Polarimetric detection of maritime floating small target based on the Complex-valued Entropy Rate Bound Minimization

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Abstract
Detection of sea-surface small floating targets in maritime high-resolution surveillance radar has been an active area of research in recent years. In this paper, we propose a new detector based on a complex-valued independent component analysis (cICA) algorithm. It uses received time series data at cell under test (CUT) with different polarizations as distinct mixtures. The proposed detector can exploit all information of polarimetric radar for an accurate detection. It does separation on the mixtures using CERBM which results in two output sources, i.e., clutter and target. Finally, the target is detected using estimation of the parameters of K-distribution for outputted sources. Our experiments on the recognized IPIX radar database show that the proposed detector obtains better detection performance in comparison to the newly proposed detectors. The robustness of the detector is also investigated by experiment in either low and high sea state which shows its appropriate results.

Keywords:
Electrical engineering
Electrical system planning
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Nonlinear signal processing
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1. Introduction
Detection of a maritime target with low Radar Cross Section (RCS) and low or zero velocity such as a floating small boat or wood on ocean environment is one of the most difficult detection problems with an increasing interest in the recent years [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20]. In addition, using polarimetric antenna for small target detection has been an active area of research during recent decade [21]. Polarimetry helps the radar to detect targets more accurately. In addition, some method based on other signal processing technique such as blind source separation (BSS) [22, 23], independent component analysis (ICA) [24], and machine learning [25, 26, 27] are proposed for doing this detection task. Here, we utilized polarimetry to detect sea surface small floating target by employing one of complex-valued Independent Component Analysis (cICA) algorithm.

For radar target detection, there are many algorithms in the radar literature that use the statistical characteristics of radar signals [28]. This class of detectors uses a threshold which is based on competition between target and clutter energy. The adaptive and constant false alarm rate (CFAR) based detectors [28] are examples of such detector that their performance degrades in low Signal-to-Clutter Ratios (SCRs) and with changes in sea state. To confront with this problem, fractal-based and feature-based detectors in single-polarization and multi-polarization are proposed [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20]. Feature-based detector using three TF features [3], 3-D polarimetric feature detector [21], Graph-based detector [29] and feature-compression-based detector [15] attain the best performance on the IPIX radar database [30] among these algorithms, but their performance is still low in some situations especially in very low SCRs as in some datasets of IPIX radars such as files #17, #26 and #30. SVM-based detector [25] has excellent performance on IPIX radar dataset, but its training in realistic environment is a challenging problem because of extensive kind of targets and varying nature of sea clutter. Most of these algorithms need to use secondary data in reference cells (RCs) to do detection task as well. Thus, with urgent requirement for more effective detectors and equipment, we motivate to develop a new detector which can perform more accurate detection in a low observation time with less dependency on secondary data, in different sea states, with different kinds of target in lower SCRs, either with a Doppler frequency that exists
in a clutter Doppler cell or not, without the needs to statistical knowledge of radar signal and any online trainings. To separate a complex source from a complex mixture, cICA algorithms exploit one of these diversities: non-Gaussianity, noncircularity, nonwhiteness, and nonstationarity. The complex-valued FastICA [31], joint approximate diagonalization of eigenmatricies (JADE) [32], and algorithms using nonlinear functions [33,34] only use non-Gaussianity, while they assume that sources are circular. Several cICA algorithms only make use of noncircularity while some of them ignore sample dependence. The Gaussian entropy rate minimization algorithm [35] separates noncircular correlated sources exploiting non-Gaussianity and nonwhiteness. Complex entropy bound minimization (CEBM) [36], noncircular FastICA [37], kurtosis maximization (KM) [38], the complex fixed-point algorithm (CFPA) [39], and algorithms using nonlinear functions [40, 41, 42, 43] utilize both non-Gaussianity and noncircularity to perform separation tasks. To the best of our knowledge, CERBM [44] is the only existing algorithm which exploits three types of diversity: non-Gaussianity, sample dependence (nonwhiteness), and noncircularity. Based on our experiments, we find that CERBM is capable of separating real-life target, while the existing cICA algorithms fail to perform separation of real-life radar mixture data. These results obtained because it uses three types of diversity simultaneously. Therefore, we have established our detector based on CERBM.

Most of the mentioned cICA algorithms (including the exploited algorithm in this paper) assume that the number of sources and mixtures (sensors) are equal. Since a monostatic radar only make use of one receiving antenna, it leads to one single mixture at the cell under test (CUT). If we assume that radar signal comprised of at least two sources (target and clutter), cICA needs at least two mixtures (or two antennas) to perform separation task. This lack of mixture is solved through the proposed detector utilizing pairs of recorded radar signal in different polarization channel. In fact, the proposed detector suppresses the clutter using received signals with different polarization at the CUT. It uses received radar signals from two different polarization channels as two input mixtures of the CERBM algorithm to achieve two independent sources, i.e. clutter and target. In the sequel, the target is selected between these two outputted sources based on estimation of the clutter parameters and comparing with a threshold related to a predetermined probability of false alarm (PFA). The proposed detector is flexible in a manner that one can choose any arbitrary length (time sample size) for separation and detection decision tasks. Other assumptions of the cICA can be used for radar signals, since as mentioned in [22], clutter and target signal are independent each other. In addition, they are non-circular and non-Gaussian distributed signals. Finally, comparison of the proposed detector against novel detectors on IPIX radar datasets shows its superiority.

In this paper, we explain the CERBM algorithm in section 2, which is used in the separation stage of proposed detection schemes. Section 3 describes the detection problem and the proposed detector. Real-life database of the IPIX radar is described in section 4. In addition, section 4 presents the experimental results and discussion. The conclusion is given in section 5.

