Research Journal of Applied Sciences, Engineering and Technology 4(16): 2844-2850, 2012
ISSN: 2040-7467

Submitted: March 31, 2012 Accepted: April 17, 2012 Published: August 15, 2012

Ship detection in Polarimetric SAR based on Support Vector Machine

[1, 2]Xuwu Su, [2]Guangyou Yang and [1]Hongshi Sang
[1]State Key Laboratory for Multi-spectral Information Processing Technologies, Institute for Pattern Recognition and Artificial Intelligence, Huazhong University of Science and Technology, Wuhan 430074, China
[2]School of Mechanical Engineering, Hubei University of Science and Technology, Wuhan 430068, China

Abstract: A Support Vector Machine (SVM) based method for ship detection in Polarimetric SAR (POLSAR) is proposed in this study. Because of similarities of ship and man-made structures on land in scattering mechanisms, land and sea are first segmented by SVM according to polarimetric features and texture features; The SVM-based Recursive Feature Elimination (RFE-SVM) approach is adopted to improve the performance of the segmentation algorithm. Then ship targets are extracted from sea by SVM classifier; Threshold-based rules and SVM-based rules are established for discriminating ship from non-ship target at last. The experiments are carried out on POLSAR data from Radarsat-2. For the available SAR images, the average accuracy of ship detection is over 95%.

Keywords: Polarimetric SAR, polarimetric decomposition, ship detection, support vector machine, texture

INTRODUCTION

Ship detection is an important application of Synthetic Aperture Radar (SAR), not only in coastguard, military sectors, but also in fishery, marine transportation sectors. Former studies with single polarization SAR data often focus on Constant False Alarm Rate (CFAR) detector and *K*-distribution clutter model. Because Polarimetric SAR (POLSAR) provides multi-channel polarization data that have the potential of exploiting the polarimetric information of target, the performance of ship detection can be improved with POLSAR data (Yeremy *et al*., 2001).

Different utilizations of polarization channels lead to different ship detection algorithms. An approach is to fuse all polarization channels into one image with Polarimetric Whitening Filter (PWF) (Novak and Burl, 1989) and then apply CFAR detector. Sciotti *et al*. (2001) proposed a multi-channel detector PG-GLRT (Polarimetric Gaussian-Generalized Likelihood Ratio Test) for ship detection. But more widely used approaches are based on polarimetric target decomposition, which can reveal the scattering mechanisms of targets. Ringrose and Harris (1999) first applied Cameron's Coherent Target Decomposition (CTD) method in ship detection using SIR-C Single-Look Complex (SLC) image. The elemental scatters of ship consist of dihedrals, narrow dihedrals and quarter waves, whereas scatters of ocean are mainly cylinders. Yeremy *et al*. (2001) stated Cloude decomposition is suitable for ocean environment and then applied it in ship detection with Van Zyl decomposition. Touzi and Charbonneau (2000) improved CTD and proposed Symmetric Scattering Characterization Method (SSCM), which is then successfully applied to ship detection and characterization with CV-580 POLSAR data (Touzi *et al*., 2004). In recent years, ship detection methods based on classification of POLSAR images are investigated (Li *et al*., 2007) and the classification method and feature extraction are the key points.

Ship targets in middle or high resolution SAR images are no longer point-like targets, but occupy a number of pixels. This helps to discriminate ship and other targets on the sea. Polarimetric parameters obtained from target decompositions, such as Krogager, Freeman-Durden or Cloude decompositions, can be used as features for classification. But it is difficult to discriminate ship and other man-made structures on land because of their similarities in scattering mechanisms. In this study, we propose a ship detection method based on Support Vector Machine (SVM).

