Automatic ship detection in Single-Pol SAR Images using texture features in artificial neural networks

E. Khesali [a]*, H. Enayati [b], M. Modiri [c] , M. Mohseni Aref [d]

[a] PhD student in Remote Sensing, K.N.Toosi University of Technology, Mirdamad, Tehran, Iran - (elahe.khesali@kntu.ac.ir)
[b] MSc degree of Photogrammetry, K.N.Toosi University of Technology, Mirdamad, Tehran, Iran -(enayati_hamid@yahoo.com)
[c] professor of Maleke Ashtar University, Isfahan, Iran - (mmodiri@ut.ac.ir)
[d]PhD student in Geomatic, Istanbul Technical University, Istanbul, Turkey – (mohseni.aref@gmail.com)

Commission VI, WG VI/4

KEY WORDS: ship detection, texture feature, neural network, sentinel, SAR

ABSTRACT:

This paper presents a novel method for detecting ships from high-resolution synthetic aperture radar (SAR) images. This method categorizes ship targets from single-pol SAR images using texture features in artificial neural networks. As such, the method tries to overcome the lack of an operational solution that is able to reliably detect ships with one SAR channel. The method has the following three main stages: 1) feature extraction; 2) feature selection; and 3) ship detection. The first part extracts different texture features from SAR image. These textures include occurrence and co occurrence measures with different window sizes. Then, best features are selected. Finally, the artificial neural network is used to extract ship pixels from sea ones. In post processing stage some morphological filters are used to improve the result. The effectiveness of the proposed method is verified using Sentinel-1 data in VV polarization. Experimental results indicate that the proposed algorithm can be implemented with time-saving, high precision ship extraction, feature analysis, and detection. The results also show that using texture features the algorithm properly discriminates speckle noise from ships.

1. INTRODUCTION

The interest in vessel monitoring and surveillance springs from the need to enforce regulations and be warned of security threats; it is for the most part authorities who have these needs. Regulations are related to maritime safety, immigration, protection of the environment and natural resources, tariffs and duties, and public and workers' health and well-being. Security threats can be related to piracy, terrorism, organized crime, and military and defence issues. SAR has the ability to penetrate clouds and provide information on both day and night. SAR imagery can potentially be used to detect a range of maritime activity, including small vessels, large ocean-going ships and even oil spills. SAR is a proven technology that can be used to detect ships at sea which have no active transponders (commonly referred to as dark targets). Another advantage of using SAR is the large swath widths that these satellite based sensors can cover (thousands of square kilometers can be covered in a single pass) which reduces the monitoring cost per square kilometers significantly when compared to manual monitoring systems. Various methods have been proposed that process SAR images to monitor these targets.
Maritime monitoring and surveillance using single- and linear dual-pol SAR modes have been extensively studied using RADARSAT-1, ERS-1/2, and ENVISAT ASAR data, demonstrating very promising results for ship detection (shirvani,2012) (see, for example (Vachon et al., 1997), (Touzi et al., 2004a), (Liu et al., 2004), (Singh et al., 1986), (Wismann et al., 1993) and (Fingas et al., 1997)).
To date, most detection algorithms try to ensure a constant false-alarm rate (CFAR) (Crisp., 2004), (Brusch et al., 2011), (Fei et al., 2012), (Novak et al., 1989) and (Novak et al., 1993), and for this purpose, the clutter distribution is always locally estimated so that the decision threshold can be adaptively determined according to a given probability of false alarms (PFA). A large number of CFAR detectors have been proposed with different local statistics of the background clutter (Crisp, 2004),(Pourmottaghi et al., 2012) and (Liu et al., 2011).
A conventional constant false alarm rate (CFAR) detector searches ship targets adaptively in the whole imagery with a sliding window, which consumes much time and cannot meet the near real-time processing requirement (Xiangwei at al., 2012).
recent works (Musman et al., 1996), (Osman et al., 2000), have been focused to exploit the polarimetric properties of polarimetric SAR (POLSAR). In that case, different procedures based on coherent target decomposition (CTD) theorems are designed in order to express the complex polarimetric scattering behavior of ships in terms of specific combinations of elemental mechanisms. Normally, such simple mechanisms have associated a physical meaning where the main geometrical properties of the observed target could be delineated with (Cloude et al., 1996) In (Touzi et al., 2002) and (Touzi., 2004b) a new method based on the symmetric scattering characterization method CTD is defined, with the aim to exploit the advantages of coherent and incoherent theorem decompositions (Touzi et al., 2007).
Although the previous approaches provide encouraging results, they demand restrictive system requirements in as much as full-pol sensors are needed. Such capability is not operationally available in most of the satellite sensors,1 and hence, their exploitation in current ship monitoring services is limited (at least at short term),(Margarit., 2011). With the aim to overcome this drawback and to fill the gap in ship classification until new

* Corresponding author

POLSAR sensors become available, this paper presents a new methodology specially conceived to work with single-pol images.

