Robust CFAR Detector based on Truncated Statistics in Multiple Target Situations

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Abstract—A new and robust constant false alarm rate (CFAR) detector based on truncated statistics is proposed for ship detection in single-look intensity (SLI) and multi-look intensity (MLI) synthetic aperture radar (SAR) data. The approach is aimed at high target density situations, such as busy shipping lines and crowded harbors, where the background statistics are estimated from potentially contaminated sea clutter samples. The CFAR detector uses truncation to exclude possible statistically interfering outliers, and truncated statistics to model the remaining background samples. The derived truncated statistic CFAR (TS-CFAR) algorithm does not require prior knowledge of the interfering targets. The TS-CFAR detector provides accurate background clutter modeling, a stable false alarm regulation property, and improved detection performance in high target density situations.

Index Terms—Target detection, constant false alarm rate, truncated statistics, statistical modeling, synthetic aperture radar, sea clutter.

I. INTRODUCTION

SYNTHETIC aperture radar (SAR) provides valuable measurements of the Earth surface for many remote sensing applications, whereof maritime target detection is one common field of use. The well-known constant false alarm rate (CFAR) target detectors adaptively determine the detection threshold based on accurate modeling of the statistical distribution of local background clutter measurements 1. They are often implemented with the sliding window technique, and the parameters of the hypothesized model are estimated within this local reference window. In practice, however, heterogeneous clutter and interfering targets can often lead to inaccurate estimation and deceptive modeling. Clutter edges and transitions in clutter intensity due to meteorological and oceanographic phenomena is one common cause of heterogeneity, and the effects can be suppressed by utilizing advanced background estimation algorithms [1]–[3]. Another problem is statistical contamination when the sliding window contains one or more interfering targets, which can result in severe degradation of the CFAR detector performance. The latter case is the focus of the current paper.

The aim of this study is to derive a robust CFAR algorithm that excludes statistical contamination in the reference window that may occur in dense target situations, such as busy shipping lines and crowded harbors, and, in a statistically rigorous manner, to model the remaining sea clutter samples. In general, a raised detection threshold results when there is one or more unwanted outliers in the reference window in the form of non-oceanic targets and their side-lobes, or ghosts. This causes the observed probability of false alarms to drop below the specified value and lowers the probability of detection, which is known as the capture effect [4]–[7]. From previous studies [3], [7]–[14], the primary solution is to remove the outliers, encompassing both interfering targets and naturally occurring spikes in the sea clutter, from the background samples, or to represent the background clutter by a statistic which is less influenced by the outliers. The outlier removal is usually done by data ranking or censoring with different restrictions. This paper proposes a new approach based on data truncation which employs a statistically rigorous analysis of the truncated data. The important distinction between censoring and truncation will be highlighted after our review of the literature on CFAR detectors. This review follows after we have defined some key terms.

In the paper, we distinguish between clutter pixels and target pixels. The term clutter is used for any radar measurement of an ocean surface which is not affected by a target. Hence, clutter can be interpreted as equivalent of background, consisting of backscatter from a natural ocean surface. The measurements of clutter and targets can in principle be modelled by respective statistical distributions. For instance, the gamma distribution will be assumed as a parametric model for homogeneous clutter, meaning clutter from an area with constant radar reflectivity. It is considered, on the other hand, that the target distribution cannot be identified because of the variable characteristics of potential targets and the unknown influence of viewing angles and target orientation. Next, an outlier is defined as a measurement which stands out by its high intensity. It can be either a clutter realisation from the tail of clutter distribution or a measurement of target plus clutter. Since the target distribution is unknown, ship detection is performed by identifying outliers with respect to the clutter distribution. The threshold is determined by the CFAR approach.

The traditional cell averaging CFAR (CA-CFAR) detector [15] represents the background data by an average over the reference window and assumes a homogeneous clutter environment. Its variations include the greatest-of CFAR (GO-CFAR) [2] and the smallest-of CFAR (SO-CFAR) [1] detectors, that divide the reference window in spatial subsets before
averaging. The GO-CFAR detector represents the clutter by the
greatest of the subset mean values, and the SO-CFAR detector
by the smallest. They deliver improved performance when the
reference window contains clutter intensity transitions or mul-
tiple targets, respectively. In homogeneous clutter, the former
suffers a loss in detection rate and the latter an increased false
alarm rate [3]. In a different manner, the variability index
CFAR (VI-CFAR) detector [3] dynamically selects the par-
ticular group of reference pixels to estimate clutter statistics.
The VI is a test statistic which is used to choose between
the CA-CFAR, GO-CFAR and SO-CFAR approach. The VI-
CFAR detector performs robustly in all the common test cases,
but is subject to inevitable performance loss when the clutter
heterogeneities have a complex distribution which cannot be
handled by the simple spatial sub-setting scheme.

The ordered statistic CFAR (OS-CFAR) detector is another
well-known CFAR algorithm which has been studied to deal
with interfering outliers within the reference window [9].
The OS-CFAR detector rank-orders the background pixel
measurements based on their magnitude. The parameters of the
hypothesized model are estimated from a single value selected
from the ordered sequence. This value, known as an order
statistic, is more robust to outliers than the mean, but provides
slightly less information for estimation purposes. Hence, the
OS-CFAR detector suffers a small loss in detection rate in
homogeneous clutter relative to the CA-CFAR, but maintains
a significantly higher detection rate and a false alarm rate
closer to the specified value in multiple target situations [16].
The improvement comes at a higher computational cost. The
trimmed mean CFAR (TM-CFAR) detector was introduced
in [11] as a generalization of the OS-CFAR detector, and
uses the mean of a set of rank-ordered values to estimate
distribution parameters. It has been shown to perform robustly
only after prior assessment of the interfering environment [17],
and optimal performance relies on a judicious choice of the
trimming parameters [18]. It notably contains both the CA-
CFAR detector and the OS-CFAR detector as special cases,
which are included in the experiments and comparisons of the
paper.

The OS-CFAR and TM-CFAR detectors represent a strategy
of radiometric sub-setting of the reference window. To extract
a subset, the pixel values must first be ranked. The sub-setting
strategy reflects the particular clutter situation that the method
is aimed at. In addition, there are many hybrid CFAR de-
tectors designed to accommodate several clutter environments
in one algorithm. These incorporate different strategies and
dynamically activate the appropriate one. One example is the
censored mean-level detector (CMLD) [8], which employs
both ranking and censoring techniques to obtain acceptable
performance in the presence of interfering targets. It excludes
the largest reference samples and uses the remaining samples
in the parameter estimation. It suffers some detection loss in
a homogeneous environment and is quite robust in mul-
tiple target situations, as long as all interfering targets are
removed from the reference clutter [19]. However, without
prior knowledge of the interfering targets, the CMLD may lose
its robustness and CFAR properties [6]. Many more hybrid
algorithms may be found, e.g. the automatic CMLD (ACMLD)
and the generalized two-level CMLD (GTL-CMLD) [7], the
automatic censored cell-averaging (ACCA) CFAR detector
based on ordered data variability (ODV) [12], and so on [17],
[20], [21]. We do not include any hybrid detectors in the
experiments. The reason is that we focus only on the multiple
target situation, and also because we want to test one single
strategy at the time to provide a simple and clear comparative
study. Different strategies can always be combined at a later
stage in a more advanced algorithm.