METHODOLOGY

Support vector machine: SVM is an excellent machine learning method. It is based on Vapnik-Chervonenkis (VC) dimension and structural risk minimization principle of statistical learning theory. SVM shows good performance in solving small samples, nonlinear, high dimension pattern classification problems (Vapnik, 2000). For a given training set $\{(x_1, y_1), (x_2, y_2), \ldots, (x_n\ y_n)\}$, x_i

Corresponding Author: Xuwu Su, State Key Laboratory for Multi-spectral Information Processing Technologies, Institute for Pattern Recognition and Artificial Intelligence, Huazhong University of Science and Technology, Wuhan 430074, China

R^p, y_i {-1, +1}, where x_i is a p-dimensional sample vector, y_i is the class labels of x_i. If the samples can be linearly separated by hyperplane $w \cdot x + b = 0$, they must satisfy the condition $y_i (w \cdot x_i + b) \geq 1$ (i = 1, 2, …, n), <·> denotes the inner product. The optimal separating hyperplane should maximize the margin between classes. This is equivalent to quadratic programming problem:

$$\min_{w,b} \phi(w) = \frac{1}{2}||w||^2 \quad (1)$$

$$\text{S.t.} y_i[w.x_i+b] \geq 1 \quad (2)$$

The optimal separating decision function can be obtained:

$$y = \text{sgn}\left[\sum_{x_i \in SV} \alpha_i^* y_i (x_i \cdot x) + b^*\right] \quad (3)$$

where, α^*_i is Lagrange multiplier. It is noted that only support vectors are used in (3).

For linearly inseparable case, the kernel function $K(x_i, x)$ is used to replace the inner product in (3) for mapping original samples to high dimensional feature space, so that transformed samples are linearly separable. The decision function changes to:

$$y = \text{sgn}\left[\sum_{x_i \in SV} \alpha_i^* y_i K(x_i, x) + b^*\right] \quad (4)$$

The most commonly used kernel function is Gaussian Radial Basis Function (RBF):

$$K(x_i, x_j) = \exp(-\gamma \, || x_i - x_j||^2) \quad (5)$$

Another approach is introduction of non-negative slack variable ξ and its penalty coefficient C to optimization objective and constraint condition. The optimization problem changes to:

$$\min_{w,b,\xi} \phi(w) = \frac{1}{2}||w||^2 + C\sum_{i=1}^{n} \xi_i \quad (6)$$

$$\text{s.t.} y_i[w.x_i+b] \geq 1-\xi_i \text{ ,(i = 1, 2, ..., n)} \quad (7)$$

The effect of ξ is to tolerate misclassified samples and C controls the punishing extent of misclassified samples.

Land and sea segmentation: Because ship structures are to some extent similar to some man-made structures on land, it is difficult to discriminate them according to scattering mechanisms and intensity information. In order to enhance the effectiveness and accuracy of ship detection, land must be removed from the images to be tested.

Land and sea segmentation can be treated as 2 classes classification problem, which is suitable for application of SVM. SVM is a supervised classification method. The selections of training sample and feature vector are very important for classification effect.

Window size: Because SAR images are polluted by speckle noise, training sample and testing sample should adopt averaged value of a certain area, usually a square window. For training sample, the window is cut out from original images. The size of the window should be large enough to ensure the reliability of sample. In this study, we adopt 11*11 window. But for images to be tested, the window is a neighborhood of every pixel, because every pixel must be tested. The size of neighborhood window can be smaller so as to avoid too much image blur. Here we use 7*7 window.

Features: There are many features of POLSAR that can be applied to classification. Two main categories of features are preferred in this study, i.e., polarimetric features and texture features.

Polarimetric features: Since the first target decomposition theorem was formalized by Huynen (1970), there have been many other decomposition methods (Cloude and Pottier, 1996; Touzi *et al*., 2004). Scattering parameters decomposed from scattering matrix S, coherency matrix T or covariance matrix C reveals the scattering mechanism from different point of view. In this study, Krogager decomposition by S, Freeman-Durden decomposition by C and Cloude decomposition by T are selected for polarimetric feature extraction.

- **Krogager decomposition:** The Krogager decomposition (Krogager, 1990) factorizes the scattering matrix as the combination of the responses of a sphere, a diplane and a helix. The three parameters k_s, k_d and k_h correspond to the weights of the sphere, the diplane and the helix components.
- **Freeman-durden decomposition:** The Freeman-Durden decomposition models (Freeman and Durden, 1998) the covariance matrix as the contribution of three different scattering mechanisms: surface or single-bounce scattering, double-bounce scattering and volume scattering.

The contribution on the dominance in scattering powers of P_s, P_d and P_v, corresponding to surface, double bounce and volume scattering.

