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UNSUPERVISED TARGET DETECTION IN SAR IMAGES USING SCATTERING CENTER MODEL AND MEAN SHIFT CLUSTERING ALGORITHM

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Abstract—A new framework for ship detection in synthetic aperture radar (SAR) images is proposed. We focus on the task of locating reflective small regions using scattering centers model and clustering algorithm. Unlike most of the approaches in ship detection, we address an algorithm that incorporates SAR super-resolution imaging and mean shift clustering instead of parameter estimation. Our approach is validated by a series of tests on real SAR images and compared with other ship detection algorithms, demonstrating that it configures a novel and efficient method for ship-detection purpose.

1. INTRODUCTION

The spaceborne SAR [1] plays a role in maritime surveillance applications. In particular, ship detection in SAR image is a very effective method in monitoring maritime traffic, ships responsible for ocean oil pollution, fishing activity, and illegally operating ships. Many investigations have been reported in the literature, in which CFAR detection is famous for its constant false alarm probability and adaptive threshold [2]. However, the acquirement of clutter distribution and detection threshold is a hard task for the CFAR algorithm.

In recent years, the sparsity-based methods of SAR imaging [3, 4] and image processing [5, 6] have drawn a lot of research attention. From the geometric theory of diffraction (GTD), if the wavelength of the incident excitation is small relative to the object extent, the backscattered field from an object consists of contributions from electrically isolated scattering centers. Therefore, scattering center

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model can yield sparse representation for the SAR echo data and is a good candidate for ship detection, classification, and identification in high-frequency SAR systems.

In this letter, an effective unsupervised ship detection algorithm is proposed by using scattering center model of SAR imaging. The preprocessing is carried out to re-sample SAR echo data on a Cartesian coordinate space. After re-sampling, algorithm of the total variation minimization is used in order to make the observed data stationary and homogeneous in a probabilistic sense. Then, SAR image is filtered after fast and adaptive SAR super-resolution imaging. Finally, ship detection is achieved by assigning each pixel of the SAR image to the ship class or background class using mean shift algorithm.

2. PROPOSED ALGORITHM

The GTD states that if the scattering centers are all assumed to be ideal point scattering centers, the backscattered field of an individual scattering center is described as a function of frequency f and aspect angle θ. Then, the total scattered field from a target can be modelled as [7]:

$$\mathbf{Y}(f,\theta) = \sum_{k=1}^{K} \mathbf{S}_k \exp\left[-i\frac{4\pi f}{c}\left(x_k\cos\theta + y_k\sin\theta\right)\right] \tag{1}$$

where K is the number of ideal point scattering centers, f the working frequency, θ the aspect angle, $\mathbf{S}_k$ the amplitude of scattering center which is independent of frequency and aspect angle, c the velocity of light, and (x_k, y_k) the locations of downrange and cross-range.

The data $\mathbf{Y}(f,\theta)$ can be re-sampled to a uniform grid on a Cartesian coordinate space (f^x, f^y), where $f^x = f\cos\theta$ and $f^y = f\sin\theta$. After re-sampling, one can obtain samples $\mathbf{Y}(f^x_m, f^y_n)$ on a grid of M samples and N samples:

$$\mathbf{Y}\left(f^x_m, f^y_n\right) = \sum_{k=1}^{K} \mathbf{S}_k \exp\left[-i\frac{4\pi}{c}\left(x_k f^x_m + y_k f^y_n\right)\right] \tag{2}$$

where $f^x_m \in [f(1-B/2), f(1+B/2)]$, $f^y_n \in [f(1-B/2), f(1+B/2)]$, $m = 1,\ldots,M$, and $n = 1,\ldots,N$, B is the relative bandwidth.

Using a vector notation, (2) can be rewritten as:

$$\mathbf{Y}\left(f^x_m, f^y_n\right) = \mathbf{U}_m\hat{\mathbf{S}}\mathbf{V}^T_n \tag{3}$$

where $m = 1,\ldots,M$, $n = 1,\ldots,N$, $\hat{\mathbf{S}}_{\lfloor k/K\rfloor+1,k-\lfloor k/K\rfloor K} = \mathbf{S}_k$, $\lfloor k/K\rfloor$ rounds the elements of k/K toward zero, resulting in an array of integers

$$\mathbf{U}_m = \left(\exp\left(-i\frac{4\pi}{c}x_1 f_m^x\right),\ \exp\left(-i\frac{4\pi}{c}x_2 f_m^x\right),\ \ldots,\ \exp\left(-i\frac{4\pi}{c}x_K f_m^x\right)\right)$$