A different approach to the multiple target situation is the
iterative censoring (IC) scheme proposed by Barboy et al. [10].
Samples that exceed an adaptive threshold are here excluded,
and the threshold is iteratively updated based on the censored
reference sample. This is repeated until there are no change
in the threshold and the reference sample, and the detection
result has converged. In more recent articles [13], [14], a
similar mechanism is implemented by applying an iteratively
updated map of outliers (potential targets). Although the
multistep adaptive detection procedure may need many cycles
and require long calculation time, the IC scheme has shown
robust performance in the dense target situation and can be
integrated with any CFAR algorithm. In this work we include
the iterative censoring implementation of the CA-CFAR and
OS-CFAR detectors in the comparison of methods. These are
referred to as ICCA-CFAR and ICOS-CFAR, respectively, and
represent in our view the state-of-the-art in CFAR detection.

The final algorithm included in the comparison is the trun-
cated statistics CFAR (TS-CFAR) detector, which is proposed
here. First note that truncation is similar to but distinct from
censoring, and these terms have sometimes been used incor-
correctly in the target detection literature. Both in truncation
and censoring, data points with a value outside specified thresholds
are excluded from the sample, or not observed. The difference
is that the number of censored data points is recorded, while
the number of truncated data points remains unknown. When
high intensity outliers are removed from a background sample,
they consist of an indistinguishable mixture of target pixels
and sea clutter spikes. Since we do not know how many
target pixels there are among the outliers, the number of sea
clutter measurements removed is effectively unknown. This
categorizes the outlier removal as truncation with respect to
the remaining sea clutter sample, thereby assuming that all
target pixels have been removed. Truncation is therefore the
relevant operation for statistical characterization of sea clutter
in a multiple target environment.

The distinction between censoring and truncation becomes
important once we start to analyze the reduced sample (with
outliers removed) in a statistically rigorous manner, that is,
when we model the reduced sample with a truncated distri-
bution and deduce parameter estimators from this model. A
common simplifying practice has been to maintain the original
model assumption also after outliers have been removed,
and to apply standard estimators derived for the untruncated
distribution to the reduced sample, which must clearly produce
wrong results. Specifically, a location or scale parameter is in-
evitably underestimated after high-intensity outliers (including
all targets) have been removed, unless this is accounted for in
the model and consequently compensated within the estimator.
Hence, apart from correcting the terminology, we also address another malpractice in the literature: From the perspective of statistical modeling, the truncated data should be represented by truncated versions of the hypothesized distribution.

In this study, the truncated exponential and the truncated gamma distributions are proposed to model the truncated samples of single-look intensity (SLI) and multi-look intensity (MLI) SAR measurements. TS-CFAR algorithms are derived to handle truncated data in a statistically rigorous manner and to improve detection performance. The assumption underlying these models for the SLI and MLI data is that the signal variation stems from fully developed speckle and that the radar cross section is locally stationary. It is well known that this assumption may be violated as the sensor resolution increases and the sea becomes rough. Hence, more advanced models, such as the K distribution or the Weibull distribution, may be called for. We nevertheless maintain these distributional assumptions, since they make it mathematically tractable to develop the truncated statistics approach to CFAR detection. The extension to more advanced distributions is deferred till later. Moreover, our scope is the high target density situation, and not high resolution or rough sea. We therefore assume that the exponential and gamma distributions will provide an adequate fit to the SLI and MLI data, respectively.

This paper is organized as follows. Section II provides an introduction to truncated statistics (TS), and derives the proposed TS-CFAR detectors for both the exponentially distributed SLI and the gamma distributed MLI measurements of sea clutter. The usefulness of TS is demonstrated by showing the loss in parameter estimation accuracy caused by the presence of interfering targets. In section III, the false alarm regulation property and the receiver operating characteristic (ROC) of the CFAR detector are examined based on simulated SLI and MLI measurements of sea clutter drawn from the exponential distribution and the gamma distribution, respectively. The TS-CFAR detector is compared with the conventional CA-CFAR and OS-CFAR detectors, whose IC schemes are also considered. Monte Carlo simulations are exploited in the analysis. The detection performance is then investigated in a comparative study in section IV. Experiments are performed on data composited from real Radarsat-2 SAR measurements. Finally, section V presents the main conclusions and perspectives.

II. TRUNCATED STATISTICS CFAR DETECTOR

A. Truncated statistics

Outliers are data points that distinguish themselves from the main group of the data by their extreme values. In the context of SAR images and ship detection these are measurements with unusually high intensity. Remark that we let the outlier term represent both strong returns from a natural sea surface, formed by constructive interference between oceanic scatterers, and the cases when a target return is superposed on the sea clutter. One of the main purposes when handling the possible occurrence of outliers is to find rigorous and robust methods to perform statistical inferences [22, Ch. 14]. The specific problem addressed here is parameter estimation in distribution models for SAR data when the sea clutter may be statistically contaminated by outliers. The proposed solution is to apply a truncation in order to eliminate possible contamination. The truncated data are then modeled with the truncated version of the statistical distribution hypothesized for the untruncated data.

Suppose we have a random variable $X$, which is distributed according to a probability density function (pdf), $p_X(x)$, and with cumulative distribution function (cdf), $P_X(x)$. Let $X$ be the truncated version of $X$ after applying a threshold $t$, which is called the truncation depth. A right truncated distribution can be defined as

$$p_X(x; t) = p_X(x \mid X < t) = \begin{cases} \frac{p_X(x)}{P_X(t)} & ; \quad 0 < x \leq t \\ 0 & ; \quad x > t \end{cases} \quad (1)$$

The normalization by $P_X(t)$ makes sure that $p_X(x; t)$ integrates to one. Note that the truncation depth is in practice a user specified empirical value. It is difficult to estimate the optimal value from local statistics because of the lack of the knowledge about the location and the quantity of targets. Therefore, it is better to fix $t$ to a value which ensures that all possible outliers are excluded, but be aware that excessive truncation may cause inaccurate parameter estimation of the distribution.

B. TS-CFAR detector

In this section, CFAR detectors based on TS are derived for SLI and MLI SAR measurements, that are modeled by the exponential distribution and the gamma distribution, respectively [23]. The intensity measurements are greater than zero and assumed to be independent and identically distributed.