- **Cloude-pottier decomposition:** Cloude and Pottier (1997) proposed a method for extracting average parameters from the coherency matrix T based on

eigenvector-eigenvalue decomposition, the derived entropy H, the anisotropy A and the mean alpha angle α.

Texture features: Textures can be categorized as either structural or stochastic. Because of speckle noise, the dominant texture of sea area is stochastic texture. Structural texture is more useful in land cover classification. Therefore, textures based on statistical properties are more suitable for land and sea segmentation. The first-order statistics based on gray-level histogram and the second-order statistics based on Gray-Level Co-occurrence Matrix (GLCM) are two alternatives. Compare of the two method shows those GLCM texture parameters, which are suitable for discriminating land and sea, have similar effect compared to first-order statistical parameters, but the calculations of GLCM parameters are much more time-consuming. The statistical texture parameters used in this study are mean m, standard deviation σ, smoothness R, third moment μ_3, uniformity U, entropy e, which are defined in (Gonzalez *et al.*, 2004). The calculation of texture features need only one polarization channel. The channel with better image contrast is preferred for better discrimination effect.

Procedure of land and sea segmentation:

Selecting samples: Some representative areas, such as sea, built-up area, agricultural land, mountain area, are cut out as sample source from original POLSAR images. Then the source images are further cut into 11*11 sample patches.

Features extraction: The sample patches are first decomposed by the three polarimetric target decomposition algorithms mentioned above. The nine features, H, A, α, Ps, Pd, Pv, ks, kd and kh of every sample patch are obtained. Then the texture features, m, σ, R, μ_3, U and e of every patch are calculated.

Generating training set: The 9 polarimetric features, 6 texture features and the class label yi of every patch are combined to a feature vector (y_i, x_1, x_2, …, x_{15}), y_i = 1 or -1, which means sea or not sea. Five hundred feature vectors of sea samples and 500 feature vectors of other samples are arranged into a training set.

Normalization: The training set is normalized to balance the effect of every feature on the classification result.

Training SVM: The SVM classifier is trained with the training set after selection of kernel function, kernel parameter and SVM parameter. The kernel function used in this study is Gaussian RBF function and the parameters that need to adjust are penalty coefficient C and kernel parameter γ.

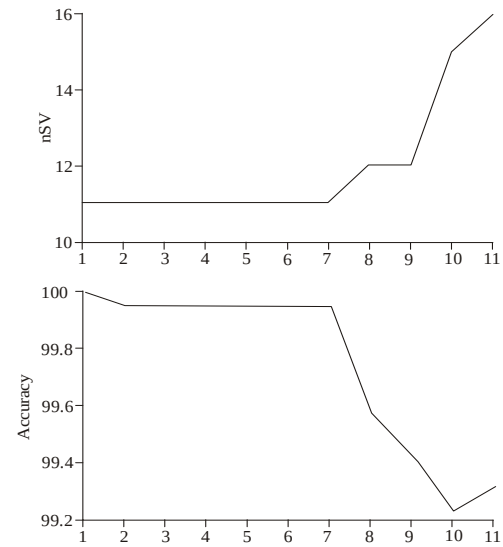


Fig. 1: Number of SV and classification accuracy after each iteratio

Generating testing set: The images to be tested are cut from POLSAR images. The feature vector of every pixel is calculated from its 7*7 neighborhood. All the feature vectors combine a testing set. The testing set is also normalized.

Classification and illustration: The testing set is classified with SVM classifier. The result is converted to a binary image, which is just the land (binary 0) and sea (binary 1) segmentation result (Fig. 4a).

Morphological fill: In order to obtain pure land mask, the isolated binary 0 areas that caused by ship-like targets are morphological filled (Fig. 4b).