$$\mathbf{V}_n = \left(\exp\left(-i\frac{4\pi}{c}y_1 f_n^y\right),\ \exp\left(-i\frac{4\pi}{c}y_2 f_n^y\right),\ \ldots,\ \exp\left(-i\frac{4\pi}{c}y_L f_n^y\right)\right)^T,$$

and $\hat{\mathbf{S}} = (\hat{S}_{k,l})_{K\times L}$ is a matrix with $K = M$ and $L = N$. Then, one will have:

$$\mathbf{Y} = \mathbf{U}\hat{\mathbf{S}}\mathbf{V}^T \tag{4}$$

where $\mathbf{U}^T = (\mathbf{U}_1^T,\ \mathbf{U}_2^T,\ \ldots,\ \mathbf{U}_M^T)$ and $\mathbf{V} = (\mathbf{V}_1,\ \mathbf{V}_2,\ \ldots,\ \mathbf{V}_N)$. For a given parameter set of locations (x_k, y_l), one can find a least square solution $\hat{S}$ to Equation (4). Using the approximate orthogonallity, the estimator of the amplitude $\hat{\mathbf{S}}$ is given by [6]:

$$\hat{\mathbf{S}} = \frac{\mathbf{U}^T\mathbf{Y}\mathbf{V}}{MN} \tag{5}$$

Let ship be described by nondispersive point scattering centers. Then the expected backscattered field of the ship in the Cartesian frequency space is given by (2). The proposed approach is made up of the following steps.

The first step of the proposed algorithm is to filter the observed data $\mathbf{Y}$, as shown in (7) and (8). The observed data are complex valued, while the standard total variation minimization algorithms have been developed for real valued signals. We break the signal into its real and imaginary parts as follows:

$$\mathbf{Y} = \Re(\mathbf{Y}) + i\Im(\mathbf{Y}) \tag{6}$$

where, $\Re(\cdot)$ and $\Im(\cdot)$ indicate the real and imaginary parts of the complex number, respectively. Because the observed data $\mathbf{Y}$ are usually non-stationary and non-homogeneous in a probabilistic sense, we consider the total variation minimization schemes:

$$\min_{Y_r} TV(\mathbf{Y}_r) + \frac{\lambda}{2}\|\mathbf{Y}_r - \Re(\mathbf{Y})\|_2^2 \tag{7}$$

$$\min_{Y_i} TV(\mathbf{Y}_i) + \frac{\lambda}{2}\|\mathbf{Y}_i - \Im(\mathbf{Y})\|_2^2 \tag{8}$$

where $\lambda > 0$ is a regularization parameter to control the tradeoff between the goodness of fit of $\mathbf{Y}_r$ or $\mathbf{Y}_i$ and a smoothness requirement due to the total variation regularization. In [8], an efficient algorithm is proposed to solve (7) and (8) for the real and imaginary parts $\mathbf{Y}_r$ and $\mathbf{Y}_i$ of the filtered complex observed data $\tilde{\mathbf{Y}}$, where $\tilde{\mathbf{Y}} = \mathbf{Y}_r + i\mathbf{Y}_i$.

The second step of the proposed algorithm is estimating the complex amplitude matrix $\hat{\mathbf{S}}$, as shown in (9)

$$\hat{\mathbf{S}} = \frac{\mathbf{U}^T \tilde{\mathbf{Y}} \mathbf{V}}{MN} \tag{9}$$

The third step of the proposed algorithm is to filter the image $\mathbf{I}$, where each element of $\mathbf{I}$ is the absolute value of the corresponding element of $\hat{\mathbf{S}}$. For ship detection, the mean shift clustering algorithm [9] requires the data to "remain stationary and homogenous" during adaptation. Because of interfering targets, large clutter discretes, spiky clutter, and other outliers of different types, the stationarity and homogeneity requirements are seldom satisfied in practice. Therefore, we consider the total variation minimization scheme:

$$\min_{\tilde{I}} TV\left(\tilde{\mathbf{I}}\right) + \frac{\lambda}{2}\left\|\tilde{\mathbf{I}} - \mathbf{I}\right\|_2^2 \tag{10}$$

In [8], the efficient algorithm is proposed to solve (10) for the filtered image $\tilde{\mathbf{I}}$.