1) Single-look intensity: The SLI measurements are represented by $X$, which is assumed to follow the exponential distribution with pdf

$$p_X(x) = \frac{1}{\mu} e^{-x/\mu} \quad (2)$$

and cdf

$$P_X(x) = 1 - e^{-x/\mu} \quad (3)$$

where $\mu$ is the mean value. The truncated version of this pdf is derived as

$$p_\tilde{X}(x) = \begin{cases} \frac{p_X(x)}{P_X(t)} = \frac{1}{\mu} e^{-x/\mu} \left( 1 - e^{-t/\mu} \right)^{-1} & ; \quad 0 < x \leq t \\ 0 & ; \quad x > t \end{cases} \quad (4)$$

where $P_X(t)$ is the exponential distribution cdf value at truncation depth $t$. The mean value is the only parameter which needs to be estimated. A maximum likelihood (ML) estimator for the mean can be obtained from the likelihood function

$$L(\mu \mid \tilde{X}) = \prod_{i=1}^{n} p_\tilde{X}(\tilde{x}_i \mid \mu)$$

$$= \exp \left( -\frac{1}{\mu} \sum_{i=1}^{n} \tilde{x}_i \right) \frac{1}{\mu^n (1 - e^{-t/\mu})^n} \quad (5)$$
where \( \hat{x} = [\hat{x}_1, \ldots, \hat{x}_n]' \) and \( \{\hat{x}_i\}_{i=1}^n \) is a size \( n \) sample of truncated SLI measurements. From the estimating equation, \( \partial / \partial \mu \log L(\mu | \hat{x}) = 0 \), the ML estimator is derived as

\[
\hat{\mu} = \frac{t}{\nu/t} + \frac{1}{n} \sum_{i=1}^n \hat{x}_i .
\]

(6)

This equation must be solved numerically. Note that \( \hat{\mu} \) equals the sample mean (SM) estimator plus a correction term which accounts for the truncation. The specified false alarm rate \( P_{FA} \) can be related to the cdf, parameterized with the estimated mean value, as

\[
P_{FA} = 1 - P_X(T) = e^{-t/\hat{\mu}} ,
\]

(7)

where \( T \) is the detection threshold which needs to be solved for.

2) Multi-look intensity: From a set \( \{X_i\}_{i=1}^n \) of independent and exponentially distributed SLI measurements with mean value \( \mu \), an \( L \)-look MLI value can be computed as

\[
X_L = \frac{1}{L} \sum_{k=1}^L x_k .
\]

(8)

The MLI variable follows a gamma distribution with order parameter \( L \) and a mean value \( \mu \). Its pdf is

\[
p_{X_L}(x) = \left( \frac{L}{\mu} \right)^L \frac{x^{L-1} e^{-x/\mu}}{\Gamma(L)} ,
\]

(9)

where \( \Gamma(a) = \int_0^\infty y^{a-1} e^{-y} dy \) is the gamma function, and its cdf is

\[
P_{X_L}(x) = \frac{\gamma(L, Lx/\mu)}{\Gamma(L)}
\]

(10)

with the lower incomplete gamma function \( \gamma(a, b) \) defined as \( \int_0^b y^{a-1} e^{-y} dy \). The pdf of the \( X_L \), the truncated MLI, becomes

\[
p_{\tilde{X}_L}(x) = \left\{ \begin{array}{ll}
\left( \frac{L}{\mu} \right)^L \frac{x^{L-1} e^{-x/\mu}}{\gamma(L, tL/\mu)} & ; 0 < x < t \\
0 & ; x > t
\end{array} \right.
\]

(11)

In the SAR context, the shape parameter \( L \) is replaced by the equivalent number of looks (ENL), which is a lowered version of \( L \) used pragmatically in the statistical modeling to account for correlation between the samples in \( \{X_i\}_{i=1}^L \) [24]. The ENL can be estimated from the data and is considered an image constant. We can assume that it is known prior to the ship detection and we are left with estimating the mean value \( \mu \).

A ML estimator for the mean can also be obtained from the likelihood function

\[
L(\mu | \tilde{x}) = \prod_{i=1}^n p_{\tilde{X}_L}(\tilde{x}_i | \mu)
\]

\[
= \left( \frac{L}{\mu} \right)^{nL} \frac{e^{-\frac{1}{\mu} \sum_{i=1}^n \tilde{x}_i}}{\left[ \gamma(L, tL/\mu) \right]^n} \prod_{i=1}^n \tilde{x}_i^{L-1} ,
\]

(12)

where \( \{\tilde{x}_i\}_{i=1}^n \) is a size \( n \) sample of truncated MLI measurements. The log-likelihood function is derived as

\[
\log L(\mu | \tilde{x}) = nL \log \frac{L}{\mu} - n \log \gamma(L, tL/\mu) - \frac{nL}{\mu} \sum_{i=1}^n \tilde{x}_i + n(L - 1) \frac{1}{n} \sum_{i=1}^n \log(\tilde{x}_i) ,
\]

(13)

where \( \frac{1}{n} \sum_{i=1}^n \tilde{x}_i \) and \( \frac{1}{n} \sum_{i=1}^n \log(\tilde{x}_i) \) are sample means of the original and logarithmic truncated MLI measurements. Thus, the ML estimate of the mean is

\[
\hat{\mu} \subseteq \arg\max_{\mu} \{ \log L(\mu | \tilde{x}) \} ,
\]

(14)

which must be solved numerically. The specified false alarm rate \( P_{FA} \) can then be related to the cdf with the estimated mean value as

\[
P_{FA} = 1 - P_{X_L}(T) = 1 - \frac{\gamma(L, LT/\hat{\mu})}{\Gamma(L)} ,
\]

(15)

where \( T \) is the detection threshold which needs to be solved for.

Since the exponential distribution is a special case of the gamma distribution, the results of section II-B1 are obtained from those in section II-B2 by setting \( L = 1 \).

C. Parameter estimation performance

All CFAR detectors rely upon accurate parameter estimation, which determines the goodness-of-fit of the hypothesized background clutter model. Both for SLI and MLI data, the mean value is the only parameter which must be estimated locally. The TS-based ML estimators are proposed in the previous section. This section provides empirical results that demonstrate how much loss the TS-based estimators experience due to the reduction of the estimation sample by truncation, and how much the TS-based estimators gain compared to the conventional ML estimators designed for untruncated data when the estimation samples are contaminated.

Two parameters used in the experiments are first introduced to characterize the simulation of contaminated data and the operation of the TS-based estimators, respectively. The contamination ratio \( (R_c) \) is defined as the fraction of contaminated data points and the truncation ratio \( (R_t) \) as the fraction of truncated samples, both given relative to the total number of samples in the estimation window. The mean value estimators are examined with simulated exponential and gamma distributed sea clutter for two levels of statistical contamination: \( R_c = 1\% \) and \( R_c = 10\% \). The contamination samples are drawn from a uniform distribution whose support is 0.8 to 5 times the maximum value of the simulated sea clutter samples. Clutter samples are randomly replaced by the contaminated samples. The total sample size is held at \( n = 1024 \).