2. Complex-valued independent component analysis (cICA)

Complex-valued independent component analysis (cICA) is based on the assumption of statistical independence which is an acceptable strong assumption in many applications. cICA has been used in a range of area such as communication, radar, biomedicine, finance, and remote sensing. Most of the approaches to achieve ICA classically exploit two type of diversity: non-Gaussianity (HOS) or sample dependence (nonwhiteness). However, if the data is complex, such as coherent radar data, another type of diversity called noncircularity can be used. cICA is formulated in the instantaneous standard form as follows:

\[ x_n(t) = \sum_{k=1}^{N} a_{nk} s_k(t) + n_r(t) = a_{nk}^{\text{c}} s(t) + n_r(t) \]  \( (1) \)

where \( t \) denotes the discrete time index (and also refers to slow-time index of radar data matrix in this study), \( x_n(t) \in \mathbb{C}^T \) is the kth complex mixture for \( 1 \leq k \leq N \), \( s_k(t) \in \mathbb{C}^T \) is the nth latent complex source for \( 1 \leq n \leq N \), \( a_{nk} \) are the coefficients of the mixing system expressed by the \( N \times N \) mixing matrix \( A = [a_{11}, \ldots, a_{NN}] \), where \( a_{nk} = [a_{1k}, \ldots, a_{nk}] \). The complex-valued mixtures contain the proposed detector against novel detectors on IPIX radar datasets non-circular and non-Gaussian distributed signals. Finally, comparison of cICA is used in the separation stage of proposed detection schemes. Section 3 shows its superiority. We can ignore the noise \( n_r(t) \) in this study, since it can be considered as a separate source in the experimental situation. However, in the proposed detector, noise and clutter can be considered as a single mixture to be separated using cICA.

2.1. Complex-valued entropy rate bound minimization (CEBM)

We use CERBM algorithm in the separation stage of the proposed detector to extract complex-valued target from unwanted clutter. Geng-Shen Fu et al. introduced the CERBM algorithm [44] which exploits three types of diversity (noncircularity, non-Gaussianity, and non-whiteness) to perform cICA using mutual information rate cost function given by:

\[ J_r(W) = \sum_{n=1}^{N} H_r(z_n) - 2 \log|\det(W)| \]  \( (2) \)

\( H_r(z_n) \) is the entropy rate of the nth process \( z_n \), CERBM minimize \( J_r(W) \) to do separation of nonwhite, noncircular, and non-Gaussian complex-valued sources (such as target and clutter signals in coherent radars). It uses an estimation of \( H_r(z_n) \) for nonwhite \( z_n(t) \) in \( (2) \). For the estimation of \( H_r(z_n) \), in [44], authors assume that a whitening filter do a whitening process on \( z(t) \) such that the complex process \( z(t) = [z_1(t), \ldots, z_N(t)] \) has equal entropy to the entropy rete of \( z(t) \), i.e. \( H_r(z) = H_r(z_1) \). This filter is given so that:

\[ z(t) = \mathbf{b}^H \mathbf{z}_{K-1}(t) = \mathbf{q}^H \mathbf{z}_{K-1}(t) \]  \( (3) \)

where \( \mathbf{b} = [p_0, \ldots, p_K]^T \in \mathbb{C}^{K-1}, \mathbf{q} = [q_0, \ldots, q_K]^T \in \mathbb{C}^{K-1} \),

\[ \mathbf{z}_{K-1}(t) = [z_1(t), \ldots, z_{K-1}(t)] \in \mathbb{C}^{K-1} \]  \( (4) \)

The whitening filter make output process \( z(t) \) to be independently and identically distributed (i.i.d.). In practical situations, the process is not necessary to be exactly i.i.d. We can always scale \( \mathbf{b} \) such as \( H_r(z) = H_r(z_1) \). For calculating \( \mathbf{b} \), the following optimization problem must be solved:

\[ \min_{\mathbf{b}} H_r(z), \text{ s.t. } |p_0|^2 - |q_0|^2 = 1 \]  \( (5) \)

Approximation of \( \mathbf{b} \) can be found in [44], and \( H_r(z) \) is estimated using \( H_r(z) \) therein as follows:

\[ H_r(z) = H_r(\mathbf{z}) = H(\mathbf{z}_{K-1}, \mathbf{z}_{K}) \leq H(\mathbf{z}_{K}) + H(\mathbf{z}_{K-1}, \mathbf{z}_{K}) \]

\[ \leq \log(2\pi e) + V_1\left\{ E\left[G_1(\mathbf{z})\right]\right\} - V_2\left\{ E\left[G_2(\mathbf{z})\right]\right\} \]  \( (6) \)
where $\mathbf{z}_k = \mathbf{z}_k / \sigma_k$, $\mathbf{z}_k = \mathbf{z}_k / \sigma_k$, $\sigma_k$ and $\tau_k$ are the standard deviations of $\mathbf{z}_k$ and $\mathbf{z}_k$, respectively, $G_1(\cdot)$ and $G_2(\cdot)$ are the measuring functions. $V_1(\cdot)$ and $V_2(\cdot)$ are the negentropies of $\mathbf{z}_k$ and $\mathbf{z}_k$, respectively. Using (5), $H_r(z_0)$ is estimated by $H_r(z_0)$. This estimation is used to minimize $J_r(W)$. For deriving the updates, like [36], CERBM divides the problem of minimization with respect to $W$ into a series of subproblems such that the cost function is minimized with respect to each of row vector $w_n, n = 1, \ldots, N$. The algorithm first updates $w_n$, while $w_m, m = 1, n - 1, n + 1, \ldots, N$, are kept constant. In the following, we can rewrite $\det(W)$ as [36]:

$$\det(W) = |\mathbf{H}^t_n w_n|$$

(6)

where $S = \sqrt{\det(W_n w_n^t)}$. $W_n$ is an $(N - 1) \times N$ matrix obtained by removing the nth row vector of $W$, $W_n = [w_1, \ldots, w_{n-1}, w_{n+1}, \ldots, w_N]^t$, and $\mathbf{h}_n$ is a vector of unit length that satisfies $W_n \mathbf{h}_n = 0$. In [36], a method for calculation of $\mathbf{h}_n$ is introduced. Therefore, the cost can be written as a function of only $w_n$:

$$J_r(w_n) = H_r(z_n) - 2 \log |\mathbf{h}^t_n w_n| + C_z = H_r(z_n) - 2 \log |\mathbf{h}^t_n w_n| + C_z$$

