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Ship Classification Based On Co-Occurrence Matrix and Support Vector Machines

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ABSTRACT

Synthetic aperture radar (SAR) is an important and efficient imaging technology. This system provides robust information for various applications such as ship detection, climate change, and agricultural land modeling. Ship detection and classification problem is an important object detection problem that involves difficulties. There are deep-learning-based studies to solve this problem. However, mathematical and statistical methods should be developed for ship classification applications. In this paper, gray-level co-occurrence matrix-based method is proposed. The gradient of the input SAR image was calculated using Gaussian derivative filters. The gradient magnitude was calculated with horizontal and vertical gradient information. Gray-level co-occurrence matrix was obtained using gradient magnitude. The meaningful features of the images were calculated by performing 4 different statistical calculations. Results on our SAR database reveal the proposed model's superior classification performance.

Index Terms— Gradient, image processing, ship classification

I. INTRODUCTION

Synthetic aperture radar (SAR) is a microwave remote sensing sensor. It works on the principle of sending electromagnetic waves to achieve microwave imaging. In particular, it has some advantages over optical, hyperspectral, or infrared imaging. Its most important advantage is that it is not affected by lighting and weather conditions. For this reason, today it is used extensively for military and commercial purposes, especially in monitoring the seas.

Ship detection and classification in SAR images plays an important role, especially in distinguishing military and commercial ships. It provides effective imaging in separating areas such as reefs and rocks from ships in seas and oceans. For this reason, image processing and artificial intelligence studies are needed in the processing and classification of SAR images.

In a recent study, a regularly weighted adaptive learning method was developed to detect thin-looking ships [1]. A dynamic framing approach has been developed to improve the impact of the learning process. Li et al. [2] used generative adversarial networks to detect thin objects from SAR images. With the deep network they designed, the resolution of the images was improved and the object detection success was improved. Zhang and Zhang [3] proposed a polarization fusion network to classify ships. They calculated geometric features of SAR images to improve the performance of the network. Effective results have been obtained in the OPENSARShip database. Zeng et al. [4] developed a new convolutional neural network and detected ships in dual-polarized SAR images. With the method they developed, they classified ships into eight different categories. This method achieved very effective results with a small training set. He et al. [5] developed a novel densely connected triplet CNN model to classify medium-resolution SAR images. By partially improving the low resolution in the images, classification performance has been increased. Yu and Shin [6] developed an effective ship detection model by improving the YOLOv5 and BiFPN models. They used attention blocks and bidirectional feature pyramid network methodologies to better calculate the features of ship regions. Gao et al. [7] proposed a cascade convolutional neural network model for ship classification. They used a three-stage training strategy by extracting distinctive geometric features. Ship images taken from different SAR satellites were manually

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labeled and used in training and testing processes. Ding et al. [8] developed a lightweight deep learning model to detect ship areas in real time. They achieved more successful ship detection with the angle-related loss function they proposed. This method gave successful results in complex backgrounds and weak ship patterns.