The estimator performances are demonstrated by analyzing the mean squared error (MSE), which is defined as

\[
\text{MSE} = \text{Var}(\hat{\mu}) + \text{Bias}(\hat{\mu})^2 = E\{(\hat{\mu} - E(\hat{\mu}))^2\} + E\{(\hat{\mu} - \mu)^2\}
\]

(16)

Fig. 1 shows the MSE versus \( R_t \) for the exponential distribution estimator in panels (a) and (c), and for the gamma distribution estimator in panels (b) and (d). Panels (a) and (b) show results for \( R_c = 1\% \) and panels (c) and (d) for \( R_c = 10\% \). Three estimators are compared in each plot: (i) The first is the ML estimator as derived for untruncated data, which is applied to the entire data sample including contamination. This
Fig. 1. Analysis of MSE versus $R_t$ for three mean estimators: (i) SM estimator without truncation (solid lines with crosses); (ii) SM estimator with truncation (dashed lines); (iii) TS-based ML estimators for truncated data (solid lines). Simulated sea clutter is drawn from an exponential distribution ($\mu = 3$) in (a) and (c) and from a gamma distribution ($\mu = 3, L = 4$) in (b) and (d). Contamination from a high intensity uniform distribution is inserted with $R_c = 1\%$ in (a) and (b) and $R_c = 10\%$ in (c) and (d). The total sample size is held at $n = 1024$.

equals the SM estimator for both the exponential distribution and the gamma distribution; (ii) The second estimator is again the SM estimator, but it is now applied to truncated data, for which it is not maximum likelihood nor theoretically justified in any other way; (iii) The third is our proposed TS-based ML estimators for the respective case. It is applied to truncated data, as it has been designed for. Estimators (i) and (ii) are included in the comparison to exemplify the outcome of a non-robust approach and a non-rigorous treatment of truncated data, respectively.

It can be observed throughout all the experiments that the SM estimator without truncation (solid lines with crosses) does not vary with $R_t$ and produces a high constant MSE value, since it does not offer any protection against contamination. The SM estimator with truncation (dashed lines) performs well when $R_t$ matches $R_c$, but the performance rapidly gets worse as $R_t$ grows, since the truncation operation has not been accounted for in the derivation of the estimator. In practice, it is impossible to know in advance how many contaminated samples there are within each local estimation window. Therefore, it is difficult to select an $R_t$ which matches the $R_c$. The proposed estimators (solid lines) perform much better than the SM estimator with truncation as $R_t$ grows beyond $R_c$. Even in the extreme case, when $R_t$ goes up to 50%, the TS-based ML estimators are still able to provide reasonable outcomes. The increase in MSE with $R_t$ is naturally a result of the estimation sample becoming smaller and smaller. Still, the number of data points that must be truncated before the MSE exceeds the level of the SM estimator without truncation is not likely to be reached in practical applications. Thus, the proposed estimators produce convincing results.

In summary, despite an inevitable increase in MSE due to the sample size reduction for the proposed TS-based ML estimators, the alternative estimators suffer more performance degradations due to contamination or non-rigorous handling of the truncated data. The gain of appropriately compensating for the truncation operation is such that the proposed estimators outperform the alternatives for all practically relevant truncation depths. Note that the estimators performance deteriorates rapidly when $R_t$ drops below $R_c$, which emphasizes the
III. CFAR DETECTOR CHARACTERISTICS

In this section, two important CFAR detector characteristics are investigated, i.e., the false alarm regulation property and the ROC, with both simulated exponentially distributed SLI clutter and gamma distributed MLI clutter. The proposed TS-CFAR detector is compared with the conventional CA-CFAR and OS-CFAR detectors, whose IC schemes are also considered and discussed.

A. Definitions of characteristics

1) False alarm regulation property: The observed false alarm rate is defined as

\[ P_{fa} = \frac{n_{fa}}{n}, \]

where \( n_{fa} \) and \( n \) are the number of false alarms and the total number of samples, respectively. The compliance of the specified false alarm rate, \( P_{FA} \), and the observed false alarm rate, \( P_{fa} \), is an indicator of the sea clutter modeling accuracy, but also depends on the accuracy in estimation of model parameters. A constant \( P_{fa} \) can be approached if the hypothesized statistical background model and the associated parameter estimates are accurate. This is a fundamental property which justifies the CFAR label. Nevertheless, a pragmatic solution is often used when a detection algorithm does not satisfy the false alarm regulation property: A \( P_{FA} \) is chosen which produces a \( P_{fa} \) that meets the practical requirements, even though the two do not match. In operational systems, the \( P_{FA} \) is set according to, e.g., the image resolution and end application. In practice, the \( P_{FA} \) is commonly set to around 0.001% (or \( 10^{-5} \)) for fine resolution SAR images.

2) Receiver operating characteristic: The detection rate is measured as

\[ P_d = \frac{n_d}{n_t}, \]

where \( n_d \) and \( n_t \) are the number of correctly detected targets and the total number of target samples, respectively. To investigate detection performance, the \( P_d \) measurements are usually evaluated at different values of \( P_{FA} \). The \( P_d \) increases monotonically with \( P_{FA} \), and a plot of these two properties against each other is commonly referred to as a ROC curve. It characterizes the trade-off between \( P_d \) and \( P_{FA} \) for a given CFAR detector and is used to compare detector performance. \( P_d \) is sometimes plotted against \( P_{fa} \) instead of \( P_{FA} \). This makes sense when the false alarm regulation property is not satisfied, since \( P_{fa} \) represents actual performance while \( P_{FA} \) is merely a design parameter.

B. Experiments with Monte Carlo simulations

In this study, experiments are based on simulated SLI and MLI measurements of sea clutter drawn from the exponential distribution (\( \mu = 3 \)) and the gamma distribution (\( \mu = 3, L = 4 \)), respectively. Random data points in these background samples are replaced by new values representing the contamination by non-oceanic targets. Like in section II-C, the contamination samples are uniformly distributed in the range of 0.8 to 5 times the maximum value of the sea clutter data. The contamination ratios considered are \( R_c = \{1\%, 5\%, 10\%, 20\%\} \).

Monte Carlo simulations are conducted, where each simulation represents one reference window with a sample size of 1024 and certain amount of contaminations defined by \( R_c \). Note that the simulated contaminated pixels also represent the potential target pixels in each reference window. All tested CFAR detectors are applied in each simulated reference window, where the falsely detected clutter pixels and the correctly detected contaminated pixels are counted. Finally, all those number of falsely and correctly detected pixels are added together, and then divided by the total number of simulated samples calculated from the product of the total number of simulations and the sample size of each simulated reference window. Therefore, the observed false alarm rate \( P_{fa} \) and the detection rate \( P_d \) can be derived as

\[ P_{fa} = \frac{\sum_{i=1}^{m} \{n_{fa}\}_i}{m \times n_{win}}, \]

\[ P_d = \frac{\sum_{i=1}^{m} \{n_d\}_i}{m \times n_{win} \times R_c}, \]

where \( m \) is the total number of simulations, \( n_{win} \) is the number of samples of each reference window, and \( \{n_{fa}\}_i \) and \( \{n_d\}_i \) are the number of falsely detected clutter pixels (false alarms) and the number of correctly detected contaminated pixels (potential targets) in each reference window, respectively. In order to reach the minimum specified false alarm rate level, \( P_{FA} = 10^{-6} \), at least \( m = 5 \times 10^6 \) simulations are conducted for all tested situations.