Optimization: The above-mentioned segmentation algorithm works well, but the calculation of 15 features is time-consuming. In fact, some of them are similar and redundant and some have little contribution for segmentation. Feature selection will greatly cut down the time for feature calculation, thus improve the performance of this algorithm. For SVM application, SVM-based Recursive Feature Elimination (RFE-SVM) approach (Guyon *et al*., 2002) is an effective solution for feature selection. It uses the absolute value of the corresponding weights calculated in the SVM as criterion to evaluate the goodness of features. At each iteration an SVM is trained, a bad feature is removed from feature subset. All features are at last ranked according to their importance. A list of features is obtained by training set as follows: e, U, H, P_s, A, k_h, σ, k_d, P_v, m, α, k_s, P_d, R and μ_3. The worst four features at right side of the list can be first removed. In order to find the optimized feature subset among the remained 11 features, a former segmented SAR image is

used as substitute for training set for better assessment of the segmentation effect. Figure 1 shows the variation of number of Support Vectors (nSV) and classification accuracy after each time the last feature of the list is removed. Normally, nSV increases while accuracy decreases. Obviously, nSV and accuracy keep invariant before 7th iteration, therefore, the optimized feature subset can be determined, which include 5 features: e, U, H, P_s and A. The number of features reduce 2/3, so that the time for feature extraction is greatly saved,

Ship extraction: In this section, the main problem is separation of ship from sea.

Window size: The average method with large window used in land and sea segmentation is no longer adopted here, because the edge of ship will be blurred. Processing of each point is also inappropriate because of speckle noise. Here we adopt a compromise solution, using the smallest 3*3 neighborhood window without the four corner pixels for testing sample, so as to maximally keep the edge detail of ship.

Feature vector: Among the 15 features used in section 3, Cloude decomposition parameters H, A, α and 6 texture parameters need average calculation with larger window, which may lead to image blurring, so Krogager decomposition parameters k_s, k_d and k_h, Freeman-Durden decomposition parameters P_s, P_d and P_v, are kept for ship detection.

Procedure of ship extraction: The procedure of ship extraction is similar to that of land and sea segmentation except following steps.

- **Ship sample selection:** First several typical ship sample masks are generated from original images by using ROI polygon tool. Sea sample masks are also obtained by the same method. Then these masks are used to extract feature vectors for training set.
- **Morphological close operation of ship mask:** After ship mask is obtained by SVM classifier, a morphological close operation is carried out on ship mask. One purpose is to fill the small holes in ship mask, the other is to merge those broken targets (Fig. 4c).
- **Logical AND of ship mask and land mask:** After logical AND operation of ship mask and land mask, a binary only-ship mask containing only ship-like targets is obtained. (Fig. 4d).
- Label only-ship mask and extract ship target (Fig. 4e).
- **Generating sea-no-ship mask:** This is obtained by logical AND of NOT only-ship mask and land mask. This mask is used for discriminating ship and non-ship targets (Fig. 4f).

Discriminating ship and non-ship targets: In only-ship mask exist not only ship targets but also non-ship targets. In order to discriminate them, several parameters should be calculated.

Parameters calculation:

Polarimetric parameters: Because diplane, double-bounce, volume scattering mechanisms are useful to discriminate ship and non-ship target, so the ratios of averaged kd, Pd and Pv parameters of every target in only-ship mask to averaged corresponding parameters of sea-no-ship mask are calculated as rkd, rPd and rPv. The purpose of ratio calculation is to eliminate the difference of images.

Geometry parameters: Geometry parameters can provide assistant information.

Area: The number of pixels of every ship-like target in only-ship mask.

Length (L), Width (W) and Length-Width Ratio (LWR): The normalized second central moments of every target are use to calculate the major axis length and minor axis length of a equivalent ellipse:

$$\mu_{yy} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{x})^2 + \frac{1}{12} \tag{8}$$

$$\mu_{yy} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{x})^2 + \frac{1}{12} \tag{9}$$

$$\mu_{xy} = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y}) \tag{10}$$

$$L = 2\sqrt{2}.\sqrt{\mu_{xx} + \mu_{yy} + \sqrt{4\mu_{xy}{}^2 + (\mu_{xx} - \mu_{yy})^2}} \tag{11}$$

$$W = 2\sqrt{2}\cdot\sqrt{\mu_{xx} + \mu_{yy} - \sqrt{4\mu_{xy}{}^2 + (\mu_{xx} - \mu_{yy})^2}} \tag{12}$$

These parameters should be calculated after adjustment of only-ship mask according to actual resolution of every POLSAR image.