(7)

where $C_z$ is a constant term with respect to $w_n$. Then, gradient update rule for nonorthogonal estimation of $W$ is:

$$\frac{\partial J_r(w_n)}{\partial w_n} = \frac{1}{\Sigma_{\omega_1}^2} \frac{\partial^2 J_r}{\partial w_n^2} + \frac{1}{\Sigma_{\omega_2}^2} \frac{\partial^2 J_r}{\partial w_n^2} = \frac{\partial J_r}{\partial w_n}$$

(8)

where $\omega_1$ and $\omega_2$ are derivatives of the negentropies $V_1$ and $V_2$, respectively. $\frac{\partial J_r}{\partial w_n}$ is the total derivative of the measuring functions $G_1$ and $G_2$, respectively. Finally, the CERBM algorithm is given as follows [44]:

1. Whiten $X = [x_1, \ldots, x_I]^t$.
2. Initialize $W$ using CERBM [36].
3. Calculate cost $J_r(W)$.

**While** $\text{iter} = 1 : 100$ **do**

4. For $n = 1, \ldots, N$, do the following:

   - calculate $\mathbf{h}_n$ using close form; (for light version of CERBM i.e., CERBM-L)
   - **if** $\text{iter} = 0$, then refine $\mathbf{h}_n$ using (4); (for CERBM)
   - calculate gradient $\frac{\partial J_r(\mathbf{w}_n)}{\partial \mathbf{w}_n}$ using (8);
   - calculate $w_{n}^{\text{new}} = w_n - r(\frac{\partial J_r(\mathbf{w}_n)}{\partial \mathbf{w}_n});$
   - normalize $w_{n}^{\text{new}} = w_{n}^{\text{new}} / \| w_{n}^{\text{new}} \|$

5. Calculate cost $J_r(W^{\text{new}})$ using (2);

   - **if** $J_r(W^{\text{new}}) < J_r(W)$, do the following: update $W$ and $J_r(W)$;

   increase step size $r = 1.5r$.

   **else** do the following:

   if $N - \text{trace}(W, W^{\text{new}}) < 10^7 N$ then break; else decrease step size $r = 0.5r$.

**End While**

Since the whitening stage waste most of the CPU time [44], introduced a lite version of this algorithm called CERBM-L by using a close approximate form of $b$.

### 3. Proposed polarimetric cICA-based detector

We use the proposed detector schemes in continuation of CERBM algorithm introduced in [44] for separation of the complex-valued sources in the radar signals. In addition, CERBM uses some approaches of [31] in its algorithm development. The proposed detector which is the innovation of this research allows us to use a cICA algorithm such as CERBM for radar detection task. In this vein, the proposed detector suggests three new approaches to realize detection of a radar target using CERBM. First, it uses received time series with different polarizations as different mixtures to allow CERBM to separate the sources without second sensor. A monostatic polarimetric radar has one antenna (sensor), while CERBM requires to use two mixtures which is recorded at the same time using two sensors (antennas). Second, the separation of the sources within CERBM must perform using an observation time which is possibly more than the maximum allowed integration time according to radar scenario. The detector solves this problem using a data manipulation strategy to allow detection of target in an arbitrary coherent processing interval (CPI). Third, the outputs of CERBM algorithm is more than one single source signal. It is not a single channel of binary decisions. Thus, the detector makes decision on the two produced time series from CERBM to construct an array of decisions based on estimation of the first and second empirical and theoretical moments of the K-distribution.

#### 3.1. Polarimetric detection problem formulation

Consider a coherent dual-polarized radar with linear polarization, which transmits a pulse train with horizontal (H) and vertical (V) polarizations at an azimuth direction. It receives four complex-valued time series with $HH, VV, VH, \text{and HV}$ polarizations, each with sample size $T$, at each range cell, so that the detection problem can be formulated as the following binary hypothesis test:

$$H_0 : x = [x_{HH}(t), x_{VH}(t), x_{HV}(t), x_{VV}(t)]$$

$$H_1 : x = x_p + a_p \mathbf{r}_p = [x_{HH}(t), x_{VH}(t), x_{HV}(t), x_{VV}(t)]$$

where $P = HH, VV, VH, HV$. The null hypothesis $H_0$ occurs when the target is absent in the cell under test (CUT). When the target is present at the CUT, the alternative hypothesis $H_1$ occurs. $x_p(t), c_f(t)$, and $\mathbf{r}_p(t)$ are the received radar signal vector, the clutter vector, and the target return vector at the $p$th polarization channel, respectively. Since clutter is the most important interference in radar, we can ignore the noise here. We can also consider clutter extra noise as a single mixture to take the noise into account. We demonstrate the validity of this consideration in our experiments. A coefficient that adjust SCR of the target is $\alpha_p$, which is corresponding to the mixing system coefficients such that, for example in $x_{HH}(t)$, we have $\alpha_p = a_{12} / a_{11}$ (see [11]).

Polarimetric techniques directly promote detection performance of radar system against clutter in environment. There are some techniques for measurement of Polarization Scattering Matrix (PSM) or Sinclair scattering matrix. PSM of a dual-polarized radar with vertical and horizontal polarization is given by:

$$\mathbf{S} = \left[ \begin{array}{cc} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{array} \right]$$

(10)
where $S_p(t) = x_p(t)$. $P = HH, VV, HV, VH$.

