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REVIEW

Ship detection and classification from optical remote sensing images: A survey

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Abstract Considering the important applications in the military and the civilian domain, ship detection and classification based on optical remote sensing images raise considerable attention in the sea surface remote sensing filed. This article collects the methods of ship detection and classification for practically testing in optical remote sensing images, and provides their corresponding feature extraction strategies and statistical data. Basic feature extraction strategies and algorithms are analyzed associated with their performance and application in ship detection and classification. Furthermore, publicly available datasets that can be applied as the benchmarks to verify the effectiveness and the objectiveness of ship detection and classification methods are summarized in this paper. Based on the analysis, the remaining problems and future development trends are provided for ship detection and classification methods based on optical remote sensing images.

1. Introduction

Ship as the key transportation tool on the vast ocean always raises much attention. The application of ship detection and classification provides essential information for strategic decision-making, thus can effectively shorten the decision-making cycle, which is an important basis for real-time battlefield situation awareness in wide range of operational environments.[1–3] With the development of remote sensing imaging technology, the monitoring of the wide-range sea surface has become possible, which arises extensive research interest in marine target detection and classification technology.[4–6]

Ship detection and classification techniques have great application value in military and civilian domains. In the civil field, it is the basis for implementing the supervision of marine resources, monitoring illegal fishing, and assisting in the maritime rescue, etc.; in the military field, it can be applied to patrols, interests and rights protection in territorial sea region, and monitor important ports, and targets.[4,7] For example, the U.S. Navy undetectably sent the John C. Stennis carrier strike group into the South China Sea and kept radio silence in March 2016 by intentionally close radio communication systems to prevent the detection and identification by the ground electronic radar.[8] If remote sensing monitoring deployed in that circumstance, continue tracking the aircraft carrier battle group is achieved even when the targets are undetectable in other monitoring system.

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In recent years, with the rapid development of satellite remote sensing imaging technology, ship targets detection and classification from remote sensing images become an important application direction of remote sensing target recognition. Optical remote sensing images are conducive to human visual interpretation, so they are more useful for observing the earth's dynamic surface.[9] Therefore, ship detection and classification based on optical remote sensing images are of main importance in future research and development.

The main contributions of this paper are as follows: (A) a comprehensive review on most popular techniques for both ship detection task and classification task from optical remote sensing images is provided; (B) the publicly available datasets for ship detection and classification on aerial view satellite images are thoroughly collected; (C) experimental results of the state of the art methods for ship detection and classification on publication dataset are compared and discussed; (D) challenges in ship detection and classification from optical remote sensing images and possible futuristic trends are analyzed and discussed.

In this literature, the term 'optical remote sensing images' includes panchromatic remote sensing images (PAN) and multispectral remote sensing images, which mainly contain Blue (B), Green (G), Red (R), Near-Infrared (NIR) bands, additionally, satellite WorldView-2 also contains four new color sensors, Red Edge (RE), Coastal (C), Yellow (Y), and Second Near-Infrared (NIR2) bands. In addition, some multispectral remote sensing images were also included infrared imaging remote sensing images, that are Short-Wavelength Infrared (SWIR), Mid-Wavelength Infrared (MWIR), and Thermal Infrared Sensors (TIRS). As for the notions, 'ship' refers to the man-made objects that sail on the sea surface. As for the term 'object detection' in remote sensing images refers to visible man-made objects in the images covering a variety of targets, such as ship, airplane, vehicle, etc. Although the majority of authors use the term 'ship detection' in their research, the expression 'sea target detection' or 'object recognition in ocean imagery' is also used to represent ship detection. All these terms will be deployed throughout this paper without an intended difference in meaning.

The remainder of this paper is organized as follows. In Section 2, chronological statistic on literatures of ship detection and classification methods is presented, and each procedure in the whole workflow is introduced. Typical methods in preprocess stage and detection and classification stage are systematically analyzed in Section 3. Besides, different levels in the classification stage are also narrated in this section. In Section 4, publicly available datasets are collected and introduced. Experimental results of some representative methods on one public dataset are provided and some issues in ship detection and classification are summarized in Section 5. Conclusions are drawn in Section 6.

2. Statistics

The analytical description in this paper is based on the collection of 153 papers (lists in Table A1 in the Appendix A) on ship detection and classification published from 1978 to July 2020, which describes the experimental results of their methods on optical satellite images. Comparative statistics and analysis between traditional feature-designed methods and the deep Convolutional Neural Networks (CNN)[10] architecture based methods are introduced in this section, which is expected to lay the foundation for subsequent research.

