Research Article

Subspace Compressive GLRT Detector for MIMO Radar in the Presence of Clutter

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The problem of optimising the target detection performance of MIMO radar in the presence of clutter is considered. The increased false alarm rate which is a consequence of the presence of clutter returns is known to seriously degrade the target detection performance of the radar target detector, especially under low SNR conditions. In this paper, a mathematical model is proposed to optimise the target detection performance of a MIMO radar detector in the presence of clutter. The number of samples that are required to be processed by a radar target detector regulates the amount of processing burden while achieving a given detection reliability. While Subspace Compressive GLRT (SSC-GLRT) detector is known to give optimised radar target detection performance with reduced computational complexity, it however suffers a significant deterioration in target detection performance in the presence of clutter. In this paper we provide evidence that the proposed mathematical model for SSC-GLRT detector outperforms the existing detectors in the presence of clutter. The performance analysis of the existing detectors and the proposed SSC-GLRT detector for MIMO radar in the presence of clutter are provided in this paper.

1. Introduction

A radar system is expected to search for designated targets within a given region by detecting the existence of the reflected components of that transmitted signal from the target. For any radar system, signal detection is the primary and the most important process. In the existing literature, different signal detection models such as Generalised Likelihood Ratio Test (GLRT) detector [1, 2] and Rao test detector [3, 4] have been widely considered for their robustness. A GLRT detector has attracted the interest of the researchers due to its robustness, simplicity, and ability to display constant false alarm rate (CFAR). Target detection performance of a radar system can be significantly affected by variations in target Radar Cross-Section (RCS). With Multiple Input and Multiple Output (MIMO) antenna connections at the radar system, it is possible to assure the existence of spatiotemporal nature within the received signal. Subsequently, MIMO radars obtained significant research attention within the relevant research community [5–9]. In MIMO radars, the received signal components from different transmitter-receiver pairs are statistically uncorrelated. By exploiting the uncorrelated nature of spatiotemporal received signals, the effect of variation of target RCS can be optimised. In the existing literature, authors have addressed different target detection problems related to MIMO radars and proposed solutions to enhance the target detection performance [10,11]. The multiple transmitters and receivers of MIMO radars can either be collocated or widely spaced. MIMO radars with widely spaced antennas are capable of achieving improved spatial diversity with respect to the target radar cross-section. On the other hand MIMO radars with collocated antennas are capable of providing improved waveform diversity and increased accuracy in signal parameter estimation. However, diversity of the signal statistics at the multiple receivers of a MIMO radar is achieved at the cost of increased processing
burden on the radar system. For a radar system, the time
taken by its detector to make a decision is relative to the
number of received signal statistics which are required to
be processed. The large number of signal statistics collected
by the multiple receiver antennas of MIMO radars imposes
huge processing burden and computational complexity on
the system. Compressive sampling has been addressed in
[8, 12–19] where the detection process is performed on
compressed received signal samples. The authors in [15] have
proposed compressive detection for MIMO radars to reduce
the processing complexity which is achieved as a trade-off
with the target detection performance. By exploiting the
target sparsity in the Doppler range, better target detec-
tion performance can be achieved with a fewer number of
received signal samples. A relatively new compressive signal
realisation technique called subspace compression has been
proposed in [20]. The authors in [8, 14] addressed a GLRT
detector known as Compressive GLRT (C-GLRT) detector,
which performs radar target detection over compressed
received signal samples. By using compressed received signal
samples, a C-GLRT detector has the ability to be faster
and operate at reduced computational complexity. However,
these traits are achieved as a trade-off between the radar
target detection performance and signal compressibility.
For an intended probability of detection, the degree of
compressibility gets poorer due to the time varying nature of
target detection environment. A time adaptive compressive
measurement scheme has been presented within the subspace
of a Gaussian measurement matrix, named SSC scheme in
[14, 20]. As subspace compressive measurement scheme takes
control over this measurement matrix which is adaptive to
the signal subspace characteristics. A Subspace Compressive
GLRT (SSC-GLRT) detector is expected to give better target
detection performance compared to a C-GLRT detector.

Clutter is comprised of all the reflected return signals
from the extraneous background environment that arrive at
the radar detector. Clutter returns appear on the same domain
as the target returns. The presence of clutter is known to
cause increased false alarms and hence compromise the target
detection performance of the radar detector at a constant
false alarm rate [21]. The deterioration in target detection
performance is significantly increased when compressive
sampling is used. In the existing literature, authors proposed
using Doppler shift caused due to moving targets to negotiate
clutter [22, 23]. While this approach yields performance
gains in the case of fast moving targets and airborne radars,
alternative approaches need to be investigated for ground
based radars with slow moving targets.

