CNN-based ship classification method incorporating SAR geometry information

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ABSTRACT

This paper proposes a ship classification method for synthetic aperture radar (SAR) images, which incorporates SAR geometry information into a convolutional neural network (CNN). Most of the conventional methods for ship classification employ appearance-based features. These features extracted from SAR image are not robust to a geometry change because the geometry difference significantly changes the appearance of target objects in SAR images. CNN has a potential to handle the variations in appearance. However, it requires huge training data, which is rarely available in SAR, to implicitly learn geometry-invariant features. In this paper, we propose a CNN-based ship classification method incorporating SAR geometry information. We focus on the incident angle information that is included in a metadata because incident angle change directly affects the appearance of objects. The proposed method enables a network to learn a relationship between the appearance and SAR geometry by utilizing the incident angle information as a condition. Experimental results show that the proposed method improves the classification accuracy by 1.1% as compared to the conventional CNN, which does not utilize incident angle information. Furthermore, our method requires 25% less training data as compared to the conventional CNN to achieve 70% classification accuracy.

Keywords: incident angle, ship classification, synthetic aperture radar, convolutional neural network, OpenSARShip

1. INTRODUCTION

In recent years, ship monitoring technology has a great demand due to increasing ship traffic, marine transportation, maritime accidents, and illegal maritime activities. Ship detection and classification by spaceborne synthetic aperture radar (SAR) attracts attention as one of key functionalities to achieve the efficient ship monitoring because SAR has all-weather and day-and-night acquisition capability, and a wide spatial coverage. Typical workflow for ship monitoring involves two steps. First, a ship is detected as a bright cluster in a SAR image. Second, the detected ship is classified into various categories such as commercial, military and fishery vessels. This workflow helps in quick identification of ships and then take immediate action against those who indulged in illegal activities.

Two popular methods for ship classification using SAR imagery are hand-crafted feature (HCF)-based method, and convolutional neural network (CNN)-based method. In the HCF-based method, features are manually designed for discriminating the appearance of different ships[1-4]. Some features describe shape parameters of a ship such as length, width, perimeter and area, while others describe backscatter patterns such as width-ratios, auto-correlation, and mean intensity. However, these features are not robust to changes in SAR geometry such as incident angle. This is because these features depend on appearance of ships that is highly affected by changes in SAR geometry.

Recently, great progress has been achieved by CNN-based method in image classification task[5]. CNN-based method automatically extracts features through a hierarchical feature learning process to discriminate different types of targets. Bentes et al.[6] applied CNN for maritime target classification and has shown effectiveness of the approach. CNN can represent a model of the target with automatically extracted features. If huge training dataset is given, the representability of CNN is significantly high. On the contrary, if training dataset is limited, CNN overfits to the training data and loses generality.

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In case of SAR images, the appearance of ship changes as SAR geometry changes. In order to achieve robust classification to the changes, CNN needs to learn all representations of the ship appearance. However, a training dataset covering all appearance is rarely available in SAR because of mainly two reasons. First, a SAR image is expensive and cannot be captured as often as an optical camera image. A SAR system has its own antenna to radiate and receive electromagnetic radiations, which makes it costlier and bulkier than an optical system. Second, interpretation of a SAR image is difficult even for an expert. Presence of speckle noise and geometric distortions result in a different representation of an object in a SAR image as compared to an optical image. This makes the interpretation and annotation of SAR images difficult. Thus, the number of SAR image dataset used in the training phase is often limited. As a result, the representation of the object learnt by a CNN is not always exhaustive.