It is assumed that the radar is designed to measure the full complex PSM, as a result there are four complex-valued received signals at the end of the receiver. The proposed detector utilizes these signals to make detection decisions.

### 3.2. Polarimetric CERBM-Based detector

Based on our experiments on the IPix radar database, CERBM is the only instantaneous cICA algorithm which is capable of separating real-life target from clutter. Thus, we apply it in the separation stage of the proposed detector. To design a detector based on CERBM algorithm, we confront with some problems which restrict using the algorithm for radar signal separation. The most important problem is the number of mixtures that must be equal to the number of sources. Since we assume that there are two sources in radar received signal, i.e. clutter and target signals, thus the CERBM needs two mixtures to separate these two sources. As known, a polarimetric radar with linear polarizations $H$ and $V$ has four received signals in the receiver $x_{HH}(t)$, $x_{HV}(t)$, $x_{VH}(t)$, and $x_{VV}(t)$. We can use any pair of these received signals as two input mixtures of the CERBM algorithm for separating clutter and target. So, we have six choices for a pair of mixtures. If we choose the pair $x_{HH}(t)$ and $x_{VV}(t)$ as a mixture vector $x$, then we can write:

$$x = [x_{HH}(t), x_{VV}(t)]^T = Ax$$

where $A = [a_{11} \ a_{12} \ a_{21} \ a_{22}]$, $x_{HH}(t) = a_{11}c_{HH}(t) + a_{12}q_{HH}(t)$, $x_{VV}(t) = a_{21}c_{VV}(t) + a_{22}q_{VV}(t)$ and $x_{HV}(t)$ and $x_{VH}(t)$ as a mixture vector $x$, then we can write:

$$x = [x_{HH}(t), x_{VV}(t)] = A^T z$$

where

$$z = \begin{bmatrix} z_1(t) \\ z_2(t) \end{bmatrix}$$

Furthermore, we estimate the desired source $s(t)$ as target signal if present. These assumptions are valid when we use CERBM for radar signal separation with different polarizations as we will see in our experiments. This is because in CERBM, there is no need for one source in different mixtures to be exactly the same. Each source in any mixture is an attenuated and rather delayed version of itself in another mixture. In the sequel, we must choose one of the outputted sources from the CERBM algorithm as target, if present.

To use CERBM in radar detection, distinguishing of target signal between the two estimated sources is second problem that must be considered. One of the estimated sources is always clutter, whether target is present or not. The other one is clutter or target, if $H_0$ or $H_1$ holds, respectively. Therefore, we use the clutter statistical characteristic for distinguishing the clutter signal using a threshold related to a predetermined PFA, which is calculated in training branch of the proposed detector in Figure 1. The sea clutter statistical characteristic is modelled as K-distribution:

$$p(|c(t)|) = \frac{4 \left(\frac{a}{b}\right)}{\Gamma \left(\frac{\nu}{2}\right)} \left(\frac{|c(t)|}{b}\right)^{\nu - 1} K_{\nu - 1} \left(\frac{2}{b} |c(t)|\right)$$

where $\Gamma(.)$ is the gamma function, $K_{\nu - 1}(.)$ is the modified Bessel function of third kind of order of $\nu - 1$, and $b$ is the scale parameter. The parameters of K-distribution PDF can be estimated through the classical method of moments (MoM), by computing the first and second empirical and theoretical moments [33], and then by solving these two equations:

\[
\begin{align*}
\mu_1 &= \int_{0}^{\infty} \frac{4 \left(\frac{a}{b}\right)}{\Gamma \left(\frac{\nu}{2}\right)} \left(\frac{|c(t)|}{b}\right)^{\nu - 1} K_{\nu - 1} \left(\frac{2}{b} |c(t)|\right) \, dc(t) \\
\mu_2 &= \int_{0}^{\infty} \frac{4 \left(\frac{a}{b}\right)}{\Gamma \left(\frac{\nu}{2}\right)} \left(\frac{|c(t)|}{b}\right)^{2(\nu - 1)} K_{\nu - 1} \left(\frac{2}{b} |c(t)|\right) \, dc(t)
\end{align*}
\]

Figure 1. Polarimetric CERBM-based Detector: scheme 1 with integration, scheme 2 without integration.
\[ b = E[|c(t)|^2] \]
\[
4\mu \left( \frac{F(o)}{F(o+1/2)} \right) = E[|c(t)|^2] / E[|c(t)|^2]
\]
where the k-th order moment is replaced by its sample estimate:
\[
\widehat{E}[|c(t)|^2] = \frac{1}{T} \sum_{t=1}^{T} |c(t)|^2 - E[|c(t)|^2]
\]
where \( T \) denotes the sample size. The clutter signal can be distinguished from non-clutter (target) signal between two separated sources based on its shape or scale parameter, or both of them. For this purpose, the shape and scale parameters are estimated using Eqs. (13) and (14), then these parameters are compared to the precalculated threshold that is computed in training branch of Figure 1 and Table 1. For example, threshold \( \xi \) (or \( \zeta \)) is a shape (or scale) parameter, or both of them, that is computed based on the desired PFA with Monte Carlo simulations. Due to the limited number of clutter data samples PFA is set to 0.001. In the selected ten datasets of the IPIX radar, there are 10 or 11 RCs that can be used for computation of the threshold. Therefore, we have approximately 10 \( \times \) 217 = 1310720 available clutter data sample. We use (100/PFA) = (100/0.001) = 100000 samples to set the PFA to 0.001, based on the Monte Carlo simulation principles. Computation of the threshold in the training branch can be summarized as Table 1. Note that this is an offline training and there is no need to online training. Thus, we can find a range for each threshold in different sea states and save it in a memory to use in corresponding situations. Since the distributions of the targets is adequately far from K-distribution, the thresholds for RCs and a typical target signal is quite different. Therefore, detection performance is less dependent on secondary data in either online or offline trainings. In this case, since the training is offline and the detector only make use of received time series at the CUT in each online detection decision, while benefiting the prestored thresholds which are calculated in offline training, based on our experiments, the results is excellent in different sea states, even with secondary data changes. Note that the detector can use online training for calculating thresholds instead of using the precalculated ones. If we decide to calculate the threshold online, it can be derived from the reference cells in the current detection stage for the next detection decision, which means it takes a CPI time to derive the threshold online.