In most of the existing research, the presence of clutter
has not been addressed by the authors in the context of
Compressive GLRT techniques. The main contribution of this
paper is providing a detailed mathematical model to optimise
the target detection performance of C-GLRT and SSC-GLRT
detectors for a MIMO radar detector in the presence of
clutter by exploiting the known knowledge of the clutter
subspace. The proposed mathematical model is applied to
Compressive and Subspace Compressive GLRT detection
schemes and the corresponding target detection performance
 gains are measured. The target detection probabilities of the
proposed and conventional GLRT detectors in the presence
of clutter are plotted to demonstrate the superiority of the
proposed model. The proposed compressing sensing tech-
niques find their applications in resource constrained security
applications with limited processing capabilities. The rest of
the paper is organised as follows. In Section 2, the system
model and the signal models for binary hypothesis testing
are introduced. In Section 3, the test statistic for a GLRT
detector in the presence of clutter is derived. In Section 4,
the proposed mathematical model for SSC-GLRT detector
in the presence of clutter is derived. The performance evaluation
and simulation results are given in Section 5. Conclusions and
future work are summarised in Section 6.

2. Signal Model and Hypothesis Testing

2.1. Signal Model. As aforementioned, the problem of interest
which is considered in this paper is detecting the presence of
a target using ground based bistatic MIMO radar. The MIMO
radar is assumed to have \( N_t \) transmitting antennas and \( N_r \)
receiving antennas. Each receiving antenna is assumed to
have \( N_t \) array elements. It is assumed that each transmitting
antenna transmits \( N_p \) coherent pulses per transmitting cycle
(Figure 1).

In the presence of a target within a cluttered background,
the received signal at each receiver element can be expressed
as a combination of target return, clutter return, and noise.
Hence the received signal at each MIMO receiver can be
mathematically modelled as

\[
y_i = S a_i + H b_i + w_i,
\]

where \( y_i \) is the received signal at the \( i \)th receiver antenna and
it is of dimensions \((N_p N_a \times 1)\), \( S \) is the steering vector of
dimensions \((N_p N_a \times N_t)\), \( H \) represents the clutter subspace
and is of dimensions \((N_p N_a \times N_t)\), \( a_i \) is the unknown
complex value accounting for target backscattering power.
and channel propagation between transmitter, target, and the
receiver and it is of dimension \((N_cN_s \times 1)\), and \(b_j\) is the
unknown complex amplitude of the clutter return which is of
dimensions \((N_s \times 1)\). Finally, \(w_i\) denotes the noise component
which is of dimensions \((N_cN_s \times 1)\).

In (1), the clutter subspace matrix \(H\) is a priori unknown.
Detection algorithms suffer deterioration in the detection
performance in the presence of unknown clutter. The knowl-
edge of clutter is necessary to achieve reliable detection
rates and hence clutter estimation is necessary prior to
target detection. To estimate clutter, the knowledge of a
set of \(K\) secondary data which are free of target returns is
necessary:
\[
y_{i,k} = Hb_i + w_{i,k}, \quad k = 1, 2, \ldots, K. \tag{2}
\]

In the existing literature, the authors have addressed the
problem of clutter estimation from the available secondary
data [24–27]. For the rest of this paper, it is assumed that a
reliable clutter estimate is available to the target detector with
clutter being relatively time invariant.

2.2. Hypothesis Testing. The performance measure of a radar
receiver, while being dedicated to detect the existence or
nonexistence of targets within a region of interest, is the
degree of reliability on such decision making. The two possible
outcomes of this decision making process are occurrence or
nonoccurrence of a phenomenon representing existence and
nonexistence of the target, respectively, which is mod-
elled as a binary hypothesis testing problem. The two possible
hypotheses are \(H_0\) and \(H_1\), where \(H_0\) represents the absence
of the target and \(H_1\) represents the presence of the target.
The corresponding signal models of these hypotheses are
[14, 21]
\[
H_0 : y = Hb + w, \tag{3}
\]
\[
H_1 : y = Sa + Hb + w.
\]
The amplitude vector \(a\) and the noise variance are assumed
to be unknown to the radar receiver, while noise is assumed
to be AWGN. The test statistic for the GLRT detector
is generated from the log-likelihood ratio function within
which the unknown parameters are estimated using Maxi-
mum Likelihood (ML) estimator. For a desired false alarm
rate \((P_{fa})\), a threshold \(\gamma\) is generated which is compared
with the likelihood ratio function such that a decision
regarding the presence or absence of the target can be
made.