In another recent study, a new SAR ship detection method based on salient region extraction has been developed. In the designed method, all regions where ships can be found are extracted according to the maximum variance between classes and unnecessary background information is filtered. The proposed method achieved approximately 89.66% and 96.97% detection success in nearshore and offshore images [9]. A dataset named AIR-SARSHIP-1.0 was created to be used for high-resolution and large-scale ship detection with 31 SAR images provided by the Gaofen-3 satellite [10]. The dataset includes many scenarios such as nearshore and open sea. The created dataset was tested with both traditional and deep learning methods and reached a detection accuracy rate of 88.1%. Lou et al. [11] proposed a generative learning network that can generate new data samples by learning the data distribution that includes a transfer learning (TL)-based knowledge network and a ship detection network in order to address the problem of data acquisition and labeling in SAR imagery. In this way, it was tried to obtain good results in ship detection even in cases of insufficient or improper labeling. This architecture was compared with the original dataset by using the images created by the Sar Ship Detection Dataset (SSDD) and AIR-SARShip-1.0 datasets and the performance was evaluated with the new images obtained. The average accuracy rate of average precision (AV) in the SSDD increased by 14.71% in optical images and 23.55% in grayscale images. Zhang et al. [12] created their own dataset LS-SSDD-v1.0 to address the lack of a reliable dataset for ship detection of large-scale SAR images. The datasets were verified by SAR experts with AIS and Google Earth support to ensure accuracy. The content provided is 15 Tagged Image File Format (TIFF) SAR images and 9000 sub-images. In another recent study, an innovative ship detection method to be used in the optical domain was proposed, based on a limited number of labeled sample data and a training and testing process [13]. During the training period, optical images were used for the initial training of the model. In the study conducted with deep learning method, an improved method based on YOLOv5 was proposed, which integrates coordinate attention blocks and uses a bidirectional pyramid network to provide better feature fusion [6]. Compared to the original Yolov5, the detection rate of the proposed method increased from 81.28% to 88.27%, and the average sensitivity rate increased from 92.57% to 95.02%. To remove complex background and detect ship regions, Ma et al. developed a network called neighborhood removal-and-emphasis [14]. They used an object neighborhood removal approach and a neighborhood feature emphasis system. Zhang et al. developed a fusion framework for SAR target detection model [15]. They use a global context perception capability of the transformer model and the feature pyramid structure. Another work proposed a new curvature-based saliency approach for ship detection [16]. They developed a nonlinear anisotropic diffusive process to remove clutter. Thus the local ship structure is preserved in SAR images.

When the methods in the literature are examined, it is seen that both traditional and current deep-learning-based approaches are used in ship detection. Deep learning methods focus on training models without extensive intervention in the architecture. Traditional feature extraction methods focus more on geometric feature extraction. However, geometric properties are methods based on simple mathematical principles. For this reason, effective results could not be produced, especially in cases such as noise and lack of contrast.

In this study, a new method is proposed for detecting ships in SAR images. The proposed paper is an extended and updated version of our conference paper [17]. In the current study, the scope of the database has been expanded. More comprehensive results have been obtained by optimizing the parameters and structure of the support vector machine. The gradient information used in the Histogram of Oriented Gradients (HOG) method has been calculated using the Gaussian function. 4 statistical features were calculated by calculating the co-occurrence matrix from the gradient information. The resulting feature vector was classified with the support vector machine. Information about the database used is given in Section II. Then, the details of the proposed method are mentioned. Section III includes the findings and conclusions obtained. In Section IV, conclusions and future studies are mentioned.

II. THE PROPOSED METHOD

A. Synthetic Aperture Radar Ship Database

A new database created by the authors was used in this study. A database containing approximately 10 000 images has been built to detect ships from SAR images with high reliability and validity. The images are SAR data from the Sentinel-1 satellite. Synthetic aperture radar images were taken from the Copernicus OpenAccess Hub database, which is open to public sharing [18]. Images of the Interferometric Mode (IW) sensor mode, which is one of the ground range multi-look detected (GRD) imaging modes of the Sentinel-1 satellite, were used. Ground range multi-look detected mode enables the use of multi-looked and focused SAR images that reflect objects on the ground. VV mode was used as polarization in the database. Thus, pixel density information was obtained with appropriate incidence angles in ship labeling.

The raw SAR images are obtained with TIFF extension. Synthetic aperture radar images with TIFF extension were converted to jpg file format so that image processing and machine learning algorithms can work more accurately and interpretably. Geospatial Data Abstraction Library (GDAL) was used to convert images into jpg extension files. The obtained raw SAR image is converted from one band to three bands. With this process, our 8-bit raw image is converted to a 24-bit format. When each image band is considered as 8 bits, a 24-bit image is obtained. In this way, it was possible to express the tiff extension image in 24-bit range. As a result, the resolution quality of the image increased and the detection of small ships became easier. The function of converting a single-band TIFF image to a three-band TIFF is shown in Fig. 1.