Discriminating rules: In order to establish reasonable rules for discriminating ship and non-ship target. From the four original polarimetric SAR images (Table 1), 16 image slices that have ship targets are cut out for experiment. After land and sea segmentation and ship detection process, 63 targets are detected. By comparison with corresponding satellite images in Google Earth and manual interpretation, 46 targets are ship samples

Table 1: Parameters of polsar images

Area	Date	Size (pixel)	Swath (km)	Res. (m)
Vancouver	20080415	2120*13299	28*65	13*5
Sanfransisico	20080409	2823*14416	28*70	10*5
Gibraltar	20080331	2156*11739	27*63	12*5
Flevoland	20080402	2823*12944	28*63	10*5

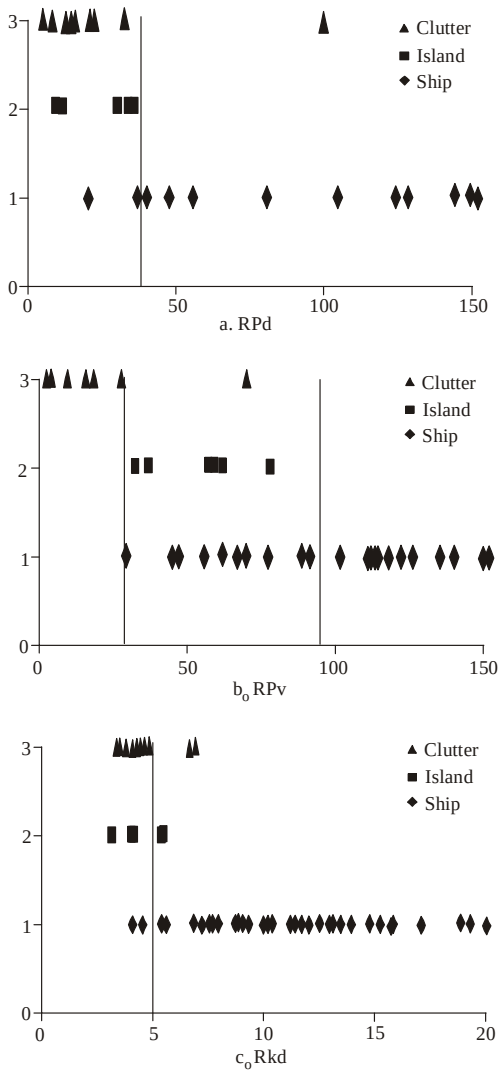


Fig. 2: Distribution of RPd, RPv, Rkd of samples

(including 9 side-by-side-docked ships), 17 targets are non-ship samples (6 islands, 11 clutters). Through the analysis of all samples, rules are established by the following method:

Threshold-based discrimination rules: In order to make full use of the samples, non-ship samples are divided into island class and clutter class. Comparison of sample data shows that RP_d parameter has certain advantages than RP_v and Rk_d in discriminate ship class from island, clutter classes and RP_v parameters can be used to discriminate clutter class from ship, island classes.

The distribution of RP_d parameters is shown in Fig. 2a. At RP_d = 40, the ship class and the other two classes can be better separated, only one sample misclassified. Distribution of the RP_v parameters is shown in Fig. 2b. At RPv = 30, the clutter class can be better separated from island and ship classes; RP_v>30 can be used to decrease misclassification as ship samples by RP_d>40; for island class, RP_v<100. RK_d parameter's distribution is shown in Fig. 2c, RK_d = 5 can be used to separate ship and island classes, but it is not as good as RP_d, so it is not adopted. Threshold rules are then obtained as follows:

- If RPd>40 & RPv>30, target belongs to ship class
- If RPd<40 & 30<RPv<100, target belongs to island class
- The other targets belong to clutter class

According to these rules, 44 ship samples are correctly classified, accuracy is 44/46 = 95.6%.

SVM-based discrimination rules: The discrimination problem is a typical small sample classification problem and sample sizes of each class are uneven. Since the class of every sample is determined, SVM can be used to solve this multi-class classification problem.