C. Compared CFAR algorithms

Before conducting experiments with simulated exponentially distributed SLI clutter and gamma distributed MLI clutter, we introduce the algorithms to be compared. The TS-CFAR detector was presented in section II. The remaining detectors: CA-CFAR, ICCA-CFAR, OS-CFAR, and ICOS-CFAR are briefly described in the following.

1) CA-CFAR detector: This is the simplest detector available, where an estimate of the mean clutter intensity is produced by averaging a set of samples surrounding the cell under test [15]. The conventional algorithm assumes that the background sample is homogeneous and contains no interfering targets. Thus the CA-CFAR offers no protection against target interference, but is still used extensively in operational systems.

2) ICCA-CFAR detector: An iterative censoring (IC) scheme was proposed by Barboy et al. [10] and similar versions were repeated in [13], [14], where iteratively updated outlier maps are used for censoring. The IC scheme is specifically aimed at dense target environments, and the algorithm is robust even in situations where targets and associated artifacts take up 30% of the reference window [10]. One weakness of the IC approach is that the censoring may remove sea clutter data as well as targets, thus removing data in the upper tail of the sea clutter distribution. This is not accounted
for in the parameter estimators, and the detection threshold is consequently underestimated, although this effect may be alleviated during iterations. Hence the detection procedure may need a number of the “spike rejection” iterations, which requires long computation time. The IC process has converged when the outlier map is stable. In the experiments, we have set an upper limit of 30 iterations to avoid an excessive number of iterations. The IC scheme can be combined with any CFAR detector, and the ICCA-CFAR detector is the specific implementation of the IC principle with the CA-CFAR detector.

3) OS-CFAR detector: The OS-CFAR trades a small loss in detection performance under homogeneous background conditions, relative to the CA-CFAR detector, for an improved performance under less ideal background scenarios. In practice, the method is performed by rank-ordering the values encountered in the neighborhood area according to their increasing magnitude and by selecting a certain predefined value from the ordered sequence \[9\]. This can be the median, the minimum, the maximum, or any other value. Thus, this procedure excludes the reference samples with larger magnitudes, which may contain contaminating targets, and estimates the background statistics from the remaining samples \[18\]. Such signal processing methods are denoted as methods with an ordered statistic.

The central idea of an OS-CFAR procedure is to select one certain value \(X_{(k)}, k \in \{1, 2, \ldots, N\}\) from the rank-ordered ascending sequence and to use it as a representation of the clutter power level as observed in the reference window. Since \(X_{(k)}\) is the \(k\)th level of the ordered statistic for the random variables \(X_1, \ldots, X_N\), its pdf can be derived as [25]

\[
p_{X_{(k)}}(x) = k\binom{N}{k}[1 - P_X(x)]^{N-k}[P_X(x)]^{k-1}p_X(x),
\]

where \(p_X(x)\) is the pdf and \(P_X(x)\) is the cdf of the random variables in the reference window. The specified false alarm ratio \(P_{FA}\) indicates the probability that the value \(Y_0\) of the cell under test is mistakenly interpreted as target during the threshold decision, and is given as

\[
P_{FA} = P[Y_0 \geq KZ] = \int_0^\infty (1 - P_X(Kx)) p_{X_{(k)}}(x) \, dx,
\]

where \(K\) is a scaling factor. Both the pdfs of \(Y_0\) and \(Z\) need to be known. When the random variables \(Y_0, X_1, \ldots, X_N\) of the clutter are assumed to follow an exponential distribution, \(P_{FA}\) can be computed from [9]

\[
P_{FA} = k\binom{N}{k} \frac{(k-1)!(K+N-k)!}{(K+N)!}.
\]

When a gamma distributed clutter is assumed, \(P_{FA}\) is derived as

\[
P_{FA} = k\binom{N}{k} \int_0^\infty \frac{1 - \gamma(L,Ky)}{\Gamma(L)} \left(1 - \frac{\gamma(L,y)}{\Gamma(L)}\right)^{N-k} \frac{\gamma(L,y)^{k-1}y^{L-1}e^{-y}}{\Gamma(L)} \, dy,
\]

where shape parameter \(L\) is replaced again by known image constant ENL and \(K\) needs to be solved numerically. Note that the scaling factor \(K\) which controls the false alarm probability \(P_{FA}\) does not depend on the average clutter power \(\mu\) of the exponentially or gamma distributed parent population. Thus, they may be considered as CFAR methods. In the following paragraphs they are denoted by the term OS-CFAR.

As suggested in a previous study [9], we choose \(k\) equal \(3N/4\).

4) ICOS-CFAR detector: As for CA-CFAR, the IC scheme can also be applied to the OS-CFAR detector, and its realization is in the following paragraphs referred to as the ICOS-CFAR detector.

D. Experimental results

This section compares all algorithms listed above, but not in the same figure. If all detectors were compared simultaneously, the wide range spanned by their performance measures and the overlap of the many curves would make it difficult to discern and interpret the details of the experiments. Instead, we first compare the CA-CFAR detector with the ICCA-CFAR detector, then the OS-CFAR detector with the ICOS-CFAR detector, before presenting results for the TS-CFAR detector alone. We finally compare the best performing algorithms: the ICCA-CFAR, the ICOS-CFAR, and the TS-CFAR detector.

1) CA-CFAR and ICCA-CFAR detectors: Fig. 2 presents an analysis of the false alarm regulation property and ROC curves for the CA-CFAR and the ICCA-CFAR detectors.

Fig. 2(a) and 2(b) show the ratio of \(P_{FA}\) to \(P_{TD}\) in decibels against \(P_{TD}\). When \(P_{TD}/P_{FA}\) goes to zero on the logarithmic scale, \(P_{TD}\) approaches \(P_{FA}\), as desired. Note that no value is plotted when there are no observed false alarms, i.e., the logarithm of the ratio goes to minus infinity. It is clear that ICCA-CFAR, as compared to CA-CFAR, has an observed false alarm rate closer to the specified false alarm rate \(P_{FA}\). As expected, we also notice that an increase of the contamination ratio \(\gamma\) points toward a larger deviation from \(P_{FA}\). Fig. 2(c) and 2(d) present the detection rate versus the specified false alarm rate, and it is clear that the ICCA-CFAR detector is much superior to the CA-CFAR detector at the same contamination levels. Especially for CA-CFAR, it is also evident that a larger \(\gamma\) decreases the detection rate.