TIFF extension images with 24-bit depth were converted to jpeg extension images with the GDAL library. This process reduced the file size of the image with minimal resolution loss. This pre-processing phases provided advantages in terms of memory management. The obtained SAR image with the dimensions of $24\,000 \times 16\,000$ was divided into sub-images of 800×800. 600 sub-images were obtained from each image. Thus, it was aimed for the effective operation of the feature extraction and classification methods to be used. The visual of this process is given in Fig. 2. As a result of the mentioned processes, a SAR ship database containing approximately 10 000 images was created. The images have been divided into two folders: those containing ships and those without ships.

```python
def convert_tiff_to_three_band(picture_name, output_name, base_path):
    options_list = [
        '-ot UInt16',
        '-b 1',
        '-b 1',
        '-b 1',
    ]
    options_string = " ".join(options_list)

    input_path = os.path.join(base_path, f"{picture_name}.tiff")
    output_path = os.path.join(base_path, f"{output_name}.tiff")

    gdal.Translate(output_path, input_path, options=options_string)
```

Fig. 1. Convert single-band TIFF image to three-band TIFF.

At this stage, each band (blue, red, and green) contains 8 bits, as a result (8 bits blue, 8 bits red, and 8 bits green), a total of 24 bits maximum value was taken. In the next stage, the TIFF image with three bands and 24 bits is converted to jpg format. The reason for this is that the TIFF format of the image is used to store raw and high quality image data. The jpg version is small/compressed in size and is used as a publication. In this way, it provides simplicity during the processing or use of machine learning and deep learning methods. Some sample images from database are given in Fig. 3.

B. The Proposed Hybrid Method

In this study, gradient calculation based on Gaussian filters was performed to obtain the differential features of each SAR image. Thus, it is aimed to precisely code pixel intensity changes between regions with and without ships. First order partial derivatives of image I are calculated with Gaussian derivative filters as follows:

$$I_x = I * G_x \tag{1}$$

$$I_y = I * G_y \tag{2}$$

G_x and G_y filters are derivative filters obtained by calculating the first derivative of the Gauss function. I_x and I_y show the horizontal and vertical derivatives of the image, respectively. Gradient magnitude was calculated as follows:

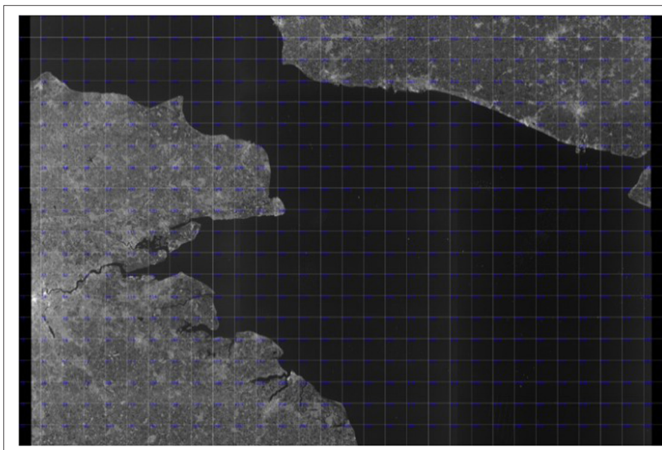

Fig. 2. Dividing a 24 000 × 16 000 synthetic aperture radar jpg image into sub-images.

$$I_{mag} = \sqrt{(I_x)^2 + (I_y)^2} \tag{3}$$

where I_{mag} refers to the gradient size. In this study, the co-occurrence matrix p was calculated using I_{mag} information.

