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SAR Ship Detection Using Image Histograms and Machine Learning Approach

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Abstract: Ship detection and classification in SAR images is an important and active research area. It provides effective surveillance by facilitating applications such as surveillance and tracking of commercial and military ships. In this study, SAR images were classified using Hessian matrix and HOG algorithm. Using the eigenvalues of the Hessian matrix, the angle and orientation information of the HOG method was calculated. Thus, distinctive pixel characteristics were coded. Our method has obtained desired results in terms of classification accuracy. The proposed method achieved 94.50% classification success.

Görüntü Histogramları ve Makine Öğrenmesi Yaklaşımı Kullanarak SAR Gemi Tespiti

Anahtar Kelimeler
Uzaktan algılama, Sentetik açıklıklı radar, Makine öğrenmesi, Özdeğerler

Öz: SAR görüntülerinde gemi tespiti ve sınıflandırması önemli ve aktif bir araştırma alanıdır. Ticari ve askeri gemilerin gözetimi ve takibi gibi uygulamalarda kolaylık sağlayarak etkin gözetim imkânı sunar. Bu çalışmada SAR görüntüleri Hessian matrisi ve HOG algoritması kullanılarak sınıflandırılmıştır. Hessian matrisinin özdeğerleri kullanılarak HOG yönteminin açı ve yönelim bilgisi hesaplanmıştır. Böylece ayırt edici piksel özellikleri kodlanmıştır. Yöntemimiz, sınıflandırma doğruluğu açısından istenilen sonuçlar elde etmiştir. Önerilen metot %94.50 sınıflandırma başarısı elde etmiştir.

1. INTRODUCTION

Ship detection and classification in remote sensing images is an important element in maritime surveillance, military missions and commercial operations. The main purpose of ship detection is to detect the type and location of ships in the images. Synthetic aperture radar images provide effective images in all weather conditions. For this reason, images taken from these radars are used extensively in ship detection. Important Synthetic Aperture Radar (SAR) satellites such as Sentinel-1 and TerraSAR-X provide a wide range of SAR data.

Image processing and artificial intelligence methods are used effectively in studies detecting ships in SAR images. The most basic approach is the Constant False Alarm Rate (CFAR) method [1]. The CFAR method detects ships with the generated polarization features and appropriate statistical models. However, achieving the fabrication of handcrafted features that require extensive prior knowledge is a key shortcoming of CFAR-based methods. Huo et al. [2] use maximally-stable extremal region method to detect proper image regions, and calculate threshold for detecting ships. The attention-guided balanced pyramid and the refined detection head are combined by Fu et al. [3] to identify ships using an anchor-free approach that aims to strike a fair balance between speed and accuracy. In order to enhance detection performance, Pan et al. [4] look into the ship's scattering mechanisms and suggest a unique ship detection technique based on the main contribution of scattering mechanisms. Liu aet al. [5] proposed an optimization filter set to detect ships. They combining a polarimetric whitening filter and a polarimetric matched filter. Thus the probability of false alarm was reduced.

Successful results have been achieved with the traditional feature extraction methods mentioned above. In addition, deep learning-based ship detection methods have also been developed. The main motivation for turning to these methods is the desire to develop methods that do not require hand-crafted feature extraction. Gao et al. [6] proposed a dualistic cascade convolution neural network to PolSAR image ship detection. They used a backbone feature calculation architecture by means of parallel cascade architecture. Thus robust geometric features and polarization features were fused to improve the network performance. Zhu et al. [7] developed a hybrid deep neural network architecture. Their model consists of a detection Network, a duplicate bilateral feature pyramid network, and a feature extraction network. Thus they reduced redundant model parameters and, they detected the small-scale ships. Currently, one difficulty is to maintain acceptable generalization performance while using a deep CNN model with limited training sets for PolSAR target identification and classification. A CenterNet++ deep neural network architecture was developed for small ship detection [8]. A feature refinement module was designed to detecting small ship detection. Complex backgrounds were eliminated using feature pyramids and discriminative feature of foreground. Efficient results have been obtained on AIR-SARShip, SSDD, and SAR-Ship datasets. To estimate ship velocity, a multitask deep learning model has been developed [9]. This study does not require prior wake detection to estimate ship speed. A dateset including 30000 ship images from Sentinel-1 SAR scenes has been constructed. Multi-scale features need to be extracted to detect ships of different scales. This prevents ships of different sizes from being overlooked. In a current study, an appropriate solution to this problem was developed by designing a Swin transformer [10]. In order to address the multi-scale ship problem, they offer a cross-level modulated deformable convolution (CLMD-Conv) for multi-scale feature fusion.