2) OS-CFAR and ICOS-CFAR detectors: Fig. 3 presents an analysis of the false alarm regulation property and ROC curves for the OS-CFAR and ICOS-CFAR detectors.

Fig. 3(a) and 3(b) show that the ICOS-CFAR detector has very good false alarm regulation properties. It confirms what was observed in Fig. 2: that the IC approach is very robust with respect to contamination within the reference window. Fig. 3(c) and 3(d) present the detection rate versus the specified false alarm rate, and again we see that the IC scheme improves the result. Our investigation shows that the OS-based detectors are able to produce reasonably good results even when the contamination ratio approaches 20%, which is not the case for the CA-based detectors.

3) TS-CFAR detector: Fig. 4 presents an analysis of the false alarm regulation property and ROC curves for the TS-CFAR detector, which was introduced in section II.

To demonstrate the robustness of the proposed TS-based algorithm, we fix \(R_t = 25\%\) while varying \(R_c\). In general, the
TS-CFAR detector shows consistent behavior and good performance. An interesting observation is that it achieves higher detection rate $P_d$ as $R_c$ increases, which should be explained: The high $R_t$ ensures at all target pixels are removed from the estimation sample, regardless of the $R_c$. The truncated samples thus consist of a constant number of sea clutter measurements, but their distribution and upper bound will vary with $R_c$. When $R_c$ is low, many pixels from the sea clutter distribution will be truncated and the truncation depth $t$ obtains a low value. As $R_c$ rises, more target pixels and less sea clutter pixels are truncated, and so $t$ becomes higher. The ROC curves clearly show that a high $t$ value is preferred to a lower value of $t$. This conclusion would be further strengthened if we evaluated $P_d$ versus the observed $P_{fa}$ instead of the specified $P_{FA}$.

4) Comparative analysis: The IC versions of the CA- and OS-CFAR algorithms show superior performance as compared to their conventional detector schemes. Therefore, for concise comparison, the proposed TS-CFAR detector is here only compared to the ICCA-CFAR and ICOS-CFAR detectors. Fig. 5 to 8 present the comparative analysis of the false alarm regulation property and ROC curves for different contamination conditions. Note that the truncation ratio of the TS-CFAR detector is still set to 25% for all tested cases, which has similarities to the OS-based algorithm when $k = 3N/4$ (see section III-C3).

The ICCA-CFAR detector shows a large deviation from $P_{FA}$ and a quick drop in detection rate as a function of increasing contamination ratio. The ICOS algorithm shows a certain degree of improvement over the ICCA algorithm. However, as the contamination ratio gets larger, it is obvious that the TS algorithm still obtains an observed false alarm rate closer to the specified values and an improved stable detection rate.

So far, two classic CFAR detector performance measures characteristics have been discussed in this section with different specified false alarm rates ($P_{FA}$), ranging from $10^{-6}$ to $10^{-2}$. In practice, false alarm rates equal or smaller than $10^{-5}$ are usually applied. Next, we fix $P_{FA} = 10^{-5}$, and
Fig. 3. False alarm regulation property and ROC analysis for OS- and ICOS-CFAR in subfigures (a,b) and (c,d). Simulated SLI and MLI sea clutter are applied with exponential ($\mu = 3$) and gamma ($\mu = 3, L = 4$) distribution, respectively. The contamination ratios considered are 1%, 5% and 10%, related to the total number of reference samples. A log-scale is applied on the x-axes of all subfigures and y-axes of subfigures (c,d).

Table I and II present the CFAR detector characteristics analysis with the specified false alarm rate at $P_{FA} = 10^{-5}$. Results are averaged from 1000 Monte Carlo simulations with a sample size of 1024. The contamination ratios considered are 1%, 5%, 10% and 20%, related to the total number of reference samples. The truncation ratio of the TS-CFAR detector is constant at $R_t = 25\%$. The best results are emphasized by boldface. Note that some ratio values go to minus infinity, which means that no false alarms are found.

For a fair comparison of detection rates, $P_d$, they should all correspond to the same observed false alarm rate, $P_{fa}$. However, the $P_d$ values are computed based on a specified false alarm rate, $P_{FA}$, since it is impractical to control $P_{fa}$, which is a stochastic variable that depends on the data sample. The approach we have taken in Table I and II is to list $P_d$ values (computed for $P_{FA} = 10^{-5}$) and $10 \log_{10}(P_{fa}/P_{FA})$ values separately, and use the latter in the interpretation of the $P_d$ values.

In the joint analysis of $P_d(P_{FA})$ versus $P_{fa}/P_{FA}$, a value of $10 \log_{10}(P_{fa}/P_{FA}) > 0$ signifies that the corresponding value of $P_d$ is higher than it would have been if $P_{fa}$ was equal to the specified $P_{FA}$, as desired. Therefore, $P_d(P_{FA})$ overestimates the performance of the algorithm. Conversely, a value of $10 \log_{10}(P_{fa}/P_{FA}) < 0$ means that the corresponding $P_d(P_{FA})$ underestimates the algorithm performance. This knowledge can be used to compensate for the inadequacy of $P_d(P_{FA})$, although the resulting analysis is only qualitative.

This leads to the following interpretations: Table I shows that TS-CFAR produces the highest values of $P_{fa}/P_{FA}$ and also obtains the highest $P_d(P_{FA})$ in the exponential case. According to the joint analysis described above, the TS-CFAR detection rates are therefore exaggerated, while the detection rates of the other algorithms are underrated. Similarly, we see in Table II that TS-CFAR has the highest $P_d$ also in the gamma case. Again, the $P_{fa}/P_{FA}$ values show that the comparison unfairly favors the TS-CFAR algorithm, and indicates that...
the internal ranking of the algorithms based on the desired $P_d(P_{fa})$ might be different than what we obtain from the listed $P_d(P_{FA})$.

In Figures 9 and 10 we plot $P_d$ versus $P_{fa}$, as desired, but with an artifact: The $P_d$ values are produced with simulated data samples that are generated according to a specified $P_{FA}$ value. Since the data samples are random, so are the $P_{fa}$ and $P_d$ values they produce. This is reflected by Fig. 9 and 10, where a colored cloud of $(P_{fa}, P_d)$ points represents the stochastic performance measures obtained at $P_{FA} = 10^{-5}$ for the different algorithms. The number of false alarms in a random generated data sample is known from (17) as $n_{fa} = P_{fa} \cdot n$. The discrete nature of the point clouds at low $P_{FA}$ levels reflects that the realizations of $n_{fa}$ are small integers, that give rise to the observed discrete levels. We see again in these figures that the TS-CFAR algorithm produces the highest $P_d$, but if all results were projected to a common $P_{fa}$ level, their $P_d$ levels would also change in an unknown manner, and so the internal ranking of the algorithms is not obvious in all cases.