Co-occurrence matrix is a method that extracts textural features by calculating the dependencies between color values of image pixels. With a given offset (positions of pixel pairs), the distribution of gradient orientations of the image is revealed mathematically. The co-occurrence matrix for the (x, y) offset value of an image of size mxn is seen in (4) as follows:

$$C_{i,j} = \sum_{p=0}^{n-1} \sum_{q=0}^{m-1} \begin{cases} 1 & \text{if } I(p,q) = i \text{ and } I(p+x, q+y) = j \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Some quantities extracted from the co-occurrence matrix contain information about the textural features of the image. Haralick developed 14 textural feature metrics to measure and describe different characteristics of images [19]. Contrast, entropy, correlation, and energy are the most used textural attributes. Mathematical expressions of these attributes are defined below:

$$Energy = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \left[p(i,j) \right]^2 \tag{5}$$

$$Contrast = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i-j)^2 \, p(i,j) \tag{6}$$

$$Correlation = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{i.j.p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{7}$$

TABLE I. METRICS OF THE CLASSIFICATION RESULTS (%) OF OUR MODEL AND THE HESSIAN-BASED MODEL

Method	Accuracy	Precision	Recall	F1-score
Hessian-based method [20]	94	94.93	94.78	94.76
The proposed method	96.10	96.06	95	95.40

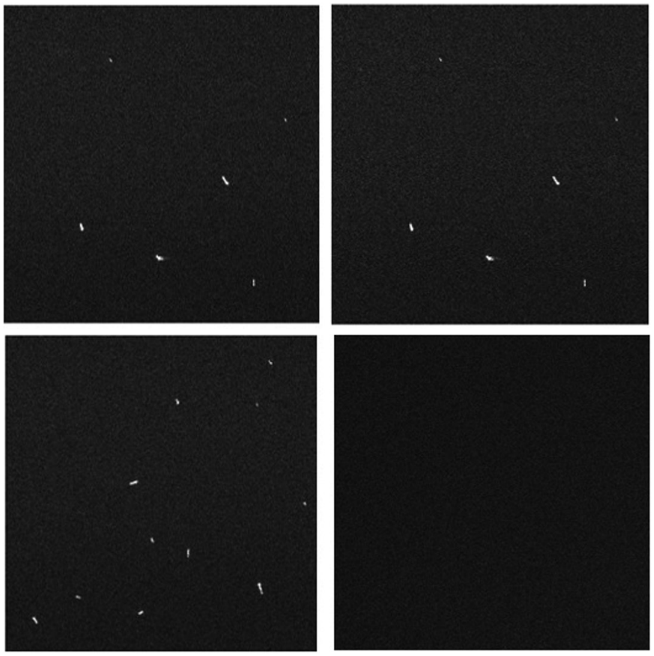

Fig. 3. Sample SAR images from our database.

$$Homogeneity = -\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{p(i,j)}{1-(i-j)^2} \tag{8}$$

where, p represents the co-occurrence matrix and G represents the number of different pixels of the image. M_x, μ_y and σ_x, σ_y represent the mean and standard deviation values of the row and column totals of the matrix, respectively.

Feature vectors of size 1 × 236 were obtained for each SAR image by using four different Gray Level Co-Occurence Matrix (GLCM) texture metrics defined above. These criteria are contrast, correlation, energy, and homogeneity. The feature vectors calculated using SAR images were given as input to the support vector machine classifier and the classification success of the method was tested. The results obtained will be discussed and interpreted together with the results of other methods in the following sections.

III. EXPERIMENTAL RESULTS

In this section, the results of the proposed method are compared with the results of a different method developed using the same database. Since the created database is new, no ship detection studies have been carried out using this database yet. For this reason, comparison studies have been limited. The constructed feature vectors were classified using support vector machines. The radial basis function was used as the kernel function in the support vector machine. Ship and non-ship images in the dataset are stored in separate folders. Therefore, the classification problem was actually addressed as binary classification. Nearly 70% of the images in the database were separated as the training set, 15% as the validation set, and 15% as the test set. Accuracy, precision, recall, and F-1 score metrics were used in comparison studies.

The results of the proposed method are compared with a method that uses the Hessian matrix and the HOG approaches [20]. In this hybrid method, Hessian matrix-based derivative analysis is performed to detect the presence of ships in the images. It is aimed to analyze the pixel changes precisely. Thus, the distribution of edge orientations within an SAR image is analyzed to obtain the shape and appearance of ship regions.