Studies in the literature show that very powerful methods have been developed for ship detection. Methods have been developed using both deep learning and traditional hand-crafted features. It is an easy method to distinguish ship areas in SAR images with the help of pixel brightness information. However, this simple approach does not give good results in the presence of noise and in detecting ships of different sizes. In this study, a ship detection method has been developed by using both the derivative approach and the Histogram Oriented Gradient (HOG) approach, which is a hand-crafted feature extraction method. The proposed method is an expanded and updated version of the study presented as an abstract conference paper [11]. By calculating the Hessian matrix of SAR images, simple pixel brightness changes were encoded. HOG features were calculated using the Hessian matrix, allowing ship regions to be identified and classified.

This paper is designed as follows: In Section 2, the proposed method is presented. The results obtained are presented in Section 3. Some conclusions are presented in Section 4.

2. THE PROPOSED METHODOLOGY

2.1 Database Construction

There are different SAR ship databases in the literature. Developed ship detection and classification methods are tested using these databases. In this study, a database of 10000 images was created using the Copernicus OpenAccess Hub [12] database, where SAR images are available for sharing free of charge. It is aimed to shed light on future studies for the development of new solutions by using Earth Observation Satellite Data and geospatial Information, which can be obtained free of charge from different sources. Images in this database are labeled as those with or without ships. In creating the database, SAR images were taken from different sea and port areas. The following basic steps were followed to create a database of images taken from the Sentinel-1 SAR satellite:

1) The raw SAR images to be obtained have a TIFF format. SAR images with TIFF format were converted to .jpg file format so that image processing and machine learning algorithms can work more accurately and interpretably. Thus, images can be stored with PASCAL VOC format. Geospatial Data Abstraction Library (GDAL) library was used to convert images into jpg extension files.

2) After the raw SAR images taken from the Copernicus OpenAccess Hub database were converted to jpg format, the jpeg images, each with an average size of 24000x16000, were divided into sub-images. Literature research shows that the size of subimages can be between 600x600 and 900x900 pixels. In this study, it is aimed to create sub-images of 800x800 size. It has been observed that many ship types of different sizes can be expressed with sufficient resolution in images of this size. It also makes a positive contribution to the computational cost. Each sub-image is divided into subparts so that there is no overlap.

With the studies carried out, a SAR ship database containing 10000 images was created. Sample images in the database are given in Figure 1. The images are divided into 2 folders: with ships and without ships. Thus, the machine learning method will be used for two-class data. Studies on different database construction models are ongoing to label images in the database for use in future deep learning-based studies.

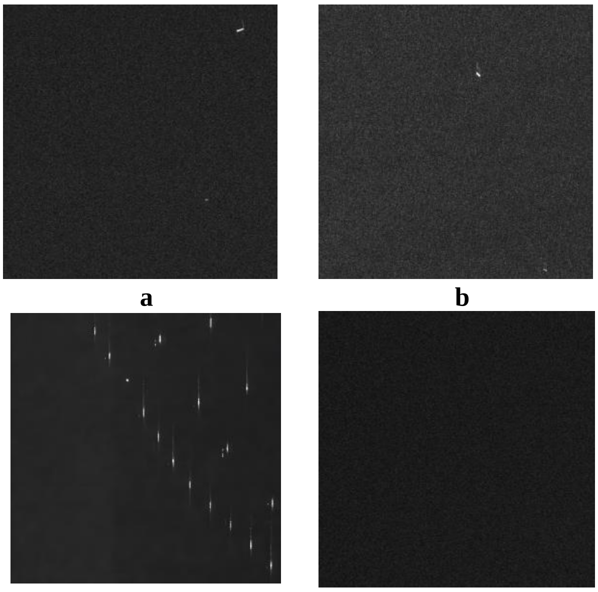

Figure 1. SAR ship and sea images, (a-b-c:ship, d:sea)

2.2 The Proposed Model

In this study, a hybrid approach was used to detect ships in SAR images. The main purpose of the hybrid approach is to extract the distinctive features of pixel shadows with different characteristics in images. Figure 1 shows SAR images containing ships. There is a difference in pixel brightness between shadows with and without ships. However, small ships can be found in some SAR images. In addition, under some imaging conditions, the brightness of ships cannot be detected sufficiently. In this case, some light reflections in the ship area and the background are mixed together. Derivative-based approaches give good results in distinguishing between light reflections on the sea surface and ship brightness. Starting from this point, the Hessian matrices of SAR images were calculated and the pixel change information was encoded. Based on this information, feature vectors of ship objects were calculated using the current HOG approach [13].