What we can conclude is that the TS-CFAR algorithm performs at least on par with the ICOS-CFAR algorithm, which we consider as state-of-the-art for the multiple target situation. The conventional CA-CFAR detector perform poorly with contaminated samples, as expected. It is worth noting that the OS-based CFAR detectors show relatively good detection rates. However, their observed false alarm rates deviate much from the specified false alarm rate, especially when operating without the IC scheme. Overall, the proposed TS-CFAR detector shows the best false alarm regulation properties and obtains excellent detection rates without resorting to the iterative censoring strategy, which is inevitably associated with high computational cost.

IV. DETECTION PERFORMANCE WITH COMPOSITE REAL DATA

In this section, a comparative study of the CFAR detectors based on example cases is presented. In all cases studied, the
sea clutter statistics are occasionally contaminated by pixels originating from targets. A proper treatment of the difficulties that may raise due to clutter edges and transitions in sea state is here left out and kept for future work. All experiments and examples discussed are carefully constructed, so the background sea clutter is kept homogeneous without any non-stationary statistics before we superimpose targets. The proposed TS-CFAR detector is compared with the conventional CA-CFAR and OS-CFAR detectors as well as their IC schemes. Note that the TS, OS, and IC schemes are all proposed to handle multiple target situations. The performance of the CFAR detectors are investigated and discussed from three practical perspectives: the impact of adjusting the design of the sliding window, the detector behavior in dense target situations, and the target blurring and merging effect due to multi-looking.

The truncation ratio of the TS-CFAR detector is kept constant at $R_t = 25\%$, to allow fair comparison with the OS-based algorithm at $k = 3N/4$. It is worth noting that the reference sample size applied under the sliding window technique directly affects the parameter estimation of the hypothesized model, and hence, the statistical analysis of the background clutter. More samples generally lead to more accurate estimates and an improved model fit. However, more samples require larger reference sliding windows, which increases the risk of including both contamination and non-stationary statistics, e.g., outliers and clutter edges. A relatively large reference sample size is implemented in our experiments, with a total number of samples set to 1024 before data truncation, and a specified false alarm rate of $P_{FA} = 10^{-5}$ is set throughout the performance evaluation of the CFAR detectors for all example cases.

A Radarsat-2 SLC fine quad-polarization SAR imagery acquired 18 August 2011 off the south coast of the UK at Portsmouth harbor is exploited to evaluate the detectors. The resolution of the imagery is approximately 5.0 and 4.7 meters along the azimuth and range directions, respectively. The scene is acquired with a mid-swath incidence angle of approximately 38°, and the test area is characterized by low wind conditions and a calm sea state [26]. Portsmouth is one of the most crowded harbors in the UK, which provides a good test opportunity for a wide range of vessel sizes and vessel types, including several small boats under 10 meters in

![Fig. 5](image_url)

Fig. 5. Comparative analysis of the false alarm regulation property of the best performing detectors. Simulated SLI sea clutter is applied with exponential distribution ($\mu = 3$). The contamination ratios considered are 1%, 5%, 10% and 20%, related to the total number of reference samples. A log-scale is applied on the x-axes.
length. The ground truth is based on Automatic Information System (AIS) positioning data and photographic evidence [26]. Three example cases are composited from the HV polarization SLI and MLI \((L = 4)\) SAR measurements, and utilized in the proceeding experiments. Note that we perform multi-looking in the spatial domain with a resolution preserving sliding window, and not with a stepping window, which is the common practice. This has no impact on the analysis and the results we obtain, except that it provides more data that can be used in the evaluation of the algorithms, and is therefore considered a valid approach.

A. Sliding window design

The sliding window technique is commonly applied in CFAR detection schemes. When the central cell under test contains a strong target, side-lobe effects may contaminate the background sample in both the azimuth and range direction. A common and pragmatic solution to this problems is to define a guard area, and confine the selection of background data to the four corners of the sliding window. A schematic illustration of this approach is given in Fig. 11(a). An alternative method is shown in Fig. 11(b), where a block estimation window centered at the cell under test is chosen.

The choice of sliding window design naturally affects the detection results of CFAR detectors. In our implementation of the design illustrated in Fig. 11(b), a \(32 \times 32\) window is applied to provide a total of 1024 reference samples, before we exclude the central test cell. For the corner approach, \(16 \times 16\) samples are drawn from each of the four corners, providing the same total number of reference samples.

Both block and corner sliding window designs are here investigated. A comparative analysis of the CFAR detectors is shown in Fig. 12 and 13. The composited SLI and MLI scenes contain one target. The IC schemes take approximately 9 iterations to reach convergence on average.

In general, with the corner approach, bright pixels originating from the target are excluded from the background clutter sample, which leads to more accurate parameter estimation, and more beneficial thresholding. In the composite case shown in Fig. 12(a) and 13(a), excessive energy from the target gives a blurred impression along the azimuth direction due to the side-lobe effect. Note, both pixels originating from the vessel
and its smeared out energy are here treated as target pixels. From Fig. 12(b), 12(c), 13(b) and 13(c), it is clear that CA-based CFAR detectors relay on a proper design of sliding window for various background clutter conditions, which is due to a lack of accommodating contaminating targets in the sea clutter estimation window. The OS-based CFAR detectors in Fig. 12(d), 12(e), 13(d) and 13(e) offer some improvements in this regard, and we note that the corner estimation approach yields superior results. As shown in Fig. 12(f) and 13(f), it is obvious that the proposed TS-CFAR detector produces the best detection results without additional iterative processing, and has a robust performance regarding the choice of estimation window approach. Hence, reference window designs incorporating guard areas are made superfluous, as the TS-CFAR detector can be readily implemented based on the block approach, thus collecting the reference samples from a more confined area centered at the cell under test.

### B. Interfering targets

Target suppression in CFAR detection is an adverse effect due to densely located targets. When a target lies within
the reference window of the target under test, the resulting overestimated threshold can cause the target under test to not be detected [1]. In Fig. 14 and 15, the performances of the different detectors are compared through an example case, where a large vessel is placed in centre with 6 small targets lining up on both sides. Note that all six interfering targets are real targets composited from other parts of the same source SAR imagery. The corner approach for sampling sea clutter pixels is applied for all detectors compared.

From Fig. 14(b) and 15(b), the CA-CFAR detector performs poorly, causing a significant number of undetected target pixels. The ICCA-CFAR detector in Fig. 14(c) completely misses the three small targets on the left side of the panel after 10 iterations, and in Fig. 15(c), it performs even worse with the applied corner sliding window after 12 iterations. It is obvious from a visual inspection of the results in Fig. 14(f) and 15(f) that the TS-CFAR detector performs best. The TS-CFAR detector detects pixels from all targets, as does the ICOS-CFAR detector after 7 and 6 iterations in Fig. 14(e) and 15(e), respectively. However, the TS-CFAR detector is superior in the total number of target pixels detected.