The final step of the proposed algorithm is generating two classes by clustering the filtered image $\tilde{\mathbf{I}}$ using the mean shift clustering algorithm [9]. We set kernel bandwidth parameter $h = (h_r, h_s)$ and multivariate kernel $K(\tilde{\mathbf{I}})$ [9]. As a result, the mean shift clustering algorithm produces M matrices $\mathbf{D}_k$, where $k = 1, 2, \ldots, M$. Each $\mathbf{D}_k$, with a size of $M \times N$, contains the cluster indices of each pixel $\tilde{\mathbf{I}}(m, n)$. This proposed process of ship detection can be viewed as unsupervised thresholding:

$$\mathbf{\Lambda}(m, n) = \begin{cases} 1 & \sum_{k=1}^{M} \mathbf{D}_k(m, n) \geq T \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

where $T = \mu \max(\sum_{k=1}^{M} \mathbf{D}_k(m, n))_{M,N}$, μ is the scale factor, and $\mathbf{D}_k(m, n)$ denotes the element of the matrix $\mathbf{D}_k$.

3. EXPERIMENTAL RESULTS

In order to assess the effectiveness of the proposed approach, a series of real SAR images are considered. An environmental satellite advanced SAR image near Hong Kong is shown in Figure 1. The two ships in Figure 1 generally appear as bright point targets compared to sea clutters. The data are C-VV, with an incidence angle $\sim 23°$. The pixel resolution is 4.1 meter in azimuth direction and 7.8 meter in range direction. The ERS-1, 2 satellites are intended for global measurements of sea wind and waves, ocean and ice monitoring, coastal studies and land sensing using active and passive microwave remote sensing systems [10]. The SAR images are shown in Figure 2 and Figure 3. A moving ship is shown in Figure 2. A medium sized ship in Figure 3, believed to be the car ferry, is visible. The data are C-VV, with an incidence angle $\sim 23°$. The pixel resolution is 30 meter in azimuth direction and 26.3 meter in range direction.

Detection results for the proposed approach on SAR images are shown in Figure 6, Figure 9 and Figure 12. Figure 4, Figure 7 and Figure 10 are the filtered images $\tilde{\mathbf{I}}$ before using the mean shift clustering algorithm. Figure 5, Figure 8 and Figure 11 are the histograms of Figure 4, Figure 7 and Figure 10, respectively. In statistics, a histogram is a graphical representation showing a visual impression of the distribution of data. In the experiments, the regularization parameter $\lambda = 4$, bandwidth parameter $h = (0.25, 0.25)$, and scale factor $\mu = 0.9$ are used.

In the CFAR approaches, the core of the CFAR detector is to get a threshold for the given false alarm rate P_{fa} and determine those pixels whose gray intensity is higher than the threshold. It is similar to the

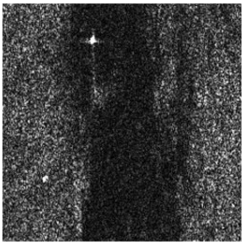


Figure 1. Real SAR image.

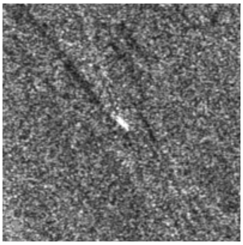


Figure 2. Real SAR image.

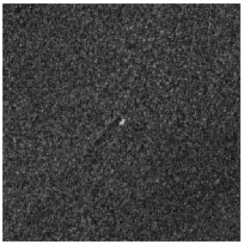


Figure 3. Real SAR image.

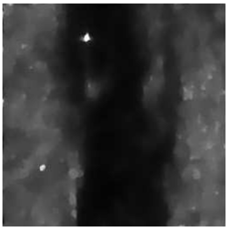


Figure 4. Filtered image.

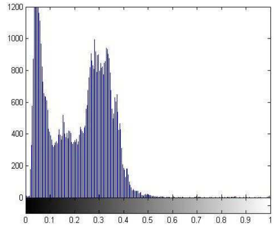


Figure 5. Histogram of Figure 4.

Figure 6. Detection result.

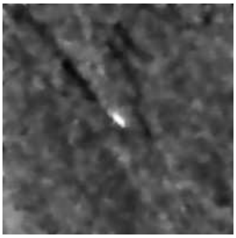


Figure 7. Filtered image.

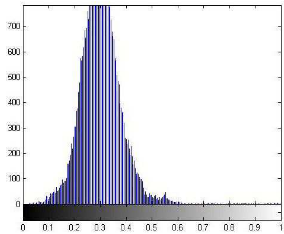


Figure 8. Histogram of Figure 7.

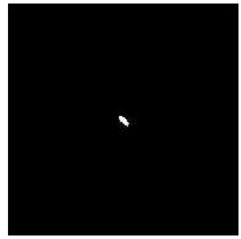


Figure 9. Detection result.