The Hessian matrix at the scale of any (x,y) pixel in a gray level image I is calculated as follows [14]:

$$H_\sigma(x,y) = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{yx} & D_{yy} \end{bmatrix} = \begin{bmatrix} I * G_{xx} & I * G_{xy} \\ I * G_{xy} & I * G_{yy} \end{bmatrix} \qquad (1)$$

where * shows the convolution operation, D_{xx}, D_{yy}, D_{xy} show the second-order derivations of image for the horizontal, vertical and diagonal directions, respectively. *G_xx, G_yy, G_xy* shows the Gaussian horizontal, vertical and diagonal derivative filters, respectively.

The basic idea in calculating the eigenvalues and eigenvectors of the Hessian matrix is to mathematically reveal the basic directions and basic curvatures on the image surface. Therefore, the local second order differential structure of the image should be examined. By calculating the eigenvalues of the Hessian matrix, the behavior of the pixels in the image and the differential relationship of neighboring pixels with each other can be analyzed. Because eigenvalues contain the magnitude information of the basic change directions in an image. The eigenvalues of the Hessian matrix are called principal curvatures and are not affected by rotation. The eigenvalues of the Hessian matrix are calculated as follows:

$$\lambda = \pm\sqrt{\frac{\left(I * G_{xx} - I * G_{yy}\right)^2}{4} + \left(I * G_{xy}\right)^2} + \frac{I * G_{xx} - I * G_{yy}}{2} \qquad (2)$$

where λ shows the eigenvalues of Hessian matrix.

In this paper, eigenvalue information was used instead of traditional gradient calculation in the HOG method. Gradient orientations and gradient magnitudes of the HOG method can be calculated using the λ_1 and λ_2 eigenvalues matrices.

In the HOG method, the gradient magnitude is calculated as follows [14]:

$$I_{\theta gradient} = \sqrt{(\lambda_1)^2 + (\lambda_2)^2} \qquad (3)$$

The gradient orientation of the HOG algorithm is calculated using the eigenvalue information as follows:

$$\theta = tan^{-1}\left(\frac{\lambda_2}{\lambda_1}\right) \qquad (4)$$

The HOG method is used extensively in object recognition problems such as pedestrian detection [13]. It was also used in the ship detection problem discussed, thus enabling the method to be used in a different field. The calculated eigenvalue information was used to calculate the gradient orientation bins in the HOG method. Histogram labeling was done with 9 different angle values. In the next step of the HOG method, histogram divisions are defined with the help of eigenvalue information. Thus, feature vectors of 1x128 size of SAR images were calculated. This feature vector contributes to the discrimination capacity of the classifier.

The artificial neural network was used to classify the resulting feature vectors. 80% of the images were used as the training set and 20% as the test set. The artificial neural network was run 10 times to obtain robust results. All experimental studies were carried out in the Matlab environment.

3. EXPERIMENTAL RESULTS

In this section, the results of ship classification studies obtained using the SAR database created are mentioned. Since the developed method was tested on a new database, the number of methods used in the comparison was limited. The proposed method is compared with the original LBP method [15]. The LBP method is used extensively in texture classification. Distinguishing ship regions from the background is also a type of texture classification problem. At this point, the LBP method was used with its original parameters.

Four different performance metrics are used to compare the methods. These metrics have been explained as follows;

- Accuracy: It is used to express the accuracy percentage of the prediction made. It is the ratio of correctly predicted values to the sum of all predicted values.
- Precision: It helps to express how much of the positive predictions made are actually positive. Precision is the ratio of true positive predictions to all positive predictions.
- Recall: It provides information about how many true positive values of the prediction operations resulted correctly.
- F1 Score: It is the harmonic average of precision and recall values.

The classification results of the methods are given in Table 1. As seen from the results, the proposed hybrid approach achieved higher classification results. The main reason for this is the use of a hybrid feature extraction scheme. In many SAR images, ship regions appear as small collections of bright pixels. While methods such as LBP interpret these bright regions, they fail due to the effects of noise. Because pixel behavior should be analyzed in more detail by calculating precise statistical properties from images. At this point, a more precise feature calculation should be made. In the proposed method, these drawbacks are prevented with a hybrid approach. By calculating the eigenvalue/eigenvector of the image, changes in the background were distinguished from the sea surface and noise. Even small pixel intensity changes have been detected with precise derivative calculations.

Table 1. Classification results (%)

Method	Accuracy	Precision	Recall	F1-score
LBP method	89.00	88.82	89.05	88.73
Our proposed method	94.50	94.23	94.98	95.09

These differential calculations were effective in improving the object detection success of the HOG method. Eigenvalues were used in the gradient and orientation calculations of the HOG method. Thus, more precise derivative information was used to label the histogram regions. The 94.50% classification success achieved is satisfactory. However, it is predicted that the success of the method will increase, especially by eliminating noise components.