The feature vector consists of the three parameters: RP_d, RP_v and Rk_d. Three typical kernel functions, Gaussian RBF kernel, the linear kernel and polynomial kernel are tested in SVM model and different model parameters are also tested, so as to select the appropriate model. The results are as follows:

- Gaussian RBF kernel function is unexpectedly not suitable in this application. No matter how the (C, γ) parameters are selected, the SVM trained needs 63 support vectors.
- Linear kernel SVM with penalty parameter C (1, 10 or 100) needs 19 support vectors. Fifty four samples are correctly classified, classification accuracy is 85.7%, among them 44 ships are detected and 1 clutter sample is misclassified as ship, so accuracy is 44/47 = 93.6%.
- Polynomial kernel SVM with parameters (order d = 3, γ = 1, C = 10) needs 15 support vectors. Sixty two samples are correct classified, the accuracy is 98.4%. Only 1 ship is misclassified as clutter, so accuracy is 45/46 = 97.8%.

Therefore, the discrimination rule is using polynomial kernel SVM to classify unknown sample.

Though geometry parameters are not applied in ship and non-ship discrimination, if the target occupy a certain number of pixels, namely, the area, Length, Width and Length-Width Ratio (LWR) can be calculated and have reasonable value, They can provide useful information for discriminating type of ships.

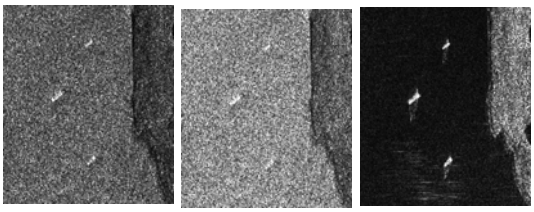
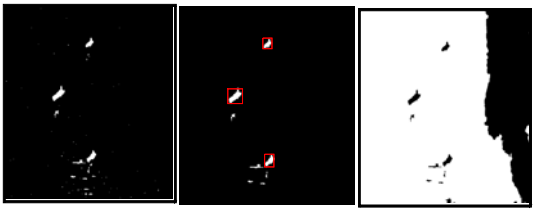


Fig. 3: Image patches from vancouver POLSAR data (HH, VV, HV)

(a) land mask (b) only-land mask (c) ship mask



(d) land removed (e) only-ship mask (f) sea-no-ship mask

Fig. 4: Ship detection procedure

Table 2: Parameters of ship-like targets

No.	rPd	rPv	rkd	Area	L	W	LWR
1	247.8	161.2	10.1	358	82	17.0	4.7
2	19.3	17.5	3.6	55	30	10.0	2.8
3	16.0	9.8	3.8	30	33	3.8	8.7
4	14.4	3.3	3.7	91	76	7.6	10.0
5	14.8	4.3	3.3	24	31	3.0	10.0
6	235.4	156.6	9.7	179	50	14.0	3.6
7	129.6	146.8	6.7	242	62	15.0	4.0
8	8.9	19.7	3.3	25	15	8.7	1.7

EXPERIMENTS AND RESULTS

POLSAR data for experiments: The POLSAR data used in the experiment were acquired by Radarsat-2 (Canadian Space Agency). The parameters of POLSAR images are listed in Table 1, The incidence angle is from 20 to 22ºC, respectively; The data format is Single Look Complex (SLC). Figure 3 is a patch cut from Vancouver data, consists of HH, VV and HV polarization channels.

Experimental results: Figure 4 shows the procedure of ship detection. The masks produced in the procedure are shown from Fig. 4a to f.

Table 2 shows the parameters of extracted ship-like targets.

According to the rules presented in section 5, it can be judged, among the eight ship-like targets, only no. 1, 6 and 7 are real ships, which are highlighted in Fig. 4e and the other targets are sea clutters.

Analyze: According to the experimental results, some facts about the algorithm in this study should be noticed as follows.

- Because SVM is a supervised classification approach, the correctness of land and sea segmentation and ship extraction, depends on the selection of training samples. The samples selected should cover most representative samples.
- Homogeneous sea area can be more easily segmented than heterogeneous sea area. The waves may lead to false segmentation and increase more non-ship targets for discriminating.
- The selection of SVM parameters, namely, the penalty coefficient C and the γ parameter of kernel function, has obvious influence on segmentation accuracy. Through cross validation and grid search method, the best C andγcan be obtained. For SVM1 in this study, C1 = 2, γ1 = 2, for SVM2, C2 = 700, γ2 = 0.5. The classification accuracy for train sets are both over 90%.
- This ship detection method is not sensitive to speckle noise. Though no filtering technique is adopted, the segmentation of land and sea and the extraction of ships are considerably successful.
- Because ships near the shore are segmented into land, so they are undetectable.