Two detection schemes 1 and 2 of the proposed detector is presented in Figure 1, Tables 2 and 3. In scheme 1, the received signals at the CUT are selected as mixtures with proper length for separation with the CERBM. The data is manipulated before separation based on an approach which is introduced in Figure 2. Six distinct pairs of the data, i.e. \( [x_{HH}(t), x_{VH}(t)]^T, [x_{HH}(t), x_{HV}(t)]^T, [x_{HH}(t), x_{VV}(t)]^T, [x_{VV}(t), x_{HV}(t)]^T, [x_{VV}(t), x_{VH}(t)]^T, \) and \( [x_{VV}(t), x_{HH}(t)]^T \), are available for separation. The proposed detector separates these pairs in six parallel branch of scheme 1 to attain six pairs of estimated sources at the outputs of CERBMs. In this way, the detector will be able to exploits all information of polarimetric radar for an accurate detection. Afterwards, the corresponding outputs in the pairs are summed up in the integration stage to achieve better performance. This kind of integration allows the detector to benefit from the returns related to the target from all four polarizations. It leads to higher detection performance in different sea states and reduces performance degradation with changes in sea conditions. At the end of the integration, we have two signals, that one of them is target, if present. Subsequently, the K-distribution moments for these two signals are estimated using the MoM to compare with the predetermined threshold for making detection decision. The detection scheme 1 is summarized in Table 2. Note that in scheme 2, only one pair is used to extract the target, and there is no integration after separation, which is given in Table 3. The K-distribution moments of the two outputted sources from CERBM are estimated to make a detection decision in each stage of the detection task.

To help the detector for making a detection decision in any arbitrary CPI, we use a data selection strategy in the data manipulation stage of the detection task. To this end, the length of the time signal in the separation stage is selected independently from the CPI, based on the under-study radar scenario. If the number of selected samples from the CUT for each detection stage at any polarization for the signals to be demixed by the CERBM is \( T_{Sep} \), and the CPI sample size is \( T_{CPI} \), then \( T_{Sel} = T_{Sep} - T_{CPI} \) samples is used from the previous detection stage in the current detection stage, to aid for better separation result based on the data manipulation strategy of Figure 2. Because of this, detection decision can be made at

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**Table 1. Computation of the threshold in the training branch.**

1. Selecting two clutter vectors from the reference cells.
2. Choosing two mixtures with proper length from the clutter vectors.
3. Process these two vectors with CERBM and attain two output sources.
4. Estimating the shape \( \kappa \) and scale \( \varsigma \) parameters of K-distribution for the two output sources.
5. Repeat step 1 to 4 based on the number of required Monte Carlo tests to maintain the constant CPI.
6. Sorting the estimated shape parameter vector \( \varsigma = [\varsigma_1, \ldots, \varsigma_{10000}] \) and the scale parameter vector \( \kappa = [\kappa_1, \ldots, \kappa_{10000}] \) in ascending mode. Then choose the thresholds as \( \varsigma = \varsigma_{2500} \) and \( \kappa = \kappa_{1000} \).

**Table 2. Detection scheme 1.**

1. Acquire the received data in four polarization channels \( x_{HH}(t), x_{VH}(t), x_{HV}(t), x_{VV}(t) \) for \( 1 \leq t \leq T \).
2. Choose six possible pairs of the signals of step 1 as six pairs of mixtures.
3. Manipulating the data of the pairs of the step 2 based on Figure 2 and above-mentioned approach.
4. Demixing these manipulated mixture pairs using CERBM in six parallel branches of Figure 1 to attain six estimated pairs of the source, i.e. clutter and target if present.
5. Integrate the six estimated source pairs of the step 4 to obtain an integrated pair of mixtures.
6. Estimating the shape and scale \( \kappa \) parameters of K-distribution for the two integrated estimated sources of the previous step.
7. Making detection decision: if \( \kappa > \zeta \) and \( \varsigma < \zeta \), hypothesis \( H_1 \) holds, else \( H_0 \) holds.

**Table 3. Detection scheme 2.**

1. Acquire the received data in four polarization channels \( x_{HH}(t), x_{VH}(t), x_{HV}(t), x_{VV}(t) \) for \( 1 \leq t \leq T \).
2. Choose pair \( x_{HH}(t) \) and \( x_{HV}(t) \) as two mixtures.
3. Manipulating the data of the pair of the step two based on Figure 2 and above-mentioned approach.
4. Demixing this manipulated mixture pair using CERBM to attain estimated pair of sources, i.e. clutter and target if present.
5. Estimating the shape \( \kappa \) and scale \( \varsigma \) parameters of K-distribution for two estimated sources of the previous step.
6. Making detection decision: if \( \kappa > \zeta \) and \( \varsigma < \zeta \), hypothesis \( H_1 \) holds, else \( H_0 \) holds.