2.1. Statistics on workflow of ship detection and classification

According to the statistics, the "Coarse-to-fine" two-stage detection scheme [11,12] is the classic processing framework on ship target detection for remote sensing images as shown in Fig. 1, which mainly includes three basic steps: image preprocessing, candidate target extraction, and target identification or classification. The one-stage detection scheme also applies in some methodologies, which completes the extraction of target candidates and identification or classification process in one step. (E.g. Refs.[13–16]) When the target is relatively large in the image to be detected, this scheme can obtain comparable efficiency with the two-stage detection scheme in the target detection task. However, in terms of time and computational saving, the two-stage detection scheme shows its superiority in treating wide-spread small target detection as in remote sensing images.[11,12,17] Therefore, the overview of existing detection algorithms in this section mainly focuses on the "Coarse-to-fine" two-stage detection scheme. The narrative of the one-stage scheme methodologies is placed in the process of target identification or classification in the following section. Some early literatures treat the term "ship classification" as the differentiation between real ship-targets and non-ships among ship candidates (E.g. Refs.[6,11,18–20]), which may cause misunderstanding of this term. To be clarifying, in this paper, the term "ship identification" denotes the distinction between ships and non-ships; the term "ship classification" indicates the distinction among different types of ship-targets.

(1) Image preprocessing

The most common processing in this step is the sea-land segmentation based on Geographic Information System (GIS) technology (E.g. Refs.[21–26]), because of the prior knowledge that large ships only appear in the marine area. The main advantages lay in this process are: firstly, reducing the computation time of feature extraction by narrowing traversal area of the core detection algorithm; secondly, improving detection precision by elimination of false detected targets caused by land part with complex texture features. Except for the sea-land segmentation process, the cloud filtering process is also applied in some ship detection and classification methods (E.g. Refs.[4,25–28]), aiming to provide reliable detection results in optical remote sensing images taken under cloudy and foggy weather conditions.

(2) Ship candidate extraction

Because the remote sensing image contains a vast sea area, the ship is relatively small and difficult to spot in the imaging result due to the image spatial resolution and the sparse distribution of targets.[29,30] If the dense feature extraction and calculation algorithms are directly executed in the entire sea area, the computational and time consumption will increase drastically. Therefore, most ship detection methods apply a "Coarse-to-fine" two-stage detection scheme. (E.g. Refs.[11,12,19,21,31]) Ship candidate extraction is the "coarse"

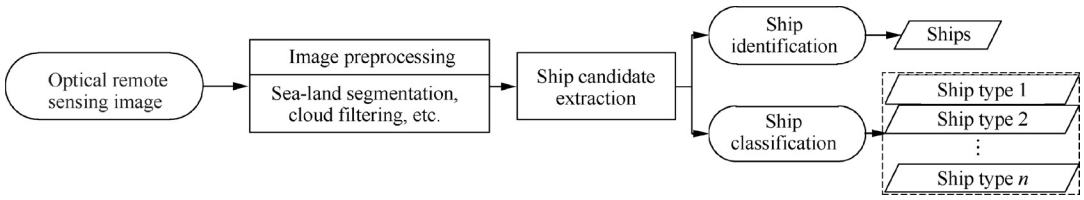

Fig. 1 A common ship detection and classification workflow from optical remote sensing image.

stage, which utilizes a relatively simple computational feature descriptor to exclude most image regions without targets retaining possible target image blocks for further identification in the next step.

(3) Ship identification and classification

The early published literature focuses its research purpose on ship identification because of the low spatial resolution of remote sensing imaging. (E.g. Refs.[6,11,13,18–20,23,32]) In the recent few decades, sophisticated ship classification methods emerge in response to the improvement in spatial resolution of the optical remote sensing imaging. (E.g. Refs.[33–37]) Therefore, ship identification and classification methods are introduced together in the following section. In this step, the common use of features such as shape, texture, and structure is to identify ships or the type of ship.