2. MATERIALS AND METHODS

A new method for ship detection using texture features in neural networks is presented. First classification of SAR images using neural networks is introduced. The texture features used here as well as ship model in SAR images are then presented. The proposed method for ship detection is finally explained in details.

2.1 Classification of SAR images using neural networks

Classification can be interpreted as a transformation from feature space to a nominal set. It means for each pixel it receives an n-dimensional input vector and defines which class it belongs to. Ship detection can be defined as a classification problem in which all pixels are divided into ship and background (sea and other objects). Neural networks are computational systems that can be replaced with any non-linear function. They receive an n-dimensional input vector by “n” available neurons in their input layer and transform it to another m-dimensional output vector at their output layer which consists of “m” output neurons (figure.1).

To use neural networks as a classifier, input vector may be fed through the neurons in the input layer, but class membership must be presented in a numeric format. This could be done in a binary expression in which being belonged to a class is shown by number one and not being belonged by zero. For each class, the network should be involved an output neuron at its output layer. The back-propagation neural network (BNN) is one of the most used networks. A BNN consists of a number of layers: input layer, output layer and one or more hidden layers connected to a feed forward way. Each layer consists of a number of neurons. Every unit feeds only and all the units in the next layer. (mokhtarzade., 2008)

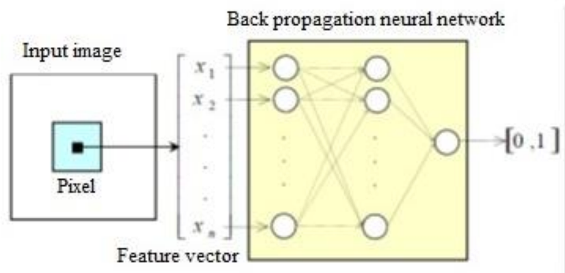

Figure 1. The structure of neural network for ship detection

2.2 Texture Analysis

Texture is a property that can be defined as regular repetition of an element or pattern on a surface. Statistical approaches are the most common methods of texture extraction used in the analysis of satellite images. (Mokhtarzade., 2008) the most widely texture analysis methods are as follows:

- First order statistical descriptors (using a one-dimensional histogram): first order statistical descriptors, based on the image histogram, or in other words, according to the probability of occurrence of gray levels in the image, the parameters are estimated.
- Second order statistical descriptors based on co-occurrence matrix: gray level co-occurrence matrix method, is the most common method of texture analysis, which not only considers the distribution of gray levels, but also position of pixels relative to each other (Haralick., 1973).

Selected texture features are shown in the figure.2 and 3.

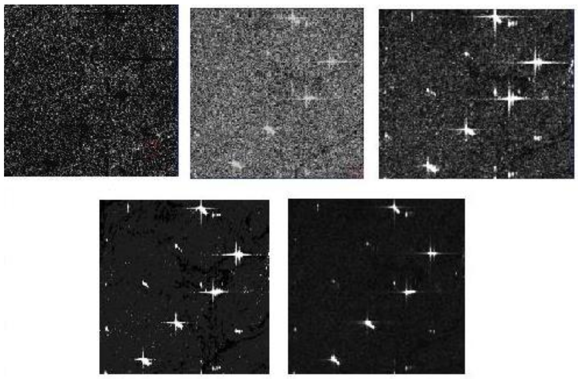

Figure 2. Occurrence texture features respectively from left to right: skewness, entropy, variance, mean and data range