**Figure 2. Data manipulation strategy.**
any CPI (for example $T_{\text{CPI}} = 10$), while the separation is done with different sample size of the CUT (for example $T_{\text{SP}} = 10$). It means that the integration time can be controlled to avoid long integration time when radar needs to make a detection decision as fast as possible. The approach used in the data manipulation block can be summarized as follows:

1. Acquire time series of received radar signal.
2. For the first detection stage, select 512 samples (or $T_{\text{SP}}$, an arbitrary sample size, but 512 is recommended here) of the series and save it in a shift register to use in the next stage of the detection.
3. For the second detection stage and after that, select 10 samples (or $T_{\text{CPI}}$, an arbitrary number of samples corresponding to a desired CPI) of the time series and shift it to the register. In the current stage, the shift register contains 502 samples (or $T_{\text{ADU}}$ samples) of the previous stage plus 10 new samples.
4. At the first stage of detection task, send the selected samples of the stage 2 to the CERBM block. In the next stage, send the selected samples of the stage 3 to the CERBM block.

The integration module integrates corresponding outputted source signals from CERBM blocks and put them in a pair as an integrated outputted source signal. In this vein, the module sums up the signals as follows:

$$s_{\text{integrated}}^{[i]}(t) = s_{\text{integrated}}^{[i]}(t) = z_i(t) + z_i(t) + z_i(t) + z_i(t) + z_i(t)$$

(15)

$$s_{\text{integrated}}^{[j]}(t) = s_{\text{integrated}}^{[j]}(t) + z_j(t) + z_j(t) + z_j(t) + z_j(t) + z_j(t)$$

(16)

where $z_i(t)$ is the $i$th estimated source at the output of $i$th CERBM block for $i = 1, 2, 3, ... n$. The shape and scale parameters of these two integrated signals, $s_{\text{integrated}}^{[i]}(t)$ and $s_{\text{integrated}}^{[j]}(t)$, are computed in the next block to be compared with its corresponding precalculated thresholds and making a detection decision. Note that $s_{\text{integrated}}^{[i]}(t)$ and $s_{\text{integrated}}^{[j]}(t)$ are an estimation of $s_{\text{integrated}}^{[i]}(t)$ and $s_{\text{integrated}}^{[j]}(t)$, respectively. This integration helps to enhance outputted sources to be detected more accurately.

4. Experimental results and discussion

4.1. IPIX radar database

The datasets used in this paper are measured by the McMaster IPX Radar [30], a fully coherent X-band radar, with advanced features such as dual transmit/receive polarization, frequency agility, and star/e/surveillance mode. It is extremely versatile, as each feature is highly adjustable through software in the control computer. In November 1993, a large database of high-resolution radar measurements was collected using the McMaster IPX radar at the east coast of Canada, from a cliff top near Dartmouth, Nova Scotia. The radio frequency of the radar is fixed at 9.39 GHz in the dwell mode with a 1-degree pencil beam for the used datasets. We choose ten datasets from Dartmouth database to cover a wide range of conditions. Table 4 gives the specification of these datasets. The pulses alternate between vertical (V) and horizontal (H) polarization with pulse repetition frequency (PRF) of 2000 Hz, but because of the pulse alternation, the effective PRF is 1000 Hz. Both $H$ and $V$ polarizations are recorded simultaneously for each pulse, leading to four possible transmit-receive polarization combinations: $HH$, $HV$, $VH$, and $VV$. The amplitude and phase of the radar returns are stored as in-phase ($I$) and quadrature (Q) components for each combination. Finally, the radar receives four complex-valued time series of signals $x_{\text{HH}}(t)$, $x_{\text{HV}}(t)$, $x_{\text{VH}}(t)$, and $x_{\text{VV}}(t)$, that can be used as different mixtures for the inputs of the signal processor.

4.2. Experimental results and performance comparison

In this subsection, we first show the time-Doppler images of five extracted targets from the datasets of Table 4 using CERBM through the proposed detector to show the detector performance qualitatively in Figure 3. In all cases, targets are detected successfully at all time slices and frequency bins, either in higher sea states or lower ones. Doppler frequency of each detected target is quasi-periodic with a period relevant to the period of sea waves. In higher sea states, when the height of sea waves is higher the Doppler frequency has more offset which is an expected result.

We also tried to separate target using other cICA algorithms. However, based on our experiments, near all other existing cICA algorithms such as CEBM, nc-FastICA, JADE, and etc. failed to do the separation. In conclusion, we can see that the noise and clutter are suppressed simultaneously, and there is a little noise in the detected target as well as clutter. Note that we use scheme 2 of the proposed detector with mixtures $[x_{\text{HH}}(t), x_{\text{VV}}(t)]$ in the experiments which do not use integration. We discuss the proofs for this selection after introducing the experiments.

To evaluate the detection performance of the proposed approach quantitatively, we compute the probability of detection (PD) for all ten datasets of Table 4 where the probability of false alarm is set to 0.001 at four observation times 0.512, 0.1024, 0.2048 and 0.4096. The computed probabilities of detection are shown in Figure 4. In this figure, the probability of detection for the 3-D polarimetric feature detector [21], tri-feature-based detector [4] at $HH$, $HV$, $VH$, and VV polarizations are