2.2. Statistics on methodologies of ship detection and classification

The CNN technology is applied in ship detection and classification of remote sensing image tasks increasingly since it demonstrates its powerful feature representation abilities in 2015.[38] For a better understanding, the term "CNN structure design based method" used in this paper refers to a method that focuses on designing and improving the CNN architecture for ship detection and classification; on the other hand, the term "feature design based method" refers to a method that focuses on designing feature descriptions for ships or backgrounds. Consequently, it provides statistical data on the number of publications, CNN structure design based methods, and feature design based methods in years respectively according to the literature collection mentioned above, as shown in Fig. 2. The feature design based methods dominant the early ship detection and classification research. However, ship detection and classification based on CNN structure design attract majority research attention in recent years as the development of CNN technology.

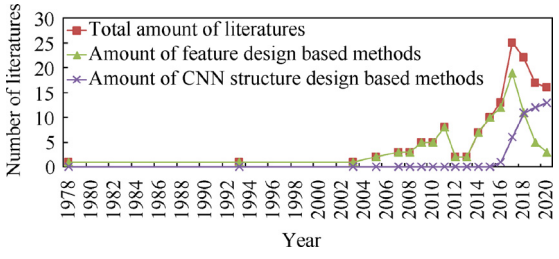

Fig. 2 Literature collection statistics compiled from 1978 to May 2020.

The research boom of ship detection and classification appears in 2017 and then slightly downwards as can be seen in Fig. 2. This is the result of continuous improvement in the spatial resolution of optical remote sensing imaging. That improvement realizes imaging meaningful yet once unidentifiable targets such as airplanes and vehicles, which attract the attention of researchers. Ship target, thereby, is regarded as one of the categories of object detection from remote sensing images.

3. Analysis

In this section, the main application techniques in each step are demonstrated in accordance with the general process sequence for performing ship detection and classification.

3.1. Methodology for image preprocessing

In the procedure of image preprocessing, commonly used operations are sea-land segmentation, and cloud filtering, aiming at reducing the environmental influence during target detection procedure.

3.1.1. Sea-land segmentation

Five basic methods lay in general utilized sea-land segmentation technology in ship detection and classification: (A) coastline matching method with the information stored in Geographic Information System (GIS); (B) regional homogeneity classification in the image; (C) methods based on the statistical model; (D) methods based on deep learning model; (E) methods based on normalized difference water index. Details of each basic method are narrated in the following.

(1) Coastline matching method

These methods mainly match the geographic location of the input image with that in GIS. The precision of its segmentation results only depends on the spatial resolution of the coastline stored in the GIS library and the accuracy of the imaging satellite positioning solution. It does not depend on the imaging quality, weather conditions or sensors. The disadvantage of these methods is that the geographic information of candidate areas is unavailable in some cases; besides, the available geographic coastline information may be outdated. The source of the coastline in GIS comes from the digital elevation model or digital terrain elevation data. The spatial resolution of the Shuttle Radar Topography Mission (SRTM) for global coverage is about 30 m, which achieves the highest possible

resolution of global topographic data.[39] Although this spatial resolution of the coastline is sufficient to perform sea-land segmentation in satellite images of less than thirty meters resolution, it is far from the needs of sea-land segmentation in high spatial resolution satellite images.

(2) Regional homogeneity classification

The initial step of the sea-land segmentation methods based on regional homogeneity classification is seed selection. Then the adjacent regions of the selected seed points are collected based on feature descriptors, and finally, the entire image is segmented.[30] Therefore, the seed selection is very vital in determining the segmentation results. Improper seed selection may lead to disastrous segmentation results. The segmentation results are also susceptible to weather conditions, sediment content in seawater, and sea surface reflections.

(3) Methods based on statistical model

These methods establish statistical models based on the histogram of sea regions to approximate the intensity distribution of sea pixels and then determine the segmentation threshold of the sea area.[40,41] Sea-land segmentation based on these methods generally works well in most cases but will misclassify sea regions with abnormal intensity due to environmental factors. In most cases, these methods usually misclassify the land covered by cloud shadows as the sea.

(4) Methods based on deep learning model

With the application of deep learning technology in the field of image segmentation, sea-land segmentation methods based on CNN technology have emerged in recent years.[42–44] In order to obtain a CNN based sea-land segmentation model, it is necessary to manually label the coastline samples at pixel-level on the image for the model training. The performance of these methods is relatively stable in resisting environmental factors in the image when performing segmentation. Comparing with methods based on statistical models or regional homogeneity classification, it obtains relatively higher precision in segmentation in most cases. However, it is easy to misclassify regions with complex contours and consume much more resources for computation and storage.

