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# Geometric mean switching constant false alarm rate detector

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ABSTRACT

Switching based detectors provide a robust solution to the problem of managing interference in sliding window detection processes. Recent developments have shown how such a detector can be formulated for the case of target detection in Pareto distributed clutter, which is a new model for X-band maritime surveillance radar clutter returns. However, an issue with this development is that the full constant false alarm rate property is not achieved. It is shown how this can be rectified, and a new switched geometric mean detector is produced, which is shown to provide a robust solution to the management of interference while achieving the full constant false alarm rate property.



## 1. Introduction

The subject of effective management of interference in sliding window detection processes is of considerable importance to designers of radar detector architecture and the associated signal processing algorithms. The current study is concerned with addressing this issue with what is known as switching detectors, where it will be demonstrated how a sliding window detection process with the constant false alarm rate (CFAR) property can be coupled with a new switching mechanism, producing a switching CFAR for operation in an X-band maritime surveillance radar context. Sliding window decision rules provide an alternative to the optimal Neyman–Pearson based detectors, where they are designed to control the false alarm rate in ideal situations. The first examinations of such detection processes can in found in [1] and [2], which exploited the fact that low-resolution X-band clutter returns could be modelled by Gaussian processes, and since such statistical processes are closed under addition, sums of Gaussian processes are Gaussian distributed, leading to the idea that an average of such clutter could provide an effective measurement of the actual clutter level. This allowed the specification of a decision rule, based upon a test measurement and clutter statistics, which was such that its probability of false alarm (Pfa) could be maintained at a fixed level based upon adjustment of a threshold multiplier. This provided a simple solution to the problem of target power estimation and parameter dependence in optimal decision rules. As a result of this, there has been extensive development of what is termed CFAR detectors in the case of Gaussian-type clutter in the complex domain, or exponentially distributed clutter in the intensity realm. See [3] and [4] for examples of the many CFAR decision rules which have been developed and analysed.

One of the problems with the design of such detectors is the appropriate selection of the function which measures the overall clutter level. The first such function was selected to be a sum of statistics, which was shown to result in reasonable detection performance when a large number of such statistics is available. However, sliding window detection processes are subjected to a number of design issues. The first is the presence of what is termed interfering targets. These are additional target returns, which can appear in the set of clutter measurements, resulting from a range-spread target or the presence of real targets appearing in the data being passed to the sliding window scheme. The second issue is that such detection processes are run over sequential measurements of clutter, and so variations in the clutter power may have an impact of the desired fixed false alarm rate. In an attempt to address such problems, the idea of using an order statistic to measure the clutter level was introduced in [5], and subsequently extended in [6] and [7]. These studies demonstrated the success of the order statistic approach, and extensions of the approach can also be found in [3].

It was demonstrated in [8] that when the clutter level is measured by a summing process, the resultant detection process achieves the best performance in the class of such detection processes operating in exponentially distributed clutter, and with a Swerling I target model for the test cell. The order statistic approach is suboptimal to this in homogeneous clutter, while providing a better solution in the case of heterogeneous returns. Hence it

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has been of interest to investigate whether the summation process could be modified so that it can manage interference and clutter power variations much better. Towards this objective, the idea of a switched summation process was proposed in [9], which applies a sorting algorithm to decide whether there are anomalous clutter measurements. In the case where the latter is true, the summation process is restricted to those clutter measurements deemed regular. This approach has been shown to work very well in exponentially distributed clutter, and consequently has been extended in a number of studies [10–13].

Analysis of the radar backscattering from the sea surface, with high resolution X-band maritime surveillance radars, has shown that the Gaussian clutter model assumption to be invalid. There has hence been an evolution in the development of models for such clutter, culminating in the acceptance of the Pareto class of clutter models for intensity data. The first such study was reported in [14], who examined the fit of a compound Gaussian model with inverse gamma texture to real sea clutter. It was shown that the resultant intensity model was a Pareto Type II model, and the fit to the upper tail region of the data was an improvement on previously analysed clutter models. A second validation of the Pareto fit to real sea clutter was reported in [15], who examined the fitting of a generalised Pareto model. A third independent validation of the Pareto model was reported in [16], who confirmed the results in the latter two studies. As a result of this validation the design and analysis of sliding window detection processes, for operation in Pareto distributed clutter, has been investigated in [17] and [18]. Developments of switching based detection processes, for operation in Pareto-type clutter, have appeared in [19] and [20]. An issue with the development of sliding window detection processes for Pareto clutter is that the resultant decision rules depend on the Pareto scale parameter. This problem has been inherited with the switching detector developed in [19]. While [20] suggested a solution to this problem, by relaxing the clutter model to a one parameter family, it was found to be an inadequate model for real data.

