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Extraction of a target in sea clutter via signal decomposition

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Dear editor,

Target detection at the sea surface is crucial for the ensuring the security of drilling platforms, ships, ports, etc. However, the presence of sea clutter poses a challenge to radar detection. Since the sea surface is a dynamic surface, its scattering properties are extremely complex. For a high-resolution radar working at a low grazing angle, sea clutter usually shows non-homogeneous, non-stationary, and time-varying properties, especially in a high sea state [1]. Moreover, the complex scattering of the sea surface can result in a wide Doppler spectrum and a large Doppler frequency migration of sea clutter. Thus, serious false alarms can be caused when using the traditional Gaussian noise receiver detector [2]. The conventional methods for suppressing sea clutter include the noise subspace algorithm [3], the block-adaptive clutter suppression method [4], and the adaptive filter method [5], however, the detection performance of these methods decreases or even fails when the target signal and sea clutter are aliasing in the frequency domain.

In this study, a target extraction method based on the application of the morphological component analysis (MCA) in conjunction with fractional Fourier transform (FrFT) and short-time Fourier transform (STFT) is proposed. The MCA method is an analysis algorithm based on a sparse model. Its essence is to find two suitable dictionaries to sparsely express the different components. Radar echoes produced by sea targets can be modeled as sparse signals by FrFT, assuming that the targets are moving at a constant acceleration during the coherent processing interval (CPI). On the other hand, despite the time-varying Doppler characteristics, sea clutter can be regarded as a stationary signal in a short time. Therefore, radar echoes produced by the sea surface can be modeled as sparse signals by STFT. First, the cost function to be minimized can be constructed by using FrFT and STFT. The fast-converging split augmented Lagrangian shrinkage algorithm (SALSA) is then used to minimize the cost function. Finally, we obtain the target by using the inverse fractional Fourier transform. To show the effectiveness of the proposed method, we evaluated the method using real-world data.

Problem formulation. After coherent demodulation and pulse compression, the slow-time sequence $x(t)$ in a certain range cell can be modeled as a summation of potential targets $s(t)$, sea clutter $c(t)$, and noise $n(t)$, as follows:

$$x(t) = s(t) + c(t) + n(t), \tag{1}$$

where $t = 0, 1, 2, \ldots$ and N is the order of the sweep periods in a CPI. Further, $s(t)$ can be modeled as a pulse signal in the appropriate fractional Fourier domain; that is, $s = \mathrm{FrFT}_{-\mathrm{opt}}(w_1)$, where w_1 is the coefficient corresponding to the fractional domain. Now, $c(t)$ has a wide Doppler spectrum and a larger Doppler frequency migration, which

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can be represented as $c = \mathrm{ISTFT}(w_2)$, where w_2 is the coefficient corresponding to the time-frequency domain. Here, $n(t)$ satisfies the condition of an independent and identical distribution and follows the Gaussian distribution. However, because of the high clutter-to-noise rate in real-world data, we used $x(t) = s(t) + c(t)$ for signal representation. Therefore, the extraction of a target in sea clutter can be reduced to the following optimization problem:

$$\{\hat{w}_1, \hat{w}_2\} = \arg\min_{w_1,w_2} \|\lambda w_1\|_1 + \|(1-\lambda)\, w_2\|_1, \quad (2)$$

$$\text{s.t.} \quad x = \mathrm{FrFT}_{-\mathrm{opt}}(w_1) + \mathrm{ISTFT}(w_2), \quad (3)$$

where $\| * \|_1$ represents the L1-norm (the sum of the absolute values of vector entries). λ is the weighting parameter. $\mathrm{FrFT}_{-\mathrm{opt}}(*)$ represents the inverse FrFT corresponding to the optimal chirp rate, and $\mathrm{ISTFT}(*)$ is the inverse STFT.

Optimization. The problem is to obtain the optimization solution using SALSA; the process of solving this problem is given in Algorithm 1 (see Appendix A for the detailed derivation steps).

Algorithm 1 Signal separation algorithm

Input: x;
1: **initialization** w_1, w_2, d_1, d_2, λ, μ, N;
2: **Iteration:**
3: **for** $i = 1$ to N **do**
4: ① Computing sparse coefficient u_1, u_2:
$u_1 = \mathrm{soft}(w_1 + d_1, 0.5\lambda_1/\mu) - d_1$,
$u_2 = \mathrm{soft}(w_2 + d_2, 0.5\lambda_2/\mu) - d_2$;
5: ② Refactoring s, c:
$s = \mathrm{FrFT}_{-\mathrm{opt}}(u_1)$, $c = \mathrm{ISTFT}(u_2)$;
6: ③ Calculating residual R:
$R = x - s - c$;
7: ④ Calculating residual coefficient d_1, d_2:
$d_1 = \frac{1}{2}\mathrm{FrFT}_{\mathrm{opt}}(R)$, $d_2 = \frac{1}{2}\mathrm{STFT}(R)$;
8: ⑤ Updating the sparse coefficient w_1, w_2:
$w_1 = d_1 + u_1$, $w_2 = d_2 + u_2$;
9: **end for**
Output: $s = \mathrm{FrFT}_{-\mathrm{opt}}(w_1)$, $c = \mathrm{ISTFT}(w_2)$.