(5) Methods based on normalized difference water index

To perform sea-land segmentation, these methods take advantage of the reflectance ratio from two different bands in the multispectral image to enhance the difference between sea and land.[32,45] However, the threshold applied to the ratio map for segmentation varies among different sensors. It needs to be adjusted when applied in images produced by other sensors. These methods are applicable to multispectral remote sensing images exclusively.

3.1.2. Cloud filtering

Optical remote sensing imaging is inevitably affected by weather conditions such as cloudy and foggy, which introduces interference within ship detection and classification and arouses false alarms.[27] Therefore, it is crucial to suppress the influence of clouds and fog on optical remote sensing images when performing ship detection and classification tasks. There are three common methods in cloud filtering: (A) cloud mask threshold based on the Gaussian distribution model;[4,25] (B) threshold segmentation based on band ratio;[26] (C) cloud filter based on Fourier transform.[27,28]

There are two fundamental assumptions of the first method: the gray-scale values of the image follow the Gaussian distribution; cloud pixels mostly correspond to the brightest pixels in the images.[4] For thick cloud imaging in panchromatic images, most of their pixels reflect high intensity, but this is not always the case.

Band ratio between the NIR and B band is applied to perform threshold segmentation to eliminate clouds in multispectral images. The basic assumption behind it is that cloud pixels dominant to the top portion of the histogram.[26]

Cloud tends to extend spatially in low frequency component of the image, therefore, the center of the Fourier transform of the image containing the cloud raises sharply. Then the cloud filter is established by taking advantage of such feature to set the signal-to-noise ratio threshold.[28] However, it is easy to remove ships beneath the cloud in the process of cloud filtering.

3.2. Methodology for ship detection and classification

According to the statistics of literature collation in this paper, the following introduces ship detection and classification methods from two aspects: CNN structure design based methods and feature design based methods.

3.2.1. Feature design based methodology

According to the statistics, ship detection and classification methods based on feature design generally adopt to the two-stage scheme, which includes ship candidate extraction and ship identification. There are basically two kinds of features in feature design based methodology, i.e., global feature and local feature. As shows in Fig. 3, a feature design based detector in two-stage manner usually applies both global feature and local feature combined with a discriminator; while a one-stage feature design based detector applies either global feature or local feature for discriminator. In ship candidate extraction stage, there mainly are six basic techniques: (A) threshold segmentation based on the statistical model; (B) background separation based on saliency; (C) anomaly detector; (D) background separation based on frequency analysis; (E) local feature descriptor on texture and shape, etc.; (F) background separation based on reflection difference. The main purpose at this stage is to quickly obtain the suspicious targets by separating the background and foreground with simple yet effective algorithms. Among them, (A)(B)(D)(F) belong to global feature; (E) belongs to local feature; (C) is a combination of global feature and local feature.

(1) Threshold segmentation based on statistical model

The statistical model derived by this technique generally bases on the difference of the gray-scale value between the ship and its local surroundings or the histogram of the gray-scale value of the whole image. Then, the statistical model distinguishes the background in the image by the threshold rule for-

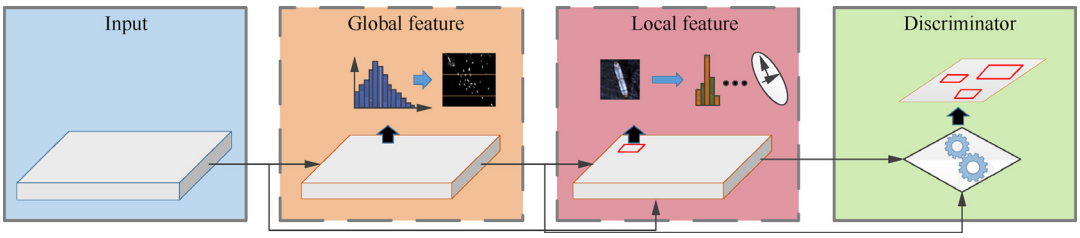

Fig. 3 Composition and workflow of a feature design based detector.

mulated from the statistical data. (E.g. Refs.[3,6,7,18,28,46–49]) Methods based on simple numerical statistics achieve ideal results in simple scene background with little environmental changes. However, the environmental variation in optical remote sensing is uncontrollable due to the imaging mechanism. The statistical threshold rules are not always applicable in background segmentation in the images.