In this paper, we propose to utilize the metadata of an input SAR image to increase the information quantity. As a metadata, we select incident angle information because it directly affects the appearance of ships, and also it is often provided along with a SAR image itself. In the proposed method, incident angle information is fed into a CNN along with the corresponding SAR image to learn a relationship between the incident angle and the appearance of ship. This relationship enables the CNN to explicitly disentangle the variations in appearance of the ship. The incident angle of each ship can be computed by interpolating the near-range and the far-range incident angles obtained from the metadata. The computed incident angles are then divided into bins to efficiently analyze their distribution and converted into vectors using one-hot encoding. Meanwhile, a ship image is input into a CNN to automatically extract appearance-based features. These features are merged with the corresponding incident angle vector so that the CNN learns a relationship between the appearance and SAR geometry using incident angle information as a condition. As a result, the CNN learns a geometry-invariant representation of the ship without requiring huge training data.

The remainder of the paper is organized as follows. Section 2 describes the conventional methods for ship classification and their limitations. Section 3 explains the proposed method. Section 4 presents the experiments describing dataset, experimental settings and evaluation metrics. Section 5 presents results and discussion of the experiments. Finally, the conclusion is drawn in Section 6.

2. CONVENTIONAL METHODS AND THEIR LIMITATIONS

2.1 Conventional Methods

2.1.1 Hand-crafted Feature (HCF)-Based Method

HCF-based method [1-4] is based on manually designing features for discriminating ships using domain knowledge. Different types of ship show discriminative geometric and scattering properties due to their scattering structures. Based on these properties, features of shape, intensity and texture have been proposed which are unique for a ship type. For example, a shape feature such as length is helpful to distinguish a fishing boat from a cargo ship due to the difference of their size. Whereas, a mean intensity feature is helpful to distinguish a cargo ship and a tanker ship due to their unique backscatter patterns. A cargo ship shows bright backscatter due to cranes on its surface used for loading and unloading cargo, while a tanker shows relatively dark backscatter due to its flat surface. In order to manually extract such discriminative features, an expert knowledge about ships is required.

2.1.2 Convolutional Neural Network (CNN)-Based Method

CNN is a type of deep neural network (DNN) where the neurons are shared and connected locally. Due to the local connections between neurons, the network is optimized to work with images and takes into account the correlation among neighboring pixels. Weights of the neurons are optimized to learn unique patterns from the images in a hierarchical manner. Initial layers of the network learn simple features such as edges, while later layers learn complex features such as corners which are built on the simple features. Due to this hierarchical learning process, CNN automatically learns optimum features from image itself without the need of domain knowledge. Currently, CNN is the state-of-the-art in image classification task [5].

Most of the previous studies have applied CNN in SAR images for military tank recognition using the benchmark MSTAR dataset[7, 8]. Recently, CNN has been employed for maritime target recognition for targets such as ships, windmills, and has shown good performance[6]. Our previous study compared a DNN-based method with the HCF-based method and proved the superiority of the former in ship classification[9].

2.2 Limitations

Features extracted by the HCF-based method are not robust to SAR geometry variations. This is because they are based on appearance of ships. The appearance highly depends on SAR geometric condition. It is possible that ships from different types appear similar while ships from the same type appear totally different with the changes in geometric condition. As a result, the features lose their discriminative ability with such variations in the appearance. There are several factors that affect the appearance of a ship in a SAR image, incident angle change is one such key factor. An example of a cargo ship imaged under two different incident angles is shown in Fig. 1. The figure shows that the same ship appears quite different as incident angle changes.

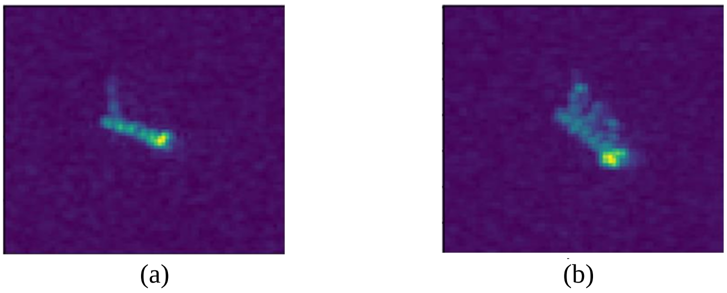

Figure 1. Appearance of a cargo ship at incident angle (a) θ = 30 degrees, and (b) θ = 40 degrees.