CONCLUSION

In this study, a ship detection method of POLSAR data is developed based on SVM. The whole process is divided into three steps, land and sea segmentation, ship extraction and discriminating ship and non-ship targets. The features used for SVM include polarimetric features obtained from polarimetric decomposition, such as Cloude decomposition, Krogager decomposition and Freeman-Durden decomposition and texture features based on first-order statistics. Through trained SVM classifiers land mask and ship mask are obtained respectively and the masks are used to extract ship target by logical and morphological operations. The rules based on threshold and SVM are established for discriminating ship from non-ship target. This method is applied with POLSAR data from Radarsat-2. The results of ship detection are satisfying. The final accuracy is over 95%. Because there are not so many ship targets in the four POLSAR images, the effectiveness of this algorithm need more SAR data for validation.

REFERENCES

Cloude, S.R. and E. Pottier, 1996. A review of target decomposition theorems in radar polarimetry. IEEE T. Geosci. Remote Sens., 34(2): 498-518.

Cloude, S.R. and E. Pottier, 1997. An entropy based classification scheme for land applications of polarimetric SAR. IEEE T. Geosci. Remote Sens., 35(1): 68-78.

Freeman, A. and S. Durden, 1998. A three-component scattering model for polarimetric SAR data. IEEE T. Geosci. Remote Sens., 36(3): 963-973.

Guyon, I., J. Weston, S. Barnhill and V. Vapnik, 2002. Gene selection for cancer classification using support vector machines. Mach. Learn., 46: 389-422.

Gonzalez, R.C., R.E. Woods and S.L. Eddins, 2004. Digital Image Processing Using Matlab. Pearson Prentice Hall, NJ, pp: 466.

Huynen, J.R., 1970. Phenomenological theory of radar targets. Ph.D. Thesis, Drukkerij Brounder off set, N.V. Roherdam.

Krogager, E., 1990. New decomposition of the radar target scattering matrix. Electr. Lett., 26(18): 1525-1527.

Li, H., Y. He and H. Shen, 2007. Ship detection with the fuzzy c-mean clustering algorithm using fully polarimetric SAR. Proceeding of Geoscience and Remote Sensing Symposium, IGARSS, pp: 1151-1154.

Novak, L.M. and M.C. Burl, 1989. Optimal speckle reduction in POL-SAR imagery and its effect on target detection. Proceeding of SPIE Conference, pp: 84-115.

Ringrose, R. and N. Harris, 1999. Ship Detection Using Polarimetric SAR Data. Proceeding of CEOS SAR Workshop, ESA-SP, 450: 687-691.

Sciotti, M., D. Pastina and P. Lombardo, 2001. Polarimetric detectors of extended targets for ship detection in SAR images. Proceeding of Int. Geosci. Remote Sens. Sympos., 7: 3132-3134.

Touzi, R. and F. Charbonneau, 2000. Characterization of target symmetric scattering using polarimetric SAR. IEEE T. Geosci. Remote Sens., 40(11): 2507-2516.

Touzi, R., F.J. Charbonneau, R.K. Hawkins and P.W. Vachon, 2004a. Ship detection and characterization using polarimetric SAR. Can. J. Remote Sens., 30(3): 552-559.

Touzi, R., W.M. Boerner, J.S. Lee and E. Lueneburg, 2004b. A review of polarimetry in the context of synthetic aperture radar: concepts and information extraction. Can. J. Remote Sens., 30(3): 380-407.

Vapnik, V.N., 2000. The Nature of Statistical Learning Theory. 2nd Edn., Springer-Verlag, NY.

Yeremy, M., J.W.M. Campbell, K. Mattar and T. Potter, 2001. Ocean surveillance with polarimetric SAR. Can. J. Remote Sens., 27: 328- 344.