(2) Background separation based on saliency

The definition of "saliency" comes from the interpretation of the pre-attention mechanism in human visual search strategies,[50] which is applied to highlight salient signals and suppress backgrounds. (E.g. Refs.[17,30,51–55]) In order to measure the degree of saliency, Fourier transform (E.g. Refs.[51–53]) or histogram statistics (E.g. Refs.[54]), etc. is applied to the image to suppress the background, and thus the candidate target and the background are separated. It well performs in images with environmental noise caused by sea waves. The extraction results are unsatisfactory in images with messy sea surface containing small islands and cotton shaped clouds, as a consequence of that the highlighted signal may fall on these objects instead of real ship target.

(3) Anomaly detector

The essential idea of an anomaly detector is similar to the saliency mechanism. The occurrence of the targets in the image disobeys the background distribution rule in the original image, thus becomes an anomaly. (E.g. Refs.[12,56–59]) The detector is usually based on statistics and analysis of the sea surface without targets to obtain "normal" background distribution laws, and then selects the area with abnormal distribution as the candidate targets. Anomaly detector can maintain comparable performance under large-scale inference scenarios caused by ocean waves, clouds, or fog with that under calm sea background. However, it cannot adapt to complex backgrounds including various small-scale inferences.

(4) Background separation based on frequency analysis

Regarding the image as a two-dimensional discrete signal, the analysis based on its frequency domain believes that the noise and interference of waves and clouds can be effectively removed in this domain. (E.g. Refs.[23,32,60–63]) The commonly applied image frequency domain transformation is the Fourier transform and wavelet transform. Methods based on frequency analysis perform well when the disturbance has a relatively consistent pattern (such as ocean waves). They may fail to detect such targets when two signals are superimposed, for example, ship occluded by mists.

(5) Local feature descriptor

These methods design detectors based on the observation of ship targets. They generalize the characteristics of ship targets' texture, shape, and structure, etc. to formulate a feature descriptor for screening the ship. (E.g. Refs.[64–69]) These detectors can detect most of the ships, but the detection fails due to the low contrast between the ship and the surrounding environment. Moreover, numerous false targets are extracted by the detectors in the case of rich texture and edge information. Many feature descriptors used in optical remote sensing image ship candidate extraction mainly build on the histogram of oriented gradients and local binary patterns. (E.g. Refs.[11,53,70–72])

(6) Background separation based on reflection difference

The principle of these methods is that the reflection intensity of the targets varies in different bands in remote sensing imaging. The ship candidates are extracted by using values from different bands to distinguish the reflection difference between the target and the background. (E.g. Refs.[6,13,45,73,74]) They take advantage of the imaging property, objects having different reflection intensity in multiple bands, to overcome the meteorological effects in optical remote sensing images. However, these methods neglect ships under the cloud shadows due to changes in the reflection intensity of these ships.

In the ship candidate extraction stage, many methods combine several of the above basic techniques to form a new model to achieve background separation under various meteorological conditions. (E.g. Refs.[3,5,11,15,23,26,28,46,53–55,60,61,71,72,75,76]).

In the ship identification and classification stage, feature design based methods mainly apply the strategy of combining classifiers and feature sets for discrimination. The frequently adopted classifier is the Support Vector Machine (SVM). The feature sets include (but not limited to) feature descriptors for ship geometric, shape, texture, and spectral signature.

3.2.2. CNN structure design based methodology

After the CNN technique achieves remarkable results in object recognition and detection of natural scene images, it is gradually applied to the object detection task in remote sensing images. In order to obtain the CNN prediction model for object detection tasks, a large amount of labeled sample data is required for network training. During the training process, the sample data is fed forward into the network. Then the values of the convolution filters in the network are updated by

minimizing the loss function, which calculates the difference between the predicted values output by the current model and the ground truth of the labeled values. The update operation is achieved by the back propagating the error from the output layer of the network. This process stops when the loss function no longer shows a downward trend. After the training process, the parameters in each convolutional layer are fixed and saved for prediction. For the l-th convolutional layer, the unit j output y_j^l can be obtained from the unit i in previous layer y_i^{l-1} by[77]

$$y_j^l = g\left(\sum_{i\in S_j} y_i^{l-1} \otimes k_{ij}^l + b_j^l\right) \tag{1}$$

where S_j represents the collection of selected previous input maps, $k_{ij}^l$is the convolution filters between y_i^{l-1} andy_j^l, b_j^l is the additive bias given by the current layer, $\otimes$ denotes convolutional operation, and $g(\cdot)$ is the activation function.