The difference in appearance is caused by different projections of the scattering points. To illustrate this fact, Fig. 2 shows an object imaged by a SAR sensor O at two different incident angles θ_1 and θ_2. As the incident angle changes, projections of the object's main scattering points A, B and C on SAR image plane change. At θ_1, B is closer to the SAR sensor followed by A and then C. Thus, the points are imaged in the order B, A and C, and their projections are denoted by B1, A1 and C1 respectively. Now as the incident angle increases from θ_1 to θ_2, the distance of the scattering points to the SAR sensor change. At θ_2, A is closer to the SAR sensor as compared to B while C lies completely in the radar shadow. Consequently, the points are imaged in the order A followed by B, and C is not imaged. Their projections are denoted by A2 and B2 respectively. These projections of the scattering points forms an appearance of the object in a SAR image. Thus, incident angle change causes different projections of the scattering points which results in different appearance of the object in a SAR image.

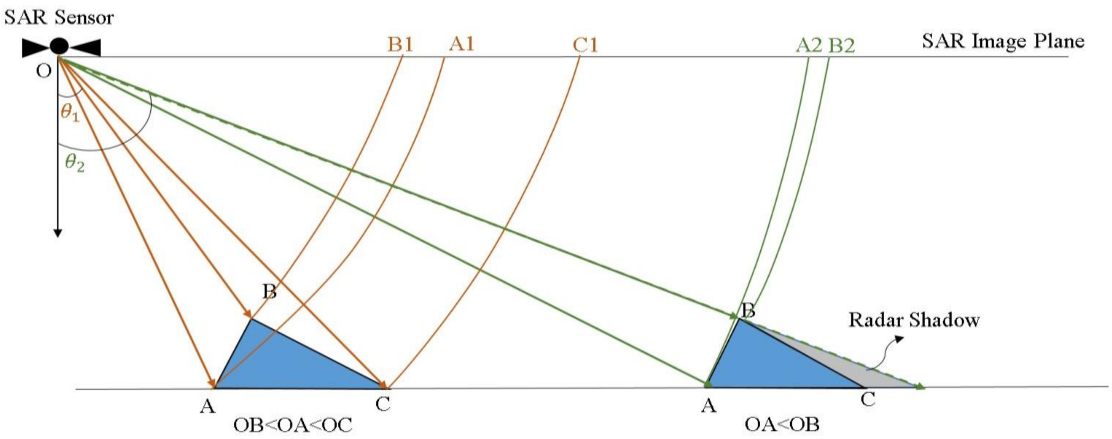

Figure 2. Relationship between projection of scattering points and incident angle.

As compared to the HCF-based method, CNN-based method learns better features in ship classification. CNN can extract discriminant features of a ship by learning a representation of the ship in each SAR geometry condition from given training data. However, in order to learn all possible representations, CNN requires huge training data which should include images captured under all geometry conditions. As discussed, training data in SAR images is small due to high observation cost and difficulty in interpretation, the CNN-based method cannot always extract optimum features.

3. PROPOSED METHOD

We propose a ship classification method which incorporates incident angle as an additional information about a SAR image in a CNN. The incident angle information is a dominant factor which affects the appearance of a ship. Conditioning a CNN using incident angle enables to explicitly disentangle the discriminant feature information and geometric information in feature space. A block diagram of the proposed method is shown in Fig. 3.

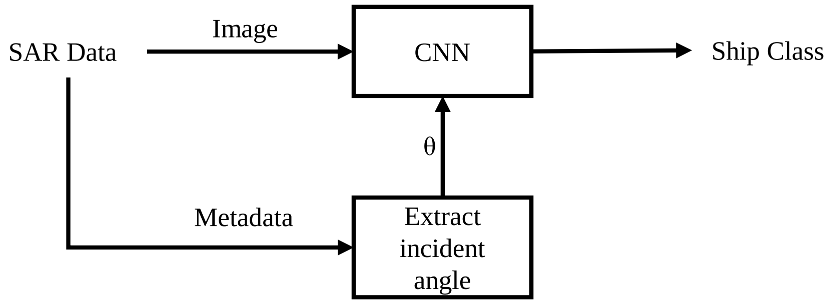

Figure 3. Block diagram of proposed method.