### Table 4. IPIX radar datasets.

| File Number | Data label | Guard Cells | CUT | Wave Height | Wind Speed | Wind Direction | Target |
|-------------|------------|-------------|-----|-------------|------------|----------------|--------|
| 1           | #54        | 19931111_163625_starea54 | 7,9,10 | 8 | 0.7 | 22 | 320 | targA at 128 deg, 2660 m |
| 2           | #30        | 19931109_191449_starea30 | 6,8 | 7 | 0.9 | 19 | 210 | targA at 128 deg, 2660 m |
| 3           | #31        | 19931109_202217_starea31 | 6,8,9 | 7 | 0.9 | 19 | 210 | targA at 128 deg, 2660 m |
| 4           | #310       | 19931118_162155_starea30 | 6,8,9 | 7 | 0.9 | 33 | 310 | targA at 170 deg, 2655 m |
| 5           | #311       | 19931118_162658_starea31 | 6,8,9 | 7 | 0.9 | 33 | 310 | targA at 170 deg, 2655 m |
| 6           | #320       | 19931118_174259_starea26 | 6,8,9 | 7 | 0.9 | 33 | 310 | targA at 170 deg, 2655 m |
| 7           | #40        | 19931110_001635_starea40 | 5,6,8 | 7 | 0.9 | 09 | 200 | targA at 128 deg, 2660 m |
| 8           | #26        | 19931108_220902_starea26 | 6,8 | 7 | 1.0 | 09 | 210 | targA at 128 deg, 2660 m |
| 9           | #280       | 19931118_023604_starea28 | 7,10 | 8 | 1.4 | 17 | 210 | targA at 170 deg, 2660 m |
| 10          | #17        | 19931107_135603_starea17 | 8,10,11 | 9 | 2.1 | 17 | 310 | targA at 128 deg, 2660 m |

* Each dataset is recorded at range resolution 30 m, sampled at 15 m and has 14 range cells with $2^7$ time samples.
* The object (target) observed by the radar is a 1 m-diameter styrofoam ball which is wrapped in radar reflective material and floats on the ocean surface on an anchor line at about 2.5 km offshore (targA and targC).
* Pulse-width is equal to 200 ns.
Figure 3. Time-Doppler image of the detected target from: (a) range cell 8 of dataset 54 (b) range cell 7 of dataset 30 (c) range cell 7 of dataset 311 (d) range cell 7 of dataset 40 (e) range cell 9 of dataset 17, with observation time 0.512 s.

Figure 4. Detection probabilities of our proposed detector, 3-D polarimetric-feature detector [21], tri-feature-based detector [4] at HH, VV, HV and VH for all ten datasets when observation time is: (a) 0.512 s (b) 1.024 s (c) 2.048 s (d) 4.096 s.
shown. As can be seen Figure 4, our proposed detector attains the highest probability of detection at all ten datasets in comparison to the other detectors. In addition, to show the detection capability of the proposed detector with lower sample size (observation time), detection probability for the targets with the observation time of 0.128 s are shown in Table 5. We can see that the performance is still superior even for files #17, #26 and #30.

Third, the receiver operation feature curves (ROCs) for the proposed CERBM-based detector, 3-D polarimetric feature detector [21], tri-feature-based detector [4], and SVM-based detector [25] at different polarizations are plotted in Figure 5 (a). The observation time is 4.096 s, and the probability of false alarm is varied among 0.001 to 0.1. These ROC curves show the superiority of the proposed detector against the other detectors, where it attains higher detection probabilities especially at lower PFAs. For more comparisons, ROC curves for fractal-based detector [11, 12] and joint-fractal-based detector [10] are depicted in Figure 5 (b) and (c) as well as the proposed detector. The observation time is 4.096 s and the probability of false alarm is varied among 0.001 to 0.1. As can be seen, the proposed detector always obtains higher probabilities of detection.

For a full comparison, we compare the detector performance to the performance of two recent detection method: feature-compression-based detector [15] and adaptive composite GLRT detector [16]. The results are shown in Figure 6. The proposed detector is the best one among these three detectors and obtains the highest detection probability for all ten datasets.

To use the detector in an experiment, some other problems arise that must be considered: first, which sample size is the best one for better detection? Second, which scheme is the best one between scheme 1 and 2? Third, which pair of mixtures is the best one among six possible pairs to use in scheme 2? Figure 7 gives answer for the first question. Based on this figure and other experiments, when the detector uses 512 samples, it attains highest detection probability for example PD = 1 in file #54. In addition, it obtains high detection probability even with 128 samples. To find solutions for the second and third problems, we make experiments on all ten datasets using scheme 1 of the detector in addition to scheme 2 with different mixture pairs. Figure 8 introduced the results of these experiments. As can be seen, scheme 1 has the best detection performance while scheme 2 with pair $[x_{HV}(t), x_{VH}(t)]^\dagger$ has the lowest. The performance of scheme 2 with pairs $[x_{HV}(t), x_{HH}(t)]^\dagger$ is the worst because $x_{HV}(t)$ and $x_{HH}(t)$ contains similar information. When we considered the time-Doppler images of the outputted targets from scheme 1 and scheme 2 with six different pairs of mixtures, we saw that the detected target of each dataset is totally similar to each other except for some portion of time in which the target was not detected in some cases. Although the performance of scheme 1 is better than scheme 2, the detection performance of scheme 2 is near to scheme 1 especially when it uses pair

### Table 5. Probability of Detection (PD) for all ten datasets with observation time set to 0.128.

| File Number | #54 | #30 | #31 | #310 | #311 |
|-------------|-----|-----|-----|------|------|
| PD          | 0.890 | 0.720 | 0.711 | 0.882 | 0.915 |
| File Number | #320 | #40 | #26 | #280 | #17 |
| PD          | 0.801 | 0.751 | 0.749 | 0.925 | 0.938 |
| PFA         | 0.001 |

Figure 5. ROC curves of (a) the proposed detector, 3D polarimetric-based detector, SVM based detector, and tri-feature-based detector, (b) the proposed detector, 3D polarimetric-based detector, and fractal-based detector [11], (c) the proposed detector, 3D polarimetric-based detector, and joint-fractal-based detector [10]. Observation time is set to 4.096 s.

Figure 6. Detection performance of the proposed detector against feature-compression-based detector [15] and adaptive composite GLRT detector [16], the observation time is 0512 s and PFA is 0.001.

Figure 7. Effect of sample size on the detection performance of the proposed detector when it does detection task on dataset 1 (file #54) with different sample sizes.