For a better understanding, we follow the illustration in Ref.[78] to unravel the components in the CNN model. As shows in Fig. 4, a CNN detector generally contains an input part, a backbone part, a head part may include a neck as an additional part. There are mainly two kinds of the CNN architectures, i.e., one-stage detector and two-stage detector. Their difference lies in whether to generate proposal regions as the intermediate result. The most representative one-stage detectors are Single Shot multibox Detector (SSD)[79] and You Only Look Once (YOLO),[80,81] which are frequently used in ship detection task from remote sensing images. As for the two stage detector, the most classic model is Faster R-CNN.[82] Due to the aerial view perspective in remote sensing imaging, the adjustment of architecture is necessary for the CNN model to predict targets with rotation variations. The usual adjustment is to add hidden layers for a specific purpose while maintaining the backbone structure of the networks. The CNN backbones commonly applied in ship detection and classification tasks are as follows (sorted according to the number of applications): ResNet[38] (E.g. Refs.[31,83–97]) and Visual Geometry Group (VGG)[98] (E.g. Refs.[99–105]). Usually Feature Pyramid Networks (FPN)[106] (E.g. Refs.[85,88,97,102,107]) or its modification version is used as the neck part. Faster R-CNN[82] (E.g. Refs.[83,86–90,97,100,103,104,108,109]), Mask R-CNN[110] (E.g. Refs.[91,92,107,111]), and Fast R-CNN[112] (E.g. Refs.[105,113,114]) are three general used sparse prediction detector heads; SSD[79] (E.g. Refs.[99,101]), and YOLO[80,81] (E.g. Refs.[115,116]) are two frequently applied dense prediction detector heads. In dealing with detection tasks in large-scale remote sensing images, these methods are far from meeting real-time requirements after consuming numerous computational resources and storage space.

The convolutional filters obtained after the training process are believed to contain abstract object feature. However, the mechanism behinds the success of CNN is not revealed.

3.2.3. Ship classification

According to Refs.[34,117,118], there are two levels in ship classification. In the first classification level, namely coarse-grained classification, ships are classified by some criteria into different categories. The second classification level refers to the fine-grained classification where ships are labeled by type, i.e., container ship, cargo ship etc.

In the coarse-grained classification, ships are conventionally divided into two categories, i.e., merchant ships or naval ships. (E.g. Refs.[28,65]) There are other coarse-grained classification criteria, e.g. Ref.[119] classifies ships into moving ships and static ships; Ref.[120] divide ships into four subclasses, namely fishing vessel, container vessel, sailing vessel and coast guard vessel; Ref.[121] classifies ships into multi, coast-ship and detail. Many coarse-grained classification methods conduct their experiment on BCCT200[122,123] dataset, which includes four classes, i.e., barge, cargo, container and tanker. (E.g. Refs.[35–37,69,122–128]) Except for Ref.[129] performs ship-fleets classification on satellite images at 10 m spatial resolution, other coarse-grained classification methods are implemented for images with a spatial resolution of more than 4 m. While the fine-grained classification methods are implemented on images with more than 2 m spatial resolution. (E.g. Refs.[34,63,97,114,130–132])

The early proposed coarse-grained ship classification methods adopt a strategy of comparing the extracted ship features with a priori-database. (E.g. Refs.[28,65]) After the BCCT200 dataset is proposed, the most often used feature descriptor is multi-scale completed local binary pattern[133] combined with Gabor filter[134] to extract local and global features. (E.g. Refs.[35,124,127]) Methods for fine-grained ship classification generally apply CNN technique to identify ship types. (E.g. Refs.[34,63,97,114,130]) There are still few studies on coarse-grained and fine-grained ship classification. The main problem with ship classification may be that there is no uniform standard for data annotations for ship categories.

4. Publicly available datasets for ship detection and classification in remote sensing image

In recent years, many organizations release publicly available Earth observation datasets for object detection in the aerial