The proposed method takes a ship image and the corresponding incident angle information as inputs with the goal of learning a relationship between them to disentangle the features from geometry variations, and outputs a ship class. The incident angle information is extracted from the metadata which is available along with the SAR image. Since the incident angle information is provided explicitly, the proposed method can achieve geometry-invariant features even with small training data.

3.1 Extraction of Incident Angle Information

Incident angle information is extracted from the metadata provided with a SAR image. The metadata consists of near range and far range incident angles. Range is the line of sight distance between the SAR sensor and the target object. Near range refers to the portion of the SAR image which is closest to the satellite flight direction while far-range refers to the portion farthest from the satellite flight direction. The incident angles for all the pixels in between the near-range and the far-range are computed using non-linear interpolation methods such as bilinear, cubic or nearest-neighbor interpolation method. After interpolation, we obtain an incident angle map. Note that the curvature of earth surface is assumed flat when extracting the angles because the monitored area is generally very small as compared to the satellite height. An example of a SAR image and its incident angle map is shown in Fig. 4.

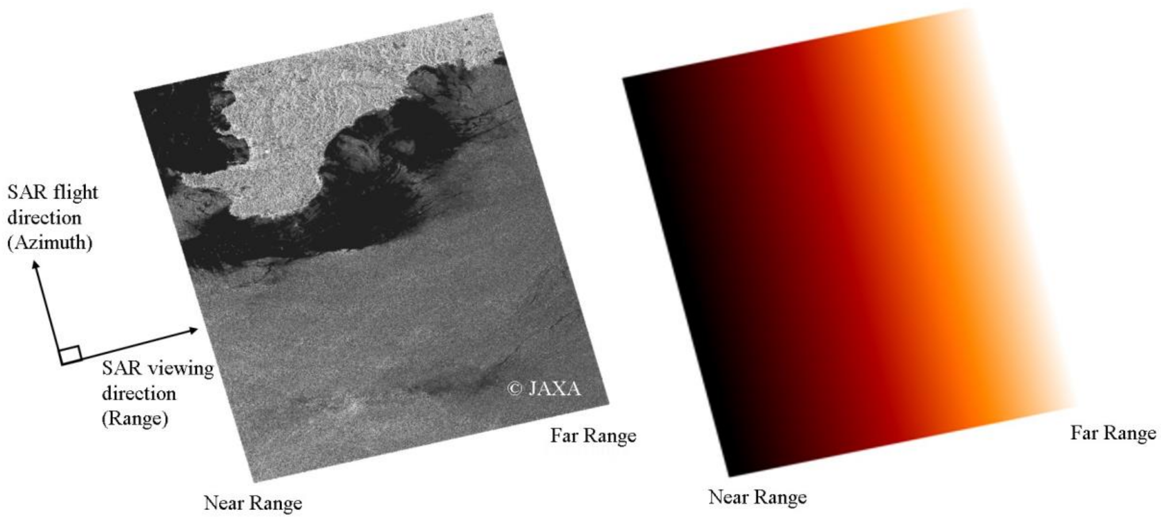

Figure 4. Example of a SAR image by ALOS and the corresponding incident angle map. Near range angle is 25 degrees (black) and far range angle is 40 degrees (yellow). Incident angles at other pixels are linearly spread between 25-40 degrees.