3. GLRT Detector in the Presence of Clutter

Clutter signal returns are spread across frequency spectrum
and away from zero frequency. Clutter returns are often
known to lead to increased false alarm rates. With relatively
small target Radar Cross-Sections (RCS), it is often the case
where the signal strengths from target returns are weaker
than the clutter returns and hence makes target detection
process more difficult at a constant false alarm rate (CFAR).
Hence careful considerations of the effect of clutter returns
are to be included in target detection design process to
maintain the required CFAR. For the received signal models
described in (3), the joint probability density functions for
the unknown parameters under hypotheses \(H_0\) and \(H_1\) are
defined as
\[
f(y \mid b, \sigma^2, H_0) = \left(\frac{1}{\pi \sigma^2}\right)^N \exp \left(-\frac{1}{\sigma^2} \left((y - Hb)^H (y - Hb) + \sum_{k=1}^{K} y_k^H y_k\right)\right),
\]
\[
f(y \mid a, b, \sigma^2, H_1) = \left(\frac{1}{\pi \sigma^2}\right)^N \exp \left(-\frac{1}{\sigma^2} \left((y - Sa - Hb)^H (y - Sa - Hb) + \sum_{k=1}^{K} y_k^H y_k\right)\right). \tag{4}
\]

It is assumed that the radar target detector does not have
the knowledge of the noise variance, represented by \(\sigma^2\),
and the complex amplitudes of clutter and target returns
which are represented by \(b\) and \(a\), respectively. To formulate
the test statistic, the unknown parameters are estimated by
maximising the unknown parameter values for a given set
of received signal samples. The Maximum Likelihood (ML)
estimator estimates these unknown parameters from the log-
likelihood function which is denoted by \(\Gamma\). The log-likelihood
functions under hypotheses \(H_0\) and \(H_1\) are summarised
as
\[
\Gamma(y \mid b, \sigma^2, H_0) = -N \log (\pi \sigma^2) - \frac{1}{\sigma^2} \left((y - Hb)^H (y - Hb) + \sum_{k=1}^{K} y_k^H y_k\right), \tag{5}
\]
\[
\Gamma(y \mid a, b, \sigma^2, H_1) = -N \log (\pi \sigma^2) - \frac{1}{\sigma^2} \left((y - Sa - Hb)^H (y - Sa - Hb) + \sum_{k=1}^{K} y_k^H y_k\right). \tag{6}
\]

3.1. ML Estimate of Noise Variance. Let the ML estimates
of the noise variance, \(\sigma^2\), under hypotheses \(H_0\) and \(H_1\) be
denoted by \(\hat{\sigma}^2_0\) and \(\hat{\sigma}^2_1\), respectively. The corresponding ML
estimates can be obtained from the partial derivatives of (5)
and (6) with respect to \(\sigma^2\):

\[
\frac{\partial}{\partial \sigma^2} \left(\Gamma(y \mid b, \sigma^2, H_0)\right) = 0, \tag{7}
\]
\[
\frac{\partial}{\partial \sigma^2} \left(\Gamma(y \mid a, b, \sigma^2, H_1)\right) = 0, \tag{8}
\]
and thus, by solving (7) and (8), ML estimates of $\sigma^2$ under hypotheses $H_0$ and $H_1$ can be summarised as

$$\hat{\sigma}^2_0 = \frac{1}{N} \left( (y - Hb)^H(y - Hb) + \sum_{k=1}^{K} y_k^H y_k \right),$$  

(9)

$$\hat{\sigma}^2_1 = \frac{1}{N} \left( (y - Sa - Hb)^H(y - Sa - Hb) + \sum_{k=1}^{K} y_k^H y_k \right).$$  

(10)

3.2. ML Estimate of Clutter Return. Let the ML estimates of the unknown complex amplitude of the clutter signal return under hypotheses $H_0$ and $H_1$ be denoted by $\hat{b}_0$ and $\hat{b}_1$, respectively. As aforementioned, the corresponding ML estimates can be obtained from the partial derivatives of (5) and (6) with respect to $b$:

$$\frac{\partial}{\partial b} \left( \Gamma(y : b, \sigma^2, H_0) \right) = 0,$$  

(11)

$$\frac{\partial}{\partial b} \left( \Gamma(y : a, b, \sigma^2, H_1) \right) = 0.$$  