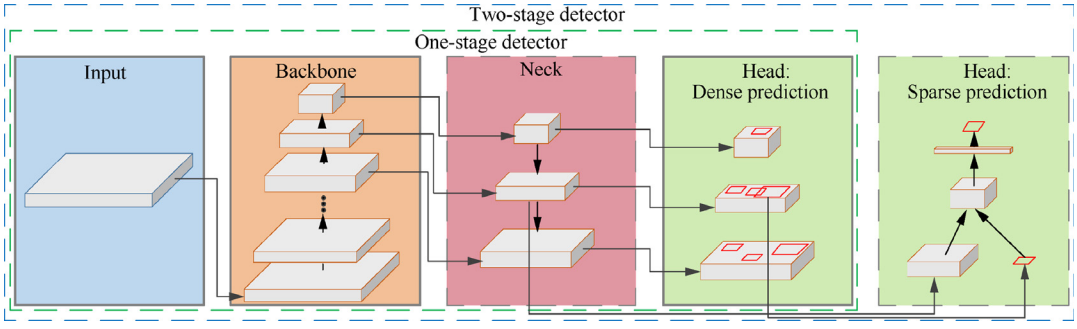

Fig. 4 Composition and workflow of ordinary CNN detector (partially source from Ref.[78]).

view. It provides researchers with a comparable platform to testify their algorithms.

There are nine datasets for ship detection and classification: (A) NWPU VHR-10, the earliest released dataset for evaluating the performance of object detection in remote sensing images[135]; (B) NWPU RESISC45 for scene classification in high-resolution optical satellite image data[136]; (C) HRSC2016, a dataset dedicated to ship detection and classification in high-resolution optical remote sensing images[117]; (D) Airbus Ship Detection dataset, from the challenge of ship detection on satellite images in Kaggle[137]; (E) xView, a dataset for object detection from satellite images[138]; (F) Dataset for Object detection in Aerial images (DOTA) dataset for object detection in aerial images[139]; (G) High-Resolution Remote Sensing object Detection (HRRSD) dataset for remote sensing image object detection applications[140]; (H) object Detection In Optical Remote sensing images (DOIR) dataset for object detection in optical remote sensing images[141]; (I) Fine-Grained Ship Detection (FGSD), the most detail labeled ship detection and classification dataset in remote sensing images so far (available soon).[118]

The NWPU VHR-10 dataset contains ten object classes: airplane, ship, storage tank, baseball diamond, tennis court, basketball court, ground track field, harbor, bridge, and vehicle.

NWPU RESISC45 dataset is a benchmark for scene classification in remote sensing images including 45 scene classes as follows: ship, airplane, airport, baseball diamond, basketball court, beach, bridge, chaparral, church, circular farmland, cloud, commercial area, dense residential, desert, forest, freeway, golf course, ground track field, harbor, industrial area, intersection, island, lake, meadow, medium residential, mobile home park, mountain, overpass, palace, parking lot, railway, railway station, rectangular farmland, river, roundabout, runway, sea ice, snowberg, sparse residential, stadium, storage tank, tennis court, terrace, thermal power station, and wetland.

The HRSC2016 dataset labels ship in three levels, namely ship class, ship category, and ship type. In the ship category level, it contains four labels: warcraft, aircraft carrier, merchant ship, and submarine. Note that, in this dataset, ships with unknown types are labeled with category level.

Airbus Ship Detection dataset contains the largest number of images in the dataset listed in this article. It reports in Ref.[142] that the combination of random forest classifier and feature sets containing the color histogram, Haralick textures and Hu moments outperforms the other four classifiers combined with the same feature sets, namely linear discriminant analysis, K-nearest neighbors, naïve bayes, and support vector machine.

The xView dataset contains 60 object categories and released by the Defense Innovation Unit Experimental (DIUx) and the National Geospatial-intelligence Agency (NGA). The 60 fine-grained classes are labeled in a parent class-child class manner. There are seven different parent classes, namely fixed-wing aircraft, passenger vehicle, truck, railway vehicle, maritime vessel, engineering vehicle, and building (some child classes have no parent class). In the maritime vessel class, it contains nine child classes: motoboat; sailboat; tugboat; barge; fishing vessel; ferry; yacht; container ship; oil tanker.

There are 15 classes in the DOTA dataset including plane, ship, storage tank, baseball diamond, tennis court, swimming pool, ground track field, harbor, bridge, large vehicle, small vehicle, helicopter, roundabout, soccer ball field and basketball court.

In dataset HRRSD, there are 13 categories containing ship, airplane, baseball diamond, basketball court, bridge, cross-road, ground track field, harbor, parking lot, storage tank, T junction, tennis court, and vehicle.

The ship samples in FGSD are annotated not only the bounding boxes but also the rotated bounding boxes. It says there are 43 categories of ships in the dataset annotated in multi-level labels follow the same annotation manner as in HRSC2016 dataset. The category level contains labels of warship, carrier, submarine, and civil ship.