$[x_{HV}(t), x_{VH}(t)]^\dagger$. Since the computational effort of scheme 1 is six times more than scheme 2, and because of high computational complexity of the CERBM algorithms in comparison to conventional detection methods such as CFAR, it is better to use scheme 2 even if we lose some detection
performance. The losses in detection performance are lower than 0.05 in each dataset which can be neglected to the benefit taken from reduced computational effort and time. Note that the computational time of CERBM is not more than the successful method for detection of sea-surface small floating targets such as tri-feature-based detector [4]. In conclusion, we chose scheme 2 with pair $|x_{HH}(t)|$, $x_{HV}(t)|^2$ as the best one and utilized it in all of my experiments in this paper.

Based on the experiments, we saw that if the estimated parameters of K-distribution for the outputted sources are not very accurate, it would not affect the detector performance very much. The statistical parameters for targets are far enough from the clutter ones. Figure 9 shows calculated thresholds for all ten datasets based on Monte Carlo simulations. As can be seen, the thresholds for all datasets are near to the average value of the thresholds. The datasets are recorded in different sea states and clutter signals have different statistical characteristic in high, medium and low sea states, but the thresholds are approximately near to each other. Therefore, it seems that we can set the thresholds for different sea states and store it in a memory to use in each detection stage as a look-up table.

In conclusion, we can say that the detector is less dependent on secondary data and uses less statistical information of radar signals to make detection decisions than other existing methods. Changes in statistical characteristic of the radar signal does not affect the detector performance very much as well as changes in secondary data.

Detection performance of the proposed detector is directly connected with the cICA model. It also depends on accurate estimation of K-distribution parameters, which is explained above. The cICA model explained in this paper is the instantaneous model. cICA is able to consider echoes of the sources using convolutive mixture model which not take into account in CERBM. For more accurate estimation of the sources and finally more accurate detection decisions, the model needs to separate complex convolutive mixtures which is as follows:

$$x_k(t) = \sum_{l=0}^{L-1} \sum_{n=1}^{N} a_{kn} s_n(t-l) \quad \text{for} \quad 1 \leq k \leq N,$$

where $L$ is a filter length and each $a_{kn}$ is a complex coefficient that attenuate the delayed version of $s_n(t)$ by I sample. All the attenuated and delayed versions of $s_n(t)$ is summed up to construct the convolutive mixture $x_k(t)$. To the best of our knowledge, there is no effective algorithm for separation of convolutive complex-valued mixtures. As CERBM is designed for instantaneous mixtures, the separation performance (and so detection performance) will be degraded in datasets which contains more echoes of the sources such as file #30. This situation probably occurs in the higher sea states. According to our results, the performance degradation with sea state changes is very low and can be neglected.

To analyze detection performance of scheme 2 when it uses pair $|x_{HV}(t)|$, $x_{HV}(t)|^2$, again we refer to the cICA model as follows:

$$x_{HV}(t) = a_{11} s_{HV}(t) + a_{12} s_{HH}(t)$$

Since we can assume that $x_{HV}(t) \simeq x_{HH}(t)$, so the separability of the target is possible with this pair. The performance of the detector with this pair is the poorest one because some parts of one of these two signals have no target information, although the corresponding part of the other contains. Integrating the outputs of this pair in scheme 1 does not damage detection performance, since that parts which contain no target information will be covered using information of other pairs. In addition, corresponding parts contain target information enhance detection capability.

The effect of noise in the temporal and spectral features of the received radar returns may be quite different, depending on the clutter-to-noise ratio (CNR). According to our estimates, the CNR ranges from about -5 dB when the texture is minimum up to about 80 dB when the texture is maximum. Also, for spiky sea clutter, we generally have $\nu \in [0.1, 2]$. Since the detection probabilities of different files in the IPIX datasets do not follow a certain pattern of CNRs, SCRs and clutter shape parameters, the detection performance of the proposed detector is approximately the same in high and low sea states. It means that we reach a robust detector for different RCSs, SCRs, CNRs and shape parameters.

Finally, from the above experiments, we conclude that: First, the proposed detector attains the highest probabilities of detection especially for lower probabilities of false alarm. Second, although the detection performance of the detectors is improved with higher observation time, F/X but the proposed detector is less dependent on observation time than the other mention detectors. Based on our experiments, it obtains excellent results even with an observation time of 0.128 s which proves that the detector needs lower observation time than the other. Note that the detector is designed to make detection decisions even using less than ten samples of the CUT. Third, in different sea states and at lower SCRs, either with a Doppler frequency that exist in a clutter Doppler cell or not, the performance of the detector is excellent and superior.

5. Conclusion

In this study, we presented a new polarimetric detector based on one of the most powerful cICA algorithms called Complex-valued Entropy Rate Bound Minimization (CERBM). This robust detector will be able to exploits all information of polarimetric radar using scheme 1 for an accurate detection in low and high sea states while is less dependent on secondary data, although scheme 2 performs detection successfully using
partial polarimetric information. The detector attained excellent results for detecting sea-surface small floating target based on our experiments on polarimetric database of IPIX radar. It makes the detection decision on received time series at the CUT with arbitrary sample size. Comparison of the detector to the newly proposed detectors shows the superiority of it. We also concluded that cICA is a powerful tool to detect radar target with less needs to statistical knowledge of radar signals as well as less dependency on changes in its statistical characteristics, and any online trainings which can obtain excellent results in radar signal processing area. It might be an alternate for existing radar signal processing and detection techniques.

Declarations

Author contribution statement

Hamzeh Gahramani: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper. Naser Parhizgar: Conceived and designed the experiments; Performed the experiments; Contributed reagents, materials, analysis tools or data; Bijn Abbas Arandi: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data. Morteza Barari: Performed the experiments; Analyzed and interpreted the data.

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Additional information

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