More comprehensive results of the method used can be found in Fig. 4. Thus, more detailed analysis of the results presented by the classifier has been made possible. Receiver operating characteristic curve is an evaluation method used to evaluate the performance of binary classification method. ROC results, which are an analytical method, are shown graphically. The diagnostic test results of the classifier should be classified according to one of the clearly defined binary categories such as the presence or absence of a ship. However, since many test results are presented as continuous or ordinal variables, a reference/cut-off value should be determined for diagnosis. Thus, it can be determined whether a ship is present in an image according to the cut-off value. Receiver operating characteristic curves are ideal for this process. The ROC curve results of the co-occurrence matrix-based feature calculation method proposed in this study are given in Fig. 4. As can be seen from the graphs, the proposed method has provided quite successful results. As can be seen from the curves, the curves approached 1 in each of the training, testing, and validation processes and showed that successful results were obtained. Here, the images were analyzed in two classes as ship and non-ship.

The classification problem considered is two class. This situation actually made positive contributions to the success of the method. However, there may be some weaknesses of the method in real-world problems. These limitations can be partially eliminated, especially by expanding the database. In the images in the database, ship regions are bright pixel regions. It is possible to obtain some results even with operations such as simple thresholding. However, brightness transitions in the background negatively affect the performance of the thresholding process. Therefore, it was necessary

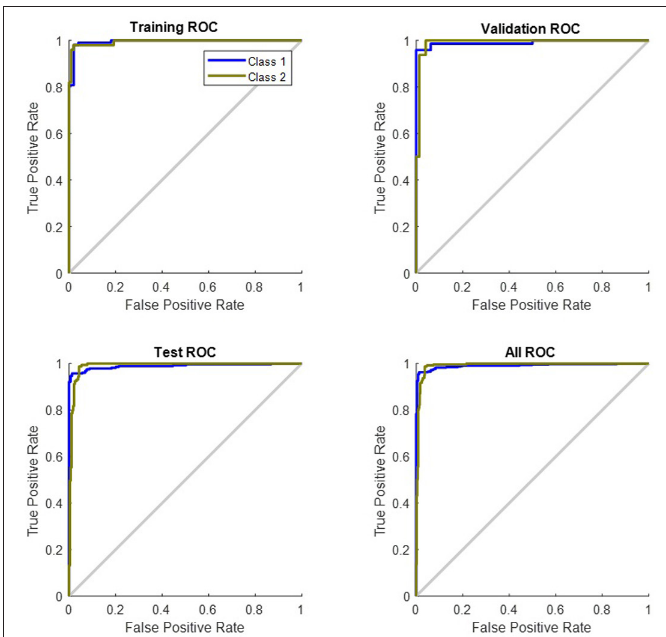

Fig. 4. Receiver operating characteristic curve results of the proposed method.

to use effective feature extraction and classification methods. The co-occurrence matrix-based method considered encoded pixel statistics quite effectively. Thus, the distinguishing feature vector could be obtained.

IV. CONCLUSION

In this study, a hybrid method has been developed for ship detection and classification of SAR images. Gradient calculation of each image has been performed on a newly constructed SAR ship database. Then, the gray-level co-occurrence matrix of the gradient magnitude is calculated. The feature vector of each image is obtained by making four statistical measurements from this matrix. All feature vectors have been classified using support vector machines. Comparison studies have shown that the proposed method classifies ship images more accurately.

The database created through future studies will be shared on a platform accessible to everyone. It is planned to develop methods that detect ships completely mathematically without using classifiers, by focusing on differential calculations for ship detection in SAR images.

There are no images of land and port/channel areas in the constructed database. However, in real-world problems, SAR images mostly include land areas and port/channel areas. Therefore, the database should include images that especially represent land areas. The current study will be developed in this respect. Data diversity will be increased by obtaining a large number of SAR images that include ship and land and sea areas. Thus, the usability of deep-learning-based methods, especially used in object detection, will be ensured.

Availability of Data and Materials: The data that support the findings of this study are available on request from the corresponding author.

Peer-review: Externally peer-reviewed.

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