(12)

Solving (11) and (12), it can be observed that ML estimate of the complex amplitude of the clutter signal return is independent of $\sigma^2$. ML estimates of $b$ under hypotheses $H_0$ and $H_1$ can be summarised as

$$\hat{b}_0 = (H^H H)^{-1} H^H y,$$  

(13)

$$\hat{b}_1 = (H^H H)^{-1} H^H (y - Sa).$$  

(14)

3.3. ML Estimate of Target Return. The complex amplitude of the radar signal which is backscattered from the target is unknown to the radar detector. Let the ML estimate of the target return under hypotheses $H_0$ and $H_1$ be denoted by $\hat{a}_0$ and $\hat{a}_1$, respectively. From (5) and (6),

$$\frac{\partial}{\partial a} \left( \Gamma(y : b, \sigma^2, H_0) \right) = 0,$$  

(15)

$$\frac{\partial}{\partial a} \left( \Gamma(y : a, b, \sigma^2, H_1) \right) = 0.$$  

(16)

Hypothesis $H_0$ is based on the assumption that there is no target return. From (16) it can be observed that the ML estimate of the target return $\hat{a}_0$ under hypothesis $H_0$ is

$$\hat{a}_0 = 0.$$  

(17)

ML estimate of $\hat{a}_1$ can be obtained from (16) and (14) as

$$\frac{\partial}{\partial a} \left( (y - Sa - Hb)^H H^H (y - Sa - Hb) + \sum_{k=1}^{K} y_k^H y_k \right).$$  

(18)

Therefore the ML estimate of complex amplitude of the target return can be summarised by solving (18) as

$$\hat{a}_1 = (S^H (P^H P)^{-1} S)^{-1} (S^H (P^H P) y),$$  

(19)

where $P = I - H(H^H H)^{-1} H^H$.

By using the ML estimates of the unknown parameters, the test statistic can be obtained as

$$\zeta = \frac{(y - H\hat{b}_0)^H (y - H\hat{b}_0) + \sum y_k^H y_k}{(y - Sa - H\hat{b}_1)^H (y - Sa - H\hat{b}_1) + \sum y_k^H y_k}.$$  

(20)

4. Proposed Subspace Compressive GLRT Detector in the Presence of Clutter

In Section 3, we derived the test statistic for a GLRT detector for MIMO radar to detect the presence of a target using a given set of received signal samples in the presence of clutter. The processing requirement within a radar receiver is a function of the number of targets that are required to be dissociated from the given set of received signal samples. In other words, to provide a preset level of target detection reliability, the required number of received signal samples varies nonlinearly with the number of targets that are required to be dissociated. With limited computational capacity within a radar receiver, such increase in processing complexity may lead towards resource saturation, hence leading towards a trade-off with the target detection reliability. To reduce the processing burden, C-GLRT has been proposed by authors in the existing literature. In C-GLRT, the received signal samples are compressed by projecting them onto a projection matrix $\Phi$. While C-GLRT has the ability to make a decision over existence or nonexistence of the target based on compressed received signal samples and hence reducing the computational complexity, it however suffers a significant deterioration in the target detection performance. Moreover, the target detection performance is further deteriorated in the presence of clutter. Subspace compression techniques are known to give better trade-off between the performance and compressibility when compared to conventional compression techniques. Hence a SSC-GLRT is expected to give a better target detection performance than a C-GLRT. The signal subspace for the radar target returns is expected to be sparse in nature. The projection matrix for SSC-GLRT is modelled to exploit this sparse nature of the received signal samples.
In this section, we derive a new mathematical framework to obtain the test statistic for SSC-GLRT detector which is expected to improve the target detection performance in the presence of clutter.

4.1. Signal Model. Unlike a C-GLRT which uses a random projection matrix to compress the received signal samples, for SSC-GLRT, we derive the projection matrix based on the knowledge of the signal subspace. The projection matrix \( \Phi \) for SSC-GLRT can be derived as

\[
\Phi = G \left( S^T S \right)^{-1} S^T,
\]

(21)

where \( G \) is the random measurement matrix.

