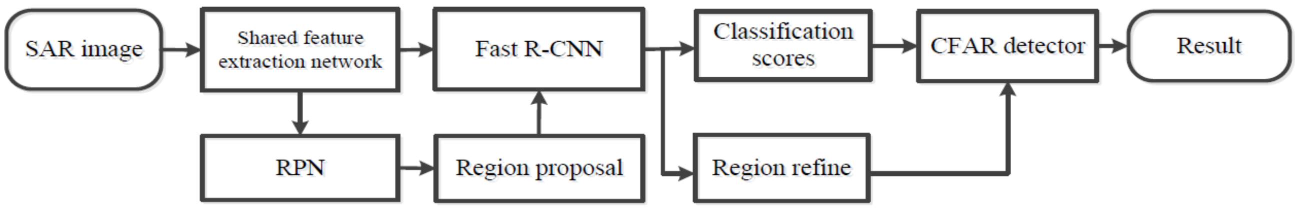
The possible improvements in the algorithm can be in the domain of extracting more accurate spatial feature extraction and accelerating algorithms of the spatial information extraction, need to be done, which may significantly improve the detection accuracy and reduce the time consumption of detection

Research Paper-2

Problem- Multi-scale ships in SAR images cause the undesirable differences of features that may be ignored by Deep Neural Network.

Proposed Solution- Aiming at this problem, CFAR takes bounding boxes with classification scores obtained from the deep neural network as the guard window to achieve greater precision.

Recently, with the development of deep neural networks such as Faster R-CNN, YOLO and SSD, SAR
image interpretation with deep learning methods has sprung up. At the same time, large SAR images have laid the foundation for ship detection with extensive and varied data to train. However, the scale variety of targets and the changes in the sensor's attitude make ships look different in the SAR image. Those differences degrade the performance of ship detection systems based on deep learning methods because they rely on the features of targets to distinguish the ship and no-ship objects. The paper proposes a slight modification in ship detection by incorporating the traditional CFAR algorithm. In a neural network, each proposal has a classification score. This score varies from low to high based on the probability of it being a ship. In the proposed method, the low classification score is used as a guard cell, and their mean is used to generate a threshold. Any classification score above that threshold is considered a successful detection.



'ig. 2 The flowchart of the proposed method

The proposed method has four steps.

<u>Step 1 – Feature Extraction</u>

The VGG16 convolution neural network is given SAR images as input for feature extraction. The neural network highlights feature in the image.

<u>Step 2 – Region Proposals</u>

Region Proposal Network proposes the location of the bounding boxes and the score of proposals depending if features highlighted by the network match with that of a ship or not.

<u>Step 3 – Classification Scores and Bounding Boxes</u>

Faster RCNN takes the top *n* proposals and generate classification scores and refined location of bounding boxes.

<u>Step 4 – CFAR Application</u>

The bounding boxes with high classification scores and low classification scores are determined to targets and false alarm, respectively. The guard windows of CFAR are the boxes with relatively low scores, then their mean is calculated, and further analysis is done similar to CA-CFAR.

When the method was tested against typical Faster RCNN, CFAR helped detect targets of small size that were previously ignored by the neural network. Based on the bounding boxes generated by Faster R-CNN, CFAR can detect the objects accurately and avoid merging the connected region pixel by pixel. However, targets that cannot be proposed by Faster R-CNN also cannot be picked up by the CFAR detector.

DETECTION PERFORMANCE COMPARISON BETWEEN OUR METHOD AND THE FASTER R-CNN

Method	N_{total_target}	N_{td}	N_{fd}	p_d	p_f
Faster R-CNN	990	786	204	0.620	0.206
The proposed method	1315	996	319	0.786	0.242
N_{ground_truth} =1267					

In the above table N_{total_target} are the number of targets classifies positive by the algorithm. N_{td} is the number of accurate detection while N_{fd} is the number of false detection. We can see we have achieved a higher probability of detection, while the false detection rate remains nearly the same in both.

There are some small-sized targets cannot be detected by Faster R-CNN, which makes relative low detection rate in this paper. The network is also not able to identify ships with fuzzy edges.

Inference

After studying CFAR, one can understand its importance as all surveillance systems rely on this algorithm for probable target detection. Both the research papers addressed the problem at suggested a modification in the traditional CFAR algorithm to mitigate the problem. I would like to share my understanding and inferences of the two research papers discussed in this term paper.

The paper that presented CFAR in Deep Neural Network used CFAR after region proposal. Thus the regions not identified by Region Proposal Network were not processed by CFAR. There is an

opportunity to apply CFAR before Region Proposal. This will help to reduce clutter and noisy background. Ships with fuzzy edges will then have smooth edges, and Neural Network can detect them.
The application of Bilateral CFAR instead of CA-CFAR in RCNN can offer better results as it takes spatial density also in the account.

The results of Bilateral CFAR have shown significant improvement from traditional CFAR. We have a nearly constant probability of detection, i.e., about 0.9 for a range of probability of false detection. Thus we can low probability of false detection, which high probability of accurate detection. It is fascinating to see how consideration of spatial density leads to refines results.

Both the algorithms do not consider the effect of masking or two targets near to each other. They fail to identify multiple masked objects.The application of CFAR in a heterogeneous environment also poses a challenge because the real environment is heterogeneous. The most significant disadvantage of the CFAR is that the scaling factor T is examined based on the assumption that noise samples follow a Gaussian distribution in the reference window.
So far, we considered keeping the size of the window fixed. If we add the adaptive size of the window that changes its size based on the last estimation of noise, it can help in modeling noise well. There is also enormous scope for the application and integration of the CFAR Algorithm with modern object recognition tools.

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