### TABLE II

CFAR detector characteristics analysis with the specified false alarm rate at $P_{FA} = 10^{-5}$. Simulated MLI sea clutter is applied with gamma distribution ($\mu = 3, L = 4$). Results are averaged from 1000 Monte Carlo simulations with a sample size of 1024. The contamination ratios considered are 1%, 5%, 10% and 20%, related to the total number of reference samples. The truncation ratio of the TS-CFAR detector is constant at $R_t = 25\%$. The best results are shown in boldface.

<table>
<thead>
<tr>
<th>$R_c$</th>
<th>$P_{fa}/P_{FA}$ [dB]</th>
<th>$P_d$ [%]</th>
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<td>CA ICCA OS ICOS TS</td>
<td>CA ICCA OS ICOS TS</td>
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<td>1%</td>
<td>$\infty$ $\infty$ -1.0261 -0.3642</td>
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<td>5%</td>
<td>$\infty$ $\infty$ -4.6803 -0.6623</td>
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<td>20%</td>
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<td>1%</td>
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From Fig. 14(b) and 15(b), the CA-CFAR detector performs poorly, causing a significant number of undetected target pixels. The ICCA-CFAR detector in Fig. 14(c) completely misses the three small targets on the left side of the panel after 10 iterations, and in Fig. 15(c), it performs even worse with the applied corner sliding window after 12 iterations. It is obvious from a visual inspection of the results in Fig. 14(f) and 15(f) that the TS-CFAR detector performs best. The TS-CFAR detector detects pixels from all targets, as does the ICOS-CFAR detector after 7 and 6 iterations in Fig. 14(e) and 15(e), respectively. However, the TS-CFAR detector is superior in the total number of target pixels detected.
C. Blurring and merging targets

So far, the proposed TS-CFAR detector shows robust and outstanding detection results. In addition, we demonstrate how the TS-CFAR detector behaves with different multi-looked SAR images. A composite example including small and closely separated targets is used in this experiment. As we know, multi-looking is often applied in SAR image processing for speckle reduction. However, the inevitable blurring effect can not be neglected, especially when aiming at detecting small targets with weak contrast. In MLI data, when two targets are closely located, the detections from both targets are likely to be merged. It is worth noting that the process of multi-looking averages the correlated measurements in real SAR images, which affects statistical modeling of the resulting multi-looked data.

Fig. 16(a)–16(c) show composite example SAR intensity images with number of looks $L = 1, 4,$ and $9,$ respectively. It is clear that the image becomes blurred with an increasing number of looks. The TS-CFAR detector performance is then examined with fixed truncation ratio $R_t = 25\%$ and specified false alarm rate $P_{FA} = 0.001\%$. For the SLI image, the TS-CFAR detector is sensitive enough to detect and distinguish all small and closely located targets as shown in Fig. 16(d). With the increasing number of looks in Fig. 16(e) and 16(f), all detected targets get blurred as expected, meanwhile closely located targets are merged.

V. CONCLUSIONS

In order to reduce the bias of the estimated background statistics in multiple target situations, the TS-CFAR detector is proposed. The TS-CFAR algorithm is based on truncated statistics and has a number of advantages. It is designed to accommodate interfering targets in the reference window. False alarms are also controlled exceptionally well by the TS-CFAR algorithm. The comparisons of the different CFAR detectors have clearly demonstrated the superiority of TS-CFAR processing over conventional CA-CFAR and OS-CFAR processing. TS-CFAR also performs on par with IC schemes, while avoiding the iterations.

In practical CA-CFAR applications, guard cells are used for separating the cell under test from the reference area in order to
Fig. 10. A ROC-type plot of observed false alarm rate against detection rate at specified false alarm rate \( P_{FA} = 10^{-5} \). Simulated MLI sea clutter is applied with gamma distribution \((\mu = 3, L = 4)\). Monte Carlo simulations are done with a sample size of 1024. Each data cloud is based on 1000 repetitions. Note that, over the selected range of contamination conditions, not all color clouds are visible due to the chosen intervals on the axes.

preventing target returns from falsifying the clutter level estimation. In TS-CFAR processing, guard cells become unnecessary since a small number of target amplitudes occurring within the reference area have almost no influence on the clutter level estimation. Due to the truncation, the TS-CFAR algorithm can be implemented with a block sliding estimation window centered at the cell under test, thus collecting the sample in a more confined area. Therefore, a reference window without guard cells can be used with TS-CFAR processing.

The TS-CFAR scheme is here derived for exponential and gamma distributed sea clutter background models with respect to SLI and MLI SAR measurements. In the future, potential expansions of the proposed algorithm could be made by deriving the TS-CFAR detector for other choices of hypothesized sea clutter models, such as the common K-distribution.

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Fig. 11. Alternative ways of selecting the estimation window for sea clutter statistics. The cell under test is marked in black and the estimation sample is shaded. In the study, four $16 \times 16$ windows in (a) and a $32 \times 32$ window in (b) are applied.
Fig. 12. Comparative analysis of detection results with block and corner sliding windows. Composite SLI HV polarization SAR image is applied with the specified false alarm rate at $P_{FA} = 0.001\%$. The color bar in (b)-(f) represents detected targets using the corner estimation approach (Win-c, white), the block estimation approach (Win-b, green), and the combined results from both approaches (Win-b&c, red). Black represents pixels detected as background clutter by the respective CFAR detector.

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Fig. 13. Comparative analysis of detection results with block and corner sliding windows. Composite MLI HV polarization SAR image with number of looks $L = 4$ is applied with the specified false alarm rate at $P_{FA} = 0.001\%$. The color bar in (b)–(f) represents detected targets using the corner estimation approach (Win-c, white), the block estimation approach (Win-b, green), and the combined results from both approaches (Win-b&c, red). Black represents pixels detected as background clutter by the respective CFAR detector.
Fig. 14. Comparative analysis of detection results with multiple interfering targets. Composite SLI HV polarization SAR image is applied with the specified false alarm rate at $P_{FA} = 0.001\%$. The composite example SAR scene contains one large vessel and six small targets. The corner approach for estimating sea clutter statistics is applied in (b)–(f).
Fig. 15. Comparative analysis of detection results with multiple interfering targets. Composite MLI HV polarization SAR image with number of looks $L = 4$ is applied with the specified false alarm rate at $P_{FA} = 0.001\%$. The composite example SAR scene contains one large vessel and six small targets. The corner approach for estimating sea clutter statistics is applied in (b)–(f).
Fig. 16. Comparative analysis of TS-CFAR detection results with multiple small closely located targets. First row (a)–(c): composite example HV polarization SAR data; one SLI and two MLI images with varying number of looks $L$. The legends are in decibels. Note, two small targets are placed close together in the upper central part of the scene, thee small targets are placed on line in the middle, while the target located in the lower central part of the image is likely to be composed of two vessels. Second row (d)–(f): TS-CFAR detection results on corresponding SLI or MLI images from the first row. The corner approach for estimating sea clutter statistics is applied. The specified false alarm rate is 0.001%, and the truncation ratio is fixed at 25%.