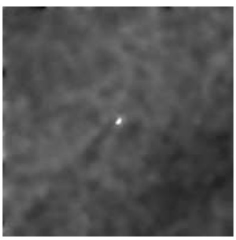


Figure 10. Filtered image.

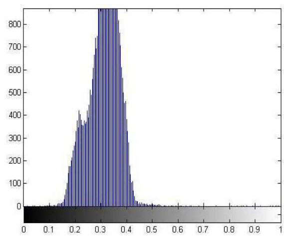


Figure 11. Histogram of Figure 10.

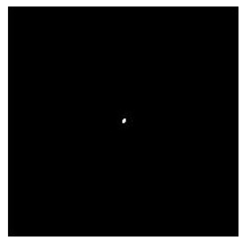
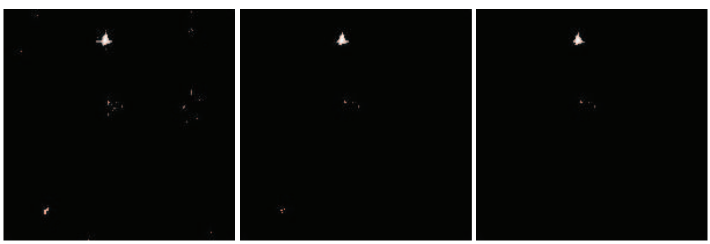


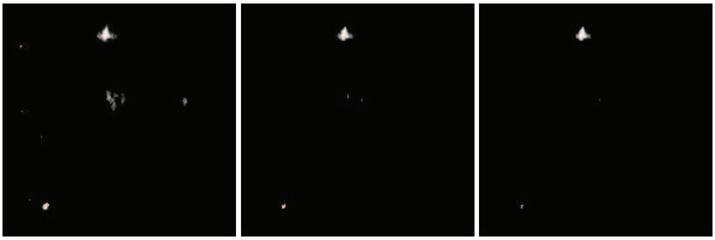
Figure 12. Detection result.



(a) $P_{fa} = 10^{-4}$ (b) $P_{fa} = 10^{-6}$ (c) $P_{fa} = 10^{-8}$

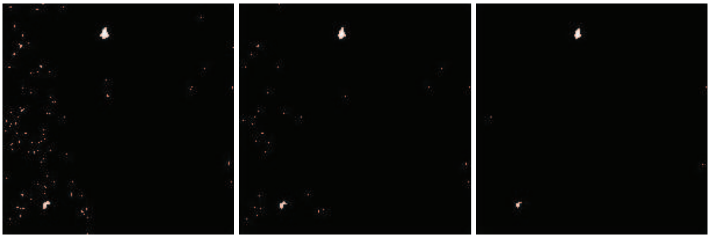
Figure 13. Biparametric CFAR detector.

false alarm rate P_{fa} in the biparametric CFAR detector and method described by [2]. The algorithm described by [2] utilizes the strong gray intensity correlation in the ship target and 2-D joint log-normal distribution of a pixel with neighboring pixels in the clutter. Generally speaking, keeping the value of P_{fa} small will reduce both the false detections and effects of the noise with the expense of increase in miss detections, and vice versa. This phenomenon is shown in Figure 13, which shows detection results on input image shown in Figure 1 when



(a) $P_{fa} = 10^{-4}$ (b) $P_{fa} = 10^{-8}$ (c) $P_{fa} = 10^{-12}$

Figure 14. Detector described by reference [2].



(a) $P_{fa} = 0.7$ (b) $P_{fa} = 0.8$ (c) $P_{fa} = 0.7$

Figure 15. Fixed thresholding detector.

different values of P_{fa} are used by the biparametric CFAR detector. This phenomenon is also shown in Figure 16, Figure 17 and Figure 18 which show detection results on input image shown in Figure 1 when different values of P_{fa} are used by the method described by [2]. Besides, the detection results of fixed threshold detector is shown in Figure 15 which shows detection results on input image shown in Figure 1 when different values of fixed threshold T are used.

In summary, it is seen that the proposed method produces better results than the biparametric CFAR detector and the method described by [2].

4. CONCLUSION

An unsupervised ship detection technique is developed by implementing scattering center model of SAR imaging. The proposed method does not estimate the statistical model of the background clutter. The total variation minimization scheme is introduced to filter data matrix. The proposed method uses mean shift clustering algorithm to detect potential ships from the revised backscattered data. The proposed algorithm is effective in identifying meaningful ships.

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