Recent advances reported in [18] showed how the Pareto scale parameter dependence could be rectified. Hence it is of interest to investigate whether the approach in [18] could be used to address the switching detector design issues reported in [19]. Thus this paper will show how this can be achieved. Section 2 introduces the study of sliding window detection processes, while Section 3 overviews the development of switching detectors. Section 4 presents the new development of a geometric mean (GM)-based switching CFAR detector. Finally Section 5 provides examples of performance. The latter will demonstrate that a switching detector can be designed so as to match the performance of the decision rule upon which it is based in the case of homogeneous clutter. However, it will be shown that the switching CFAR developed can manage interference better than the conventional detector. It will be demonstrated that during clutter transitions the switching CFAR regulates the probability of false alarm similarly to the detector on which it is based. When strong interference is introduced into this scenario the switching detector tends to regulate the false alarm probability more efficiently, which will be shown via numerical simulations. A brief investigation of the performance of the decision rules in real data, with a synthetic target model, will complete the numerical analysis of the detectors.

## 2. Constant false alarm rate detectors

The theoretical development of CFAR detectors is outlined in this section. A useful reference on this is the classic text [4], while [3] contains a very useful analysis of such detectors in the case of exponentially distributed clutter. Fig. 1 provides a schematic of a sliding window detector to facilitate the understanding of the process. A series of raw radar returns are passed to a serial shift register (SSR) which can be used to subsample in an attempt to produce approximately independent returns. These are then passed to a square law detector (SLD) which transforms the returns to intensity measurements. The resultant series identifies a cell under test (CUT), which is separated from data that is taken to produce a measurement of clutter. The clutter statistics are denoted $C_j$ in Fig. 1, and are separated from the CUT by a series of guard cells, where the latter are denoted $G$. The collection of clutter statistics is referred to as the clutter range profile (CRP). The purpose of guard cells is to compensate for a range spread target. As shown in the figure, the two sets of clutter measurements are processed by two functions, denoted $f_1$ and $f_2$ respectively, which are then synthesised into a single measurement of clutter by a third function $g$. The next process applies a threshold multiplier $\tau$ to $g$, which is used to produce adaptive control of the Pfa. Finally the CUT is compared with $\tau g$ and a detection decision can be reached. A sliding window detector of the form in Fig. 1 can be run across radar returns sequentially, with the results passed to a tracking algorithm.

The above description is now formulated in a statistical hypothesis testing setting. Suppose that the CRP consists of the measurements $\{Z_1, Z_2, \dots, Z_N\}$, which will be assumed independent and identically distributed. Let the CUT statistic be $Z_0$, and $g$ be the $N$-dimensional clutter measurement function, which is linear in scale and nonnegative. Define $H_0$ to be the hypothesis that the CUT does not contain a target, and $H_1$ the alternative hypothesis that the CUT contains a target embedded within clutter. Then if $\tau > 0$ is a normalising constant, the binary test can be specified in the form

$$Z_0 \underset{H_0}{\overset{H_1}{\gtrless}} \tau g(Z_1, Z_2, \dots, Z_N), \tag{1}$$

where the notation employed in (1) means that $H_0$ is rejected in the case where $Z_0$ exceeds $\tau g(Z_1, Z_2, \dots, Z_N)$. The factor $\tau$ is used so that the detection process (1) can have its Pfa controlled adaptively. In the case where the clutter is modelled by exponentially distributed returns the detector (1) has a corresponding Pfa that is independent of the clutter model's parameter, implying it is CFAR. The corresponding Pfa is given by the expression

$$\mathrm{P_{FA}} = \mathbb{P}(Z_0 > \tau g(Z_1, Z_2, \dots, Z_N)|H_0), \tag{2}$$

where $\mathbb{P}$ denotes probability. The selection of an appropriate $g$ is based upon the way in which the clutter statistics are to be processed, and upon the need to manage interference as discussed previously. Since the Pareto model will be the focus, its distribution is discussed next.

There are several forms of the Pareto distribution, but only the two key ones applied in radar signal processing will be discussed. The first type, known as a Pareto Type I model, has cumulative distribution function (CDF) given by

$$F_{W_1}(t) = \mathbb{P}(Z \le t) = 1 - \left(\frac{\beta}{t}\right)^{\alpha}, \tag{3}$$

where $t \ge \beta$ and is zero otherwise. Hence this model has support the interval $[\beta, \infty)$. The second model is referred to as a Pareto Type II, and has CDF

$$F_{W_2}(t) = 1 - \left(\frac{\beta}{t+\beta}\right)^{\alpha}, \tag{4}$$

where $t \ge 0$ and is zero otherwise. The associated probability densities can be produced by differentiation of (3) and (4) respectively. The parameter $\alpha > 0$ is the Pareto shape, while $\beta > 0$ is referred to as the scale. These two models are interrelated; in particular, for the two random variables $W_1$ and $W_2$ with CDFs (3) and (4) respectively, it can be shown that