Here, w and d are the intermediate variables representing the sparse coefficients before and after updating, respectively, and they are initialized as zero vectors with the same length as an input signal x. Further, λ is a user-specified scalar parameter for SALSA, and selected empirically. The optimal value of λ is mainly related to the CPI and signal-to-clutter ratio (SCR) of the target. However, for radar echo from a specific time and specific sea area, significant SCR gains are achieved for λ values within a wide range [6]. The algorithm parameter μ is related to the convergence rate of the cost function, which is usually taken from 0 to 10, and the number of iterations N generally does not exceed 100. Function $\mathrm{soft}(y, T)$ represents the soft-threshold rule with the threshold T, which is defined as follows:

$$\mathrm{soft}(y,T) = y \max(0, 1 - T/|y|), \ \ y \in C, \ \ T \in R. \quad (4)$$

As described in the algorithm, the input signal x is radar echo, and in order to solve this problem, N iterations are needed until target signal and sea clutter are separated. In the iterative process, the first step is to calculate the sparse coefficient by using the soft threshold rule, and then, the target signal component and sea clutter component are reconstructed by using the sparse coefficient. In the third step, the original radar echo is differentiated from the target component and sea clutter to obtain the residual. Subsequently, the sparse coefficient corresponding to the residual is calculated. In the last step, the sparse coefficient is used to correct the sparse coefficient obtained in the first step. When the separation quality of radar echo into target signal and sea clutter is not significantly improved, the iteration ends, and the target echo s and sea clutter c are output. Further explanation of this method can be found in [7].

Experimental results. Two datasets-the McMaster IPIX radar datasets and the Council for Scientific and Industrial Research's (CSIR) datasets-were used for analysis. Detailed descriptions of these two datasets can be obtained from website[1)2)].

For datasets 19931111_163625 and TFC16-023, Figures 1(a) and (b) represent the two typical cases of the relationship between target and sea clutter, namely, the target at the edge of sea clutter and the target covered by sea clutter, respectively. The STFT plot of the radar echo is shown at the top part of the Figure.

For signal separation, we first estimated the chirp rate roughly by using discrete polynomial-phase transform. Then, the cost function was established by combining the FrFT and STFT. After 50 iterations with parameters $\lambda = 0.1$, $\mu = 10$, and a window-length of 32 for STFT, the radar echo was decomposed into two parts, i.e., the sea clutter and the extracted target. The extracted target is shown in the bottom part of the Figure. As shown in Figure 1(a), for a target on the edge of sea clutter, the method effectively extracts the target from the sea clutter background. Besides, as shown in Figure 1(b), this method can also extract the target even when it is covered by sea clutter.

As in [1], the detection performances were investigated by Monte Carlo methods. Real sea clut-

1) The McMaster IPIX radar dataset. http://soma.ece.mcmaster.ca/ipix/.
2) The CSIR dataset. http://www.csir.co.za/small_boat_detection/.

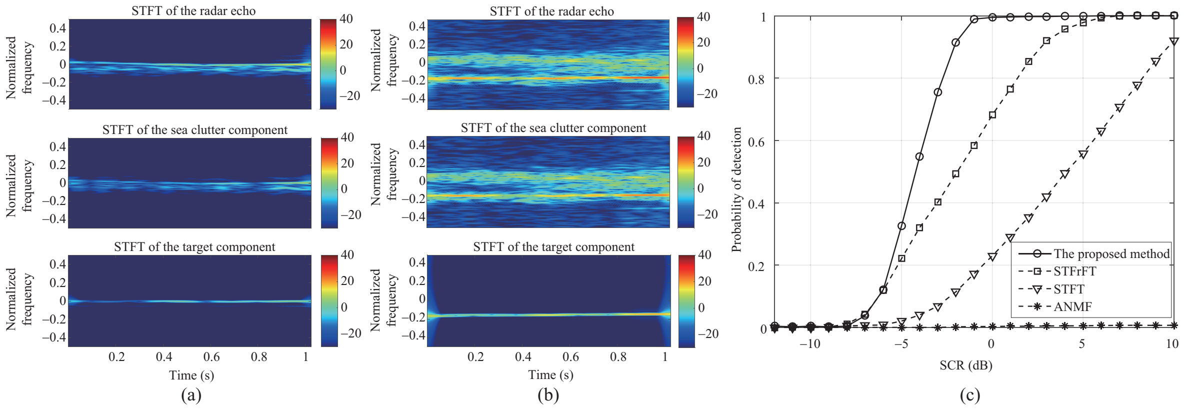

Figure 1 (Color online) (a) Target at the edge of sea clutter; (b) target covered by sea clutter; (c) probability of detection versus different SCR levels.

ter was added to the manoeuvring target signal, and Monte Carlo simulations were performed 800 times with false alarm $P_{\rm fa} = 10^{-3}$. Figure 1(c) shows the probability of detection versus different SCR levels. As is shown in the figure, the adaptive normalized matched filter method fails when the target is covered by sea clutter. Besides, when SCR > -6 dB, the detection probability of the proposed method is significantly better than that of the short-time fractional Fourier transform method (STFrFT) and STFT method. However, when SCR < -6 dB, the detection performance of this method is comparable to that of STFrFT method because of the mismatch of parameter λ.

Conclusion. The objective of this study was to develop a method for extracting targets in heavy sea clutter. By analyzing the difference between the target signal and sea clutter, we proposed an MCA algorithm based on FrFT and STFT; the problem was formulated as an optimization problem by defining a novel cost function. Fast-converging SALSA was used to minimize the cost function. The proposed method was evaluated by using IPIX radar and CSIR datasets, and two typical cases of the relationship between target and sea clutter were considered. The results demonstrated that the proposed method effectively extracts the target from a sea clutter background even when the target signal is covered by sea clutter.

Supporting information Appendix A. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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