The map contains incident angle at each pixel and shows a variation of incident angles in the entire image. Dark red color indicates small incident angles while lighter red color indicates large incident angles. From this map, incident angle corresponding to each ship location is extracted. Note that the ship locations are obtained in the detection process which is conducted before classification. The proposed method converts the incident angle, which is a real number, into a meaningful information by first assigning it a label and then converting the label into a one-hot-encoded vector. The process of assigning labels is called binning. Equally spaced bins are created between the range of incident angles in the image. For example, for the range of 25-40 degrees, we create three bins as 25-30, 30-35 and 35-40 degrees, and assign them numeric labels as 1, 2 and 3 respectively. Each angle is categorized into one of the bins and assigned a label. The number of bins are decided based on an empirical analysis which is detailed in Section 5.3.

3.2 Network Architecture

The network architecture of our proposed method is shown in Fig. 5, which inputs a SAR image and the corresponding metadata and outputs a vector containing a probability to belong to each class.

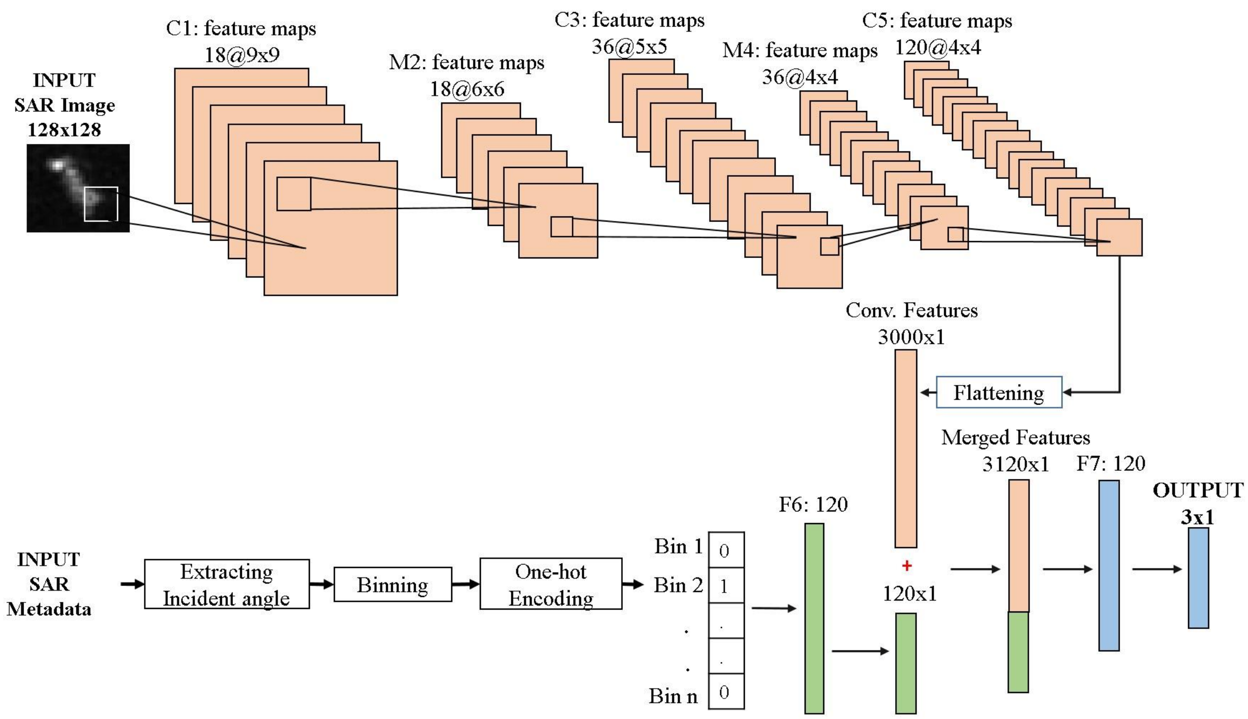

Figure 5. Network architecture of proposed method.