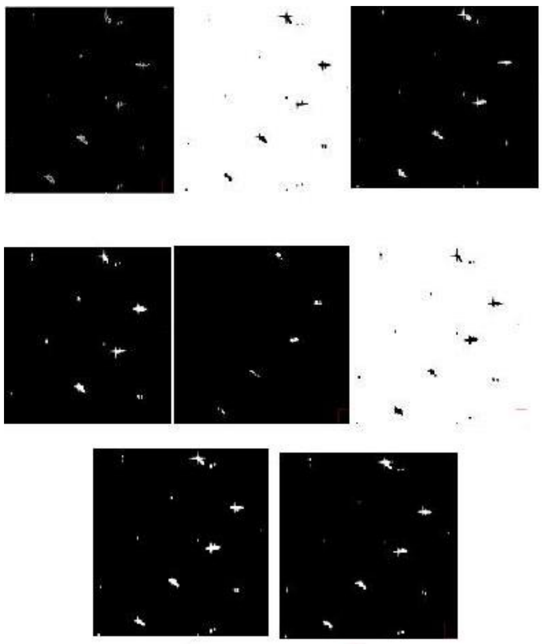

Figure 3. Co-occurrence texture features respectively from left to right: correlation, second moment, entropy, dissimilarity, contrast, homogeneity, variance and mean

2.3 Specification of the Used Data

The study area is located in the Persian Gulf in the south of Iran. The data used in this study is Sentinel-1 SAR image with a resolution of 5×20 m and VV polarization in IW GRDH mode taken in June 17, 2015. Figure 4 shows the image of the study area.

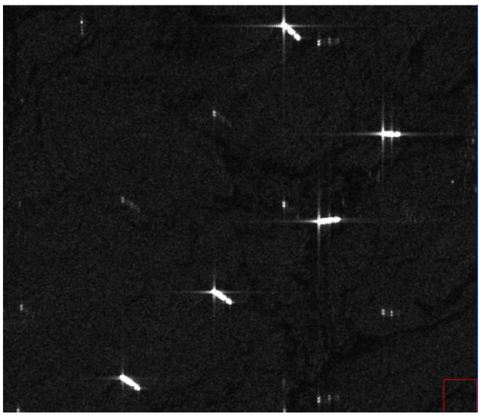

Figure 4. The image of the study area

2.4 Ship Model in SAR Images

In SAR images, ships have higher radar cross section (RCS) than the surrounding sea clutter. This is due to the effect of multiple bounces of incoming radar waves from the ship's superstructure (Ai et al., 2010) As a result, with a proper threshold, ships can be detected and separated from the sea clutter.

However, the homogeneous regions in low to medium resolution SAR images become uneven in high-resolution SAR images (Wang et al., 2014). Sea waves, bright clutter, and even system noise are distinct. Although land masking is finished before ship detection, false alarms may occur at the water–land interface, such as dock areas and off-shore fishing zones (Wang.,2014). Sometimes, a single ship is detected multiple times. This is due to some reasons, such as the presence of side lobes in both the azimuth and the range directions, as well as the presence of discrete scatters on a ship, causing the appearance of numerous areas of bright and dark texture. Ship detection with low false alarms in high resolution SAR images faces more challenges than it does in low-resolution SAR images of ships (Wang.,2014).

As the new generation of SAR sensors are free and the demand for sea application in high-resolution scenes grows rapidly, a fast algorithm needs to be designed to deal with the mass data and to achieve wide area ocean surveillance.

2.5 Ship Detection method

Ship detection is the classification of image pixels into two classes of ship and sea.

Figure 3 shows the ship detection algorithm. First, in pre-processing step, land masking and radiometric correction are necessary. This steps are done by sentinel toolbox. Feature extraction then is done. In this step, ship features, including occurrence and co-occurrence texture parameters are extracted and introduced as input neurons to the neural network. A hidden layer is used in structure of neural network.

The texture parameters were calculated using different window sizes including 3×3, 5×5 and 7×7. Then the texture parameters and the intensity were introduced into neural network as input vector. Different input vectors and neural network structures were used for ship detection. A back propagation neural network with 13 input neurons and one hidden layer with 20 neurons were used. Finally in post processing step morphological filters including erosion and dilation were used to make the results more clear and remove noises. Figure 6 and 7 show the output of CFAR algorithm and our proposed algorithm. In figure 6, green circles are the noises that in the CFAR algorithm have been detected as ship by fault. There was not any ground truth for accuracy assessment this stage was done by visual and comparison between a manually–produced map (figure 8) and the algorithm result. This algorithm is also faster than CFAR.