For SSC-GLRT, the compressed received signal model under hypotheses \( H_0 \) and \( H_1 \) can be obtained from (3) and (21) as

\[
H_0: \bar{y} = \Phi H_b + \Phi w,
\]

\[
H_1: \bar{y} = \Phi S a + \Phi H_b + \Phi w.
\]

(22)

SSC-GLRT detector uses the received signal models as described in (22) to make a decision regarding the existence or nonexistence of a target. As mentioned in Section 3, the unknown parameters are statistically estimated using ML estimator. The joint probability density functions for the unknown parameters for SSC-GLRT under hypotheses \( H_0 \) and \( H_1 \) are defined as

\[
f(\bar{y}: b, \sigma^2, H_0) = \left( \frac{1}{\pi \sigma^2} \right)^N \exp \left( -\frac{1}{\sigma^2} \left( (\bar{y} - \Phi H_b)^H \right) \cdot \left( \Phi \Phi^H \right)^{-1} (\bar{y} - \Phi H_b) + \sum \bar{y}_k^H \left( \Phi \Phi^H \right)^{-1} \bar{y}_k \right),
\]

(23)

\[
f(\bar{y}: a, b, \sigma^2, H_1) = \left( \frac{1}{\pi \sigma^2} \right)^N \exp \left( -\frac{1}{\sigma^2} \left( (\bar{y} - \Phi Sa - \Phi H_b)^H \right) \cdot \left( \Phi \Phi^H \right)^{-1} (\bar{y} - \Phi Sa - \Phi H_b) + \sum \bar{y}_k^H \left( \Phi \Phi^H \right)^{-1} \bar{y}_k \right).
\]

While the measurement matrix \( \Phi \) is known to the radar detector, the noise variance and the complex amplitudes of the clutter and target returns are the unknown parameters. For the probability density functions as defined in (23), the log-likelihood functions for SSC-GLRT under hypotheses \( H_0 \) and \( H_1 \) are expressed as

\[
\Gamma(\bar{y}: a, b, \sigma^2, H_1) = -N \log \left( \pi \sigma^2 \right) - \frac{1}{\sigma^2} \left( (\Phi^{-1} (\bar{y} - \Phi Sa - \Phi H_b))^H \cdot \left( \Phi \Phi^H \right)^{-1} (\bar{y} - \Phi Sa - \Phi H_b) \right) + \sum \bar{y}_k^H \left( \Phi \Phi^H \right)^{-1} \bar{y}_k,
\]

(24)

\[
\Gamma(\bar{y}: a, b, \sigma^2, H_0) = -N \log \left( \pi \sigma^2 \right) - \frac{1}{\sigma^2} \left( (\Phi^{-1} (\bar{y} - \Phi H_b))^H \cdot \left( \Phi \Phi^H \right)^{-1} (\bar{y} - \Phi H_b) \right) + \sum \bar{y}_k^H \left( \Phi \Phi^H \right)^{-1} \bar{y}_k.
\]

(25)

4.2. ML Estimate of Noise Variance. Let the ML estimates of the noise variance \( \sigma^2 \) under hypotheses \( H_0 \) and \( H_1 \) be denoted by \( \hat{\sigma}^2_0 \) and \( \hat{\sigma}^2_1 \), respectively. The corresponding ML estimates can be obtained from the partial derivatives of (24) and (25) with respect to \( \sigma^2 \):

\[
\frac{\partial}{\partial \sigma^2} \left( \Gamma(\bar{y}: a, b, \sigma^2, H_0) \right) = 0,
\]

(26)

\[
\frac{\partial}{\partial \sigma^2} \left( \Gamma(\bar{y}: a, b, \sigma^2, H_1) \right) = 0.
\]

(27)

Solving (24), (25), (26), and (27), ML estimates for \( \sigma^2 \) under hypotheses \( H_0 \) and \( H_1 \) can be summarised as

\[
\frac{\partial}{\partial \sigma^2} \left( \Gamma(\bar{y}: b, \sigma^2, H_0) \right) = 0,
\]

(28)

\[
\frac{\partial}{\partial \sigma^2} \left( \Gamma(\bar{y}: a, b, \sigma^2, H_1) \right) = 0.
\]

(29)

4.3. ML Estimate of Clutter Return. The ML estimates of the complex amplitude of the clutter signal returns under hypotheses \( H_0 \) and \( H_1 \) which are denoted by \( \hat{b}_0 \) and \( \hat{b}_1 \) can be obtained from the partial derivatives of (24) and (25) with respect to \( b \):

\[
\frac{\partial}{\partial b} \left( \Gamma(\bar{y}: b, \sigma^2, H_0) \right) = 0,
\]