The network consists of three convolutional layers (C1, C3, and C5), two max-pooling layers (M2, M4) and two fully-connected layers (F6, F7). Batch-normalization and dropout are applied after each convolutional layer to avoid over-fitting. RELU non-linearity is used at each convolutional layer to extract the appearance-based features from the input SAR image. The key point in the network is the concatenation of incident angle information and the features extracted by the convolutional layers. First, the incident angle is extracted from SAR metadata provided along with the image. The angle is converted into a meaningful information by binning and one-hot-encoding. The one-hot-encoded vector is passed through a fully-connected layer (F6) to represent the angle information as features. These features are merged with the features extracted by the convolutional layers through concatenation. The merged features are fed into a fully-connected layer (F7) with softmax loss so that the network learns a relationship between the appearance and the SAR geometry to achieve a geometry-invariant feature representation. Finally, using such representation, a probability to belong to each class is assigned.

4. EXPERIMENTS

4.1 Dataset

A public dataset of ships OpenSARShip[10] is used in our experiments. The images of ships are collected from Sentinel-1 having 20 m spatial resolution and VH polarization. They are labelled using automatic identification system (AIS) messages into 11 classes. Out of these classes, we selected container, bulk-carrier and tanker as our target classes because they cover 80% of the maritime traffic. The total number of images are 1371 with container, bulk-carrier and tanker having 213, 812 and 346 images respectively. From each class, 200 images are randomly selected in experiments to avoid data imbalance. Further, the images are normalized to reduce variance in their intensities. Incident angle is extracted from the SAR metadata available with the corresponding image. A few SAR images from the dataset and their corresponding optical images are shown in Fig. 6. In this dataset, the incident angles are provided along with the images. Thus, the incident angle map is not generated.

(a) (b) (c)

Figure 6. Sample images from OpenSARShip dataset (a) Container, (b) Bulk-carrier, and (c) Tanker. Left image: optical image (for reference), and right image: SAR image from the dataset.

4.2 Experimental Settings

We have compared our proposed method with the HCF-based method and the CNN-based method. For HCF-based method, several geometric and backscattering features need to be extracted from the ship images. Backscattering features are not useful in low resolution SAR images of Sentinel-1[4]. Therefore, we extracted geometric features which are listed in Tab. 1. The description about the features and their extraction process can be found in [3]. These features are fed into a support vector machine (SVM) classifier to classify the images into the three classes. The parameters of the SVM classifier are selected using grid-search and five-fold cross-validation.

For CNN-based method, we used the same architecture as of the proposed method except for inputting incident angle information. Thus, the conventional CNN-based method takes only SAR image as an input. The size of the input image is set to 128×128 in both the networks. The size of the output class vector is 3×1 which gives a probability to belong to each class. The hyper-parameters (learning rate, number of epochs, batch-size, dropout-ratio and momentum of batch-normalization layer) used for training each network are listed in Tab. 2. In the proposed method, the incident angles are divided into eight bins prior to using in the network. The number of bins is based on an empirical analysis which is discussed in Section 5.3.

To avoid any bias due to random splitting of dataset into training and testing data, we used five-fold cross-validation in each method and averaged the experimental results over 10 trials with different initial random seed. The networks are implemented using Keras library[11]. We evaluated the methods based on overall accuracy, precision, recall and f-measure.

Table 1. Hand-crafted features for HCF method.

Feature	Formula	Feature	Formula
Length	L	Compactness	$P / 2\pi L$
Width	W	Elongatedness	L / W
Perimeter	$2 \times (L + W)$	Aspect Ratio	W / L
Area	LW	Centroid X	M_{10} / M_{00} , M_{ij}: image moments
Shape Complexity	$P^2 / 4\pi A$, P: perimeter	Centroid Y	M_{01} / M_{00} , M_{ij}: image moments

Table 2. Hyper-parameter setting for CNN and proposed method.