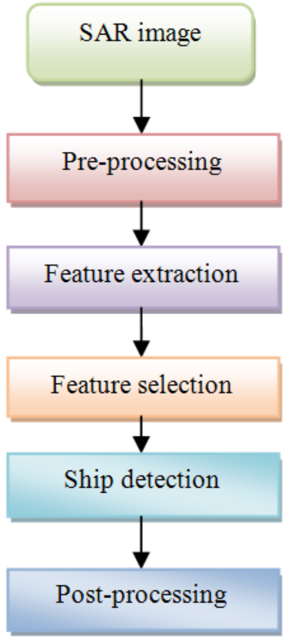

Figure 1. Flowchart of the proposed algorithm

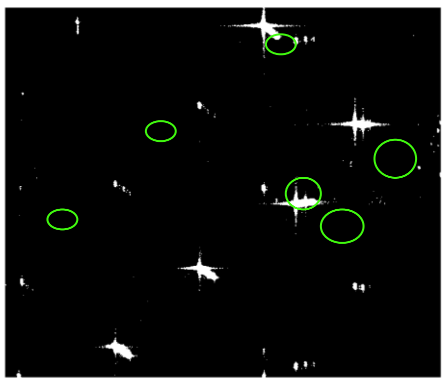

Figure 2. ship detection result

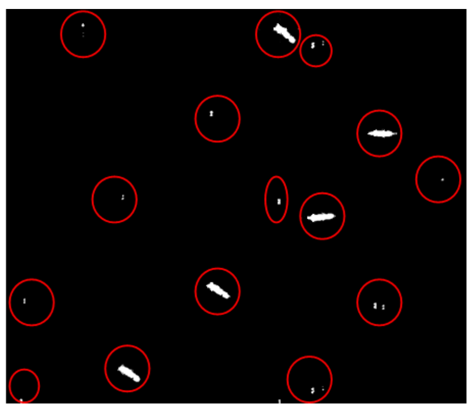

Figure 3. Ship detection result after post processing

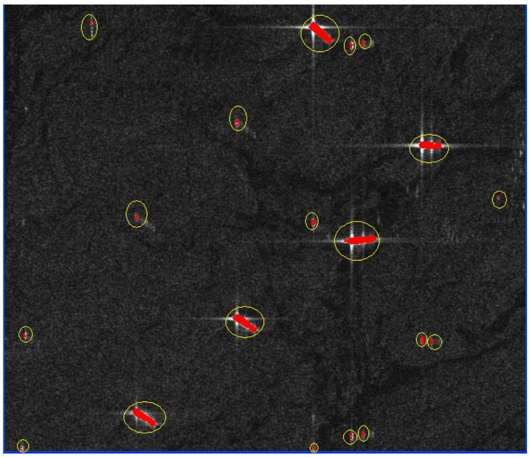

Figure 4. manually-produced reference map

3. CONCLUSION

This letter proposed a new ship detection method based on texture features for SAR images. Optimized results were observed with texture analysis in single-pol SAR images, such as Sentinel-1. The proposed method could guarantee a high estimation of target detection probability and a low estimation of undetected target probability. The experimental results showed that our method could quickly detect ships at the sea or by the sea. The extracted features, including occurrence and co-occurrence textures, could be an important foundation for ship classification. Ship identification using texture features will be investigated in the future works.

REFERENCES

Ai. J., Qi. X., Yu. W., Deng. Y., Liu. F., and Shi. L., 2010. A new CFAR ship detection algorithm based on 2-D joint log-normal distribution in SAR images. IEEE Geosci. Remote Sens. Lett., vol. 7, no. 4, pp. 806–810.

Brusch. S., Lehner. S., Fritz.T., Soccorsi. M., Soloviev.A., and Van. B SchieShip., 2011. Ship surveillance with TerraSAR-X, IEEE Trans. Geosci. Remote Sens., vol. 49, no. 3, pp. 1092–1103.

Cloude.S. R and Pottier. E, Mar. 1996. A review of target decomposition theorems in radar polarimetry, IEEE Trans. Geosci. Remote Sens., vol. 34, no. 2, pp. 498–518.

Crisp. D. J., 2004. The state-of-the-art in ship detection in synthetic aperture radar imagery, DSTO, Inf. Sci. Lab., Edinburgh, Australia.

Fei. C., Liu. T., and Lampropoulos. G. A., 2012. Markov chain CFAR detection for polarimetric data using data fusion, IEEE Trans. Geosci. Remote Sens., vol. 50, no. 2, pp. 397–408.

Fingas. M . F and Brown. C. E., 1997. Review of oil spill remote sensing, Spill Sci. Technol. Bull. vol. 4, no. 4, pp. 199–208.