(30)

\[
\frac{\partial}{\partial b} \left( \Gamma(\bar{y}: a, b, \sigma^2, H_1) \right) = 0.
\]

(31)

Solving (30) and (31) and rearranging terms, we can obtain the ML estimates \( \hat{b}_0 \) and \( \hat{b}_1 \) as

\[
\hat{b}_0 = \mathbf{V} \bar{y},
\]

(32)

\[
\hat{b}_1 = \mathbf{V} (\bar{y} - \Phi Sa),
\]

(33)

where \( \mathbf{V} = \left( \Phi \Phi^H \right)^{-1} \left( \Phi \Phi^H \right)^{-1} \left( \Phi \Phi^H \right)^{-1} \left( \Phi \Phi^H \right)^{-1} \).

4.4. ML Estimate of Target Return. Target return is the energy gathered by the radar receiver which is backscattered from
In this section, we demonstrate the performance of the proposed mathematical model for a MIMO radar target detector in the presence of clutter. As a measure of radar target detection performance we denote the terms probability of detection \( P_D \) which is defined as the percentage of cases in which the true presence of targets is detected and Probability of False Alarm \( P_F \) which is defined as the percentage of cases in which the presence of targets is falsely assumed. The experiments are conducted based on Monte Carlo simulations averaged over 10000 samples. A ground based bistatic MIMO radar is considered with \( N_t = 1 \) transmitting antenna and \( N_r = 3 \) receiving antennas. It is assumed that each receiving antenna has \( N_a = 4 \) array elements and the transmitting antennas transmit \( N_p = 5 \) coherent pulses per transmitting cycle. The received signal samples are considered to be corrupted by clutter and noise. While noise is assumed to be zero-mean Gaussian, clutter is assumed to follow Rayleigh distribution. Simulations are conducted under CFAR with \( P_F \) maintained at \( 10^{-4} \). In Figure 2, the target detection performance of the conventional GLRT and the proposed GLRT detectors in the presence of clutter is plotted. The performance of the GLRT detector in the absence of clutter is also plotted for comparative reasons. A clear loss of target detection performance for a conventional GLRT detector in the presence of clutter can be observed from the figure while the proposed GLRT detector demonstrated a significant improvement in the target detection performance.

Similarly in Figures 3 and 4 the target detection performance of the proposed C-GLRT and SSC-GLRT detectors is plotted. While conventional SSC-GLRT detectors are known to reduce the computational complexity of the radar detector while providing target detection performances which are comparable to conventional GLRT detectors, however, when tested in the presence of clutter, a severe loss of target detection performance has been observed. From Figures 3 and 4 it can be clearly observed that our proposed C-GLRT and SSC-GLRT detectors achieve significantly higher target detection rates with reduced computational complexities. In Figure 5 the computational complexities of a conventional GLRT detector and the proposed SSC-GLRT detector are compared. The computational complexities are measured as a function of the number of arithmetic operations involved for a given set of received signal samples during the target detection process.

6. Conclusion

In this paper, we have proposed a novel mathematical model to optimise the target detection performance of a MIMO radar in the presence of clutter. A GLRT detector is known to provide robust performance. The proposed mathematical model is tested on the conventional GLRT detector in the presence of clutter and a significant improvement in the target detection performance has been observed. A GLRT detector however requires a large number of received signal samples to provide optimal detection performance at CFAR. Compressive sensing for GLRT detector has been investigated to reduce the computational complexity of the target detector. From the simulation results, it can be clearly observed that a C-GLRT detector, while reducing the computational
complexity, also suffers a significant loss of target detection performance. C-GLRT detector is tested in the presence of clutter and a further deterioration in the target detection performance has been observed. Our proposed mathematical model, when tested on C-GLRT detector, produced a significant improvement in the target detection performance. However, a SSC-GLRT detector in known to provide superior target detection performance when compared to C-GLRT detector. Hence, a SSC-GLRT detector has been tested in the presence of clutter and our proposed mathematical model has been applied to produce a clear improvement in target detection performance. Results are plotted for each of the three aforementioned detectors where the ideal performance, performance in the presence of clutter, and performance of the proposed model in the presence of clutter can be compared. It can be clearly observed that our proposed model provides significant performance gains in each of the three cases. Dynamic clutter suppression for SSC-GLRT detector is believed to provide better performance if added as signal preprocessing which we intend to investigate in our future work.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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