Hyper-parameter	Value
Learning rate	0.0001
No. of epochs	40
Batch-size	32
Dropout ratio	0.2
Momentum	0.6

5. RESULTS AND DISCUSSION

5.1 Effectiveness for ship classification

The overall accuracy of the methods for three-class classification is shown in Fig. 7. The figure shows that the proposed method outperforms the CNN-based method, which excludes incident angle information, by 1.10% and HCF-based method by 11.25% respectively. Although, the improvement with respect to the conventional CNN-based method is not significantly large, the result shows that conditioning with incident angle information has the potential to improve classification accuracy. Other evaluation measures such as precision, recall and f-measure are depicted in Tab. 3. The table shows that the proposed method achieves the superior performance in bulk-carrier and tanker. When SAR geometry changes, the appearance of bulk-carrier changes due to different projections of its cranes while that of a tanker changes due to different projections of its oil pipeline. The conventional methods using appearance-based features are unable to extract features robust to the geometry changes. Whereas our method can extract robust features by conditioning the CNN using incident angle information which improves the classification performance. In case of container, HCF is giving the best performance. The appearance of a container does not vary significantly even when SAR geometry changes due to symmetrical boxes on its surface. At a low-resolution of 20 m, discriminative patterns of container are difficult to extract. Therefore, CNN-based methods, which are based on pattern-recognition, could not achieve better performance.

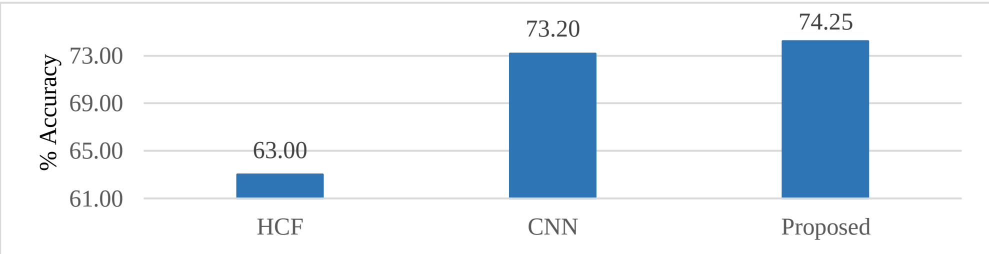

Figure 7. Comparison of overall accuracy.

Table 3. Comparison of precision, recall and f-measure.

(a) HCF

Class	Precision	Recall	F-measure
Container	0.77	0.70	0.74
Bulk-carrier	0.54	0.57	0.56
Tanker	0.59	0.61	0.60
Avg. total	0.63	0.62	0.62

(b) CNN

Class	Precision	Recall	F-measure
Container	0.73	0.65	0.69
Bulk-carrier	0.72	0.72	0.72
Tanker	0.73	0.81	0.77
Avg. total	0.73	0.72	0.72

(c) Proposed

Class	Precision	Recall	F-measure
Container	0.74	0.68	0.71
Bulk-carrier	0.73	0.75	0.74
Tanker	0.75	0.82	0.79
Avg. total	0.74	0.74	0.74

5.2 Effect of training data size on classification accuracy

We compared the classification accuracies of the proposed and the CNN-based method for different training data size as shown in Fig. 8. In the figure, the size of the training data is represented as a percentage. Different percentage are obtained by randomly splitting the total training data. The figure shows that the proposed method requires smaller number of training data as compared to the CNN-based method to achieve equivalent performance. For example, to achieve 70% accuracy, the CNN-based method requires around 50% of the total training data while the proposed method requires only 25% of the total training data. Moreover, the proposed method achieves 3% higher classification accuracy when using only 20% of the total training data. This shows that incident angle information serves as an additional discriminative information when the training data is limited and results in higher classification accuracy.