Liu. C., Vachon. P. W,, and Geling. G. W., 2004. Improved ship detection using polarimetric SAR data, in Proc. IGARSS, Anchorage, AK, vol. 3, pp. 1800–1803, vol. 3.

Liu. J., Zhang. Z., Yang. Y., and Liu. H., 2011. A CFAR adaptive subspace detector for first-order or second-order Gaussian signals based on a single observation. IEEE Trans. Signal Process., vol. 59, no. 11, pp. 5126– 5140.

Margarit. G., Tabasco.A., 2011. Ship Classification in Single-Pol SAR Images Based on Fuzzy Logic. IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. 49, NO. 8.

Mokhtarzade. M., 2008. Integration of Textural and Spectral Information in Neural Networks for Automatic Road Extraction from High Resolution Satellite Images, PHD thesis, Department of Geomatic KNToosi University of technology .

Musman. S., Kerr. D., and Bachmann. C., 1996. Automatic recognition of ISAR ship images. IEEE Trans. Aerosp. Electron. Syst., vol. 32, no. 4, pp. 1392–1404.

Novak. L. M., Sechten. M. B., and Cardullo. M. J., 1989, Studies of target detection algorithms that use polarimetric radar data. IEEE Trans. Aerosp. Electron. Syst., vol. 25, no. 2, pp. 150–165.

Novak, L. M., Burl. M. C., and Irving. E. W., 1993. Optimal polarimetric processing for enhanced target detection, IEEE Trans. Aerosp. Electron. Syst., vol. 29, no. 1, pp. 234–244.

Osman. H and Blostein. S. D., 2000. Probabilistic winner-take-all segmentation of images with application to ship detection,"IEEE Trans. Syst., Man, Cybern. B, Cybern., vol. 30, no. 3, pp. 485–490, Jun. 2000.

Pourmottaghi. A., Taban. M. R., and Gazor. S. A., 2012. CFAR detector in a nonhomogenous Weibull clutter, IEEE Trans. Aerosp. Electron. Syst., vol. 48, no. 2, pp. 1747–1758.

Shirvani, R., Tourneret, J., 2012. Ship and Oil-Spill Detection Using the Degree of Polarization in Linear and Hybrid/Compact Dual-Pol SAR. IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, VOL. 5, NO. 3.

Singh. K., Gray. A., Hawkins. R., and O'Neil. R., 1986, The influence of surface oil on C-and Ku-band ocean backscatter. IEEE Trans. Geosci. *Remote Sens.*, vol. GE-24, no. 5, pp. 738–744.

Touzi. R., and Charbonneau. F., 2002. Characterization of target symmetric scattering using polarimetric SARs, IEEE Trans. Geosci. Remote Sens., vol. 40, no. 11, pp. 2507–2516.

Touzi. R., Charbonneau. F. J., Hawkins. R. K., and Vachon. P. W., 2004a. Ship detection and characterization using polarimetric SAR, Can. J. Remote Sens. vol. 30, no. 3, pp. 552–559.

Touzi. R., Raney. R. K., and Charbonneau. F., 2004b. On the use of permanent symmetric scatterers for ship characterization, IEEE Trans. Geosci. Remote Sens., vol. 42, no. 10, pp. 2039–2045.

Touzi. R., 2007. Target scattering decomposition in terms of roll-invariant target parameters, IEEE Trans. Geosci. Remote Sens., vol. 45, no. 1, pp. 73–84.

Vachon. P. W., Campbell. J. W. M., Bjerkelund. C., Dobson. F. W., and Rey.M .T, 1997. Ship detection by the RADARSAT

SAR: Validation of detection model predictions, Can. J. Remote Sens., vol. 23, no. 1, pp.48–59.

Wang. C., Zahng. H., Wu. F., Zhang. B., 2014. Ship Detection for High-Resolution SAR Images Based on Feature Analysis. IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, VOL. 11, NO. 1.

Wismann. V., Gade. M., Alpers. W., and Hühnerfuss. H., 1993. Radar signatures of mineral oil spills measured by an airborne multi-frequency multi-polarization microwave scatterometer. in Proc. OCEANS Eng.Harmony With Ocean, Victoria, BC, Canada, vol. 2, pp.II348–II353.

Xiangwei. X ., Kefeng. J., Huanxin. Z., and Jixiang. S., 2012, A fast ship detection algorithm in SAR imagery for wide area ocean surveillance, in Proc. IEEE Radar Conf. (RADAR), pp. 570–574.