4. CONCLUSION

In this study, a new method for ship classification was developed using the newly created SAR ship database. The developed method used a hybrid approach. An effective feature extraction process was performed using the second order derivatives of the images. In the feature calculation of the HOG method, eigenvalue information was used instead of the traditional gradient. Gradient magnitudes and orientations calculated with eigenvalues increased the success of the HOG method. Thus the current HOG method can be used to detect ships in SAR images.

It is planned to improve the database with future studies. It is also considered to develop more powerful feature extraction and classification methods such as deep learning.

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REFERENCES

[1] Huang S qi, Liu D zhi, Gao G qing, Guo X jian. A novel method for speckle noise reduction and ship target detection in SAR images. Pattern Recognit 2009;42:1533–42. https://doi.org/10.1016/J.PATCOG.2009.01.013.

[2] Huo W, Huang Y, Pei J, Zhang Q, Gu Q, Yang J. Ship Detection from Ocean SAR Image Based on Local Contrast Variance Weighted Information Entropy. Sensors 2018, Vol 18, Page 1196 2018;18:1196. https://doi.org/10.3390/S18041196.

[3] Fu J, Sun X, Wang Z, Fu K. An Anchor-Free Method Based on Feature Balancing and Refinement Network for Multiscale Ship Detection in SAR Images. IEEE Trans Geosci Remote Sens 2021;59:1331–44. https://doi.org/10.1109/TGRS.2020.3005151.

[4] Pan X, Wu Z, Yang L, Huang Z. Ship Detection Method Based on Scattering Contribution for PolSAR Image. IEEE Geosci Remote Sens Lett 2022;19. https://doi.org/10.1109/LGRS.2021.3138796.

[5] Liu T, Jiang Y, Marino A, Gao G, Yang J. The Polarimetric Detection Optimization Filter and its Statistical Test for Ship Detection. IEEE Trans Geosci Remote Sens 2022;60. https://doi.org/10.1109/TGRS.2021.3055801.

[6] Gao G, Bai Q, Zhang C, Zhang L, Yao L. Dualistic cascade convolutional neural network dedicated to fully PolSAR image ship detection. ISPRS J Photogramm Remote Sens 2023;202:663–81. https://doi.org/10.1016/J.ISPRSJPRS.2023.07.006.

[7] Zhu H, Xie Y, Huang H, Jing C, Rong Y, Wang C. DB-YOLO: A Duplicate Bilateral YOLO Network for Multi-Scale Ship Detection in SAR Images. Sensors 2021, Vol 21, Page 8146 2021;21:8146. https://doi.org/10.3390/S21238146.

[8] Guo H, Yang X, Wang N, Gao X. A CenterNet++ model for ship detection in SAR images. Pattern Recognit 2021;112:107787.

[9] Heiselberg P, Sørensen K, Heiselberg H. Ship velocity estimation in SAR images using multitask deep learning. Remote Sens Environ 2023;288:113492. https://doi.org/10.1016/J.RSE.2023.113492.

[10] Liu L, Fu L, Zhang Y, Ni W, Wu B, Li Y, et al. CLFR-Det: Cross-level feature refinement detector for tiny-ship detection in SAR images. Knowledge-Based Syst 2024;284:111284. https://doi.org/10.1016/J.KNOSYS.2023.111284.
[11] Hanbay K, Özdemir TB. SAR Ship Detection Based on Differential Image Analysis and Machine Learning Approach. Int. Conf. Eng. Soc. Sci. Humanit., Mecca: 2024, p. 46.
[12] Copernicus Data Space Ecosystem | Europe's eyes on Earth 2024. https://dataspace.copernicus.eu/.
[13] Dalal N, Triggs B. Histograms of oriented gradients for human detection. Proc - 2005 IEEE Comput Soc Conf Comput Vis Pattern Recognition, CVPR 2005 2005;I:886–93. https://doi.org/10.1109/CVPR.2005.177.
[14] Hanbay K, Alpaslan N, Talu MF, Hanbay D, Karci A, Kocamaz AF. Continuous rotation invariant features for gradient-based texture classification. Comput Vis Image Underst 2015;132:87–101. https://doi.org/10.1016/J.CVIU.2014.10.004.
[15] Ojala T, Pietikäinen M, Mäenpää T. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Trans Pattern Anal Mach Intell 2002;24:971–87. https://doi.org/10.1109/TPAMI.2002.1017623.