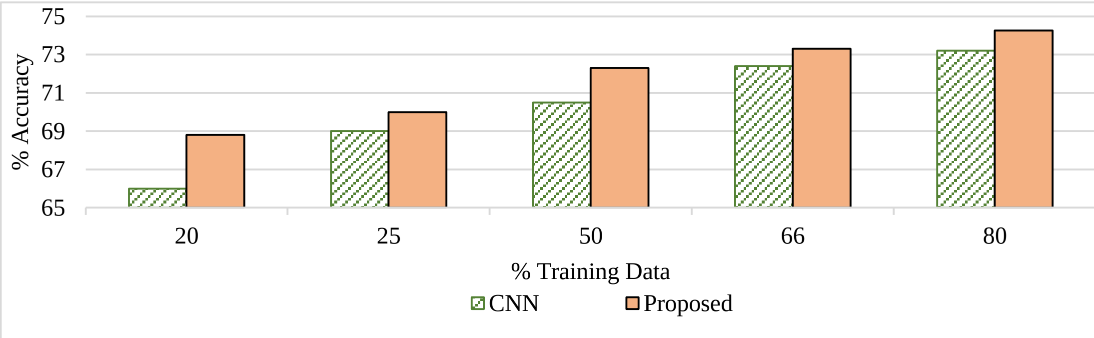

Figure 8. Effect of training data size on classification accuracy.

5.3 Effect of incident angle binning separation

In our proposed method, it is required to quantize the incident angles into several bins. To obtain an optimal number of bins, an empirical analysis has been done. Figure 9 shows the effect of the number of incident angle bins on the classification accuracy. The figure shows that eight bins results in the highest classification accuracy. Less number of bins results in loss of information, while too many bins result in increased sparsity and noise. In both these cases, classification accuracy of the proposed method degrades. Eight bins give the highest classification accuracy of 91.50%. Thus, we have used eight bins to quantize the incident angles.

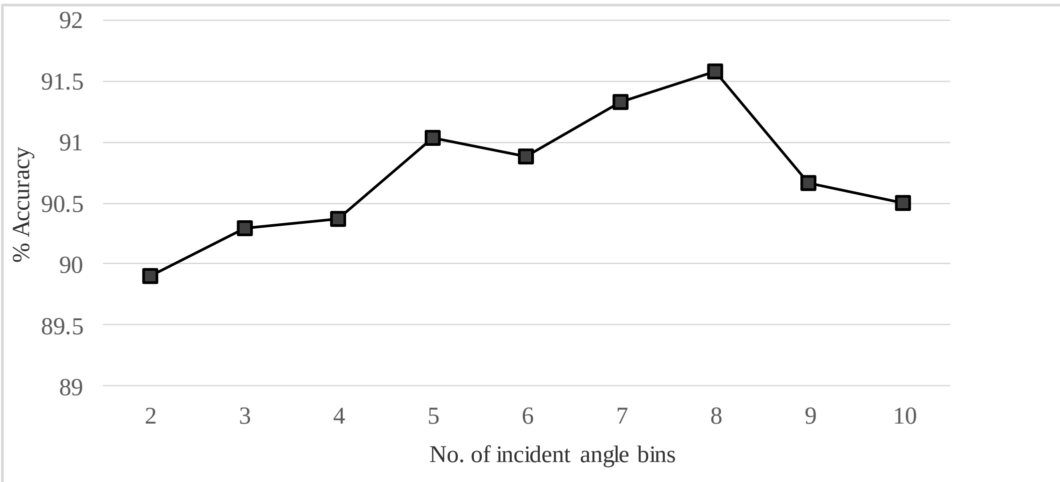

Figure 9. Effect of number of incident angle bins on classification accuracy.

6. CONCLUSION

A CNN-based ship classification method incorporating incident angle information has been proposed. The incident angle is extracted from SAR metadata and converted into a useful information through binning and one-hot encoding. The incident angle information is used to condition a CNN so that it can separate discriminant feature information and geometry information in feature space. This enables the CNN to learn geometry-invariant features from small training data. Experiments have been conducted for three-class ship classification into container, bulk-carrier and tanker using OpenSARShip dataset. The experiments conclude that the proposed method outperforms the conventional CNN-based method, which excludes incident angle information by 1.10% and a hand-crafted feature based method by 11.25% respectively. Moreover, for a given number of SAR images, the proposed method requires 25% less training data as compared to the CNN without incident angle information to achieve 70% classification accuracy. Future research will include exploring other SAR metadata information for small data learning and testing the method for more challenging classes such as fishing vessels.

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