Table A2 in the Appendix A lists the detailed information of these datasets, including the acquisition source, resolution of images, image amount, and image size.

5. Discussion and future work

In this section, ship detection and coarse-grained classification results of mostly considered methods[83,86,95,96,114,117,143,144] on dataset HRSC2016 present in Table 1. The ship detection and classification tasks in HRSC2016 include three levels, i.e., L1, L2, and L3. L1 contains 1 class, namely ship; L2 contains 4 classes, i.e., Aircraft carrier (Air.), War craft (War.), Merchant ship (Mer.) and ship; L3 contains 19 classes, i.e., ship, Aircraft carrier, War craft, Merchant ship, Nimitz class aircraft carrier (Nim.), Enterprise class aircraft carrier (Ent.), Arleigh Burke class destroyer (Arl.), Whidbey Island class landing craft (Whi.), Perry class frigate (Per.), Sanantonio class amphibious transport dock (San.), Ticonderoga class cruiser (Tic.), Austen class amphibious transport dock (Aus.), Tarawa class amphibious assault ship (Tar.), Container ship (Con.), Command ship (Com.A), Car carrier A (Car.A), Container ship A (Con.A), Medical ship (Med.), Car carrier B (Car.B). Average precision (AP) and mean average precision[145] are used as the measurement criteria. The baseline method denotes to the BL2 algorithm in Ref.[117] and the RR-CNN refers to the RC1 algorithm in Ref.[114] in Table 1. It can be seen from Table 1 that RBox-CNN method achieves the best performance in both L1 and L2 tasks in HRSC2016 dataset. It yields a 91.9% AP value in L1 task and 79.4% mean AP in L2 task.

The L3 task performance of some representative methods on HRSC2016 displays in Table 2. The RC1 and RC2 algorithms both from Ref.[114], where RC2 is basically the same as RC1 but adds a multi-task loss to learn non-maximum suppression score (Multi-NMS). The R-DFPN2 is based on R-DFPN and uses Proposals Simulation Generator (PSG) data augmentation in training process. Its input size is fixed at 335×58 and is calculated by the k-means algorithm.[97] The results in Table 2 shows that the PSG data augmentation can improve the performance of the R-DFPN[83] in L3 task. Besides, the SHDRP[97] achieves the best preformation on L3 task of HRSC2016 so far and obtains 74.2% AP.

Based on the introduction and analysis of the literature collection on ship detection and classification from optical remote sensing images published in different periods, this chapter summarizes the main problems in these literatures as follows.

First, due to the passive remote sensing imaging characteristics of optical remote sensing images, the impact of environmental factors such as lighting and meteorological conditions

Table 1 Comparisons of ship detection and classification methods on HRSC2016 (Source from Refs.[86,95]).

Methods	AP (%)					
	L1	L2				
		Air.	War.	Mer.	Ship	Mean
Baseline[117]	69.6	51.0	75.2	63.9	45.1	58.8
RR-CNN[114]	75.7	74.5	74.4	69.3	36.4	63.6
RRD[144]	84.3					
RBox-CNN[86]	91.9	95.1	93.1	77.5	51.9	79.4
R-DFPN[83]	79.6					
R-FCN[96]	82.3					
RoI Transformer[145]	86.2					
LAFCR[95]	90.3					

Table 2 Comparisons of AP values on the L3 task of HRSC2016 (Source from Refs.[97,114]).

Class	AP (%)						
	Baseline[117]	RC1[114]	RC2[114] (RC1 + Multi-NMS)	Faster R-CNN[82]	R-DFPN[83]	R-DFPN2[83] (R-DFPN + PSG[97])	SHDRP[97]
Ship	41.9	34.3	32.9	45.6	46.7	36.8	**52.3**
War.	3.9	3.9	4.8	6.8	11.8	**33.4**	11.5
Car.A	53.1	61.0	56.7	72.7	55.5	70.8	**77.7**
Con.	36.8	56.2	40.2	42.1	42.1	58.4	**64.7**
Med.	78.8	**98.5**	62.5	0.0	34.5	90.9	95.5
San.	51.4	45.5	31.5	0.0	13.7	**95.0**	92.4
Whi.	50.9	51.8	45.8	20.9	20.4	75.4	**86.3**
Air.	41.2	53.9	40.3	18.9	30.8	72.3	**77.7**
Arl.	71.0	65.3	61.0	85.0	68.9	87.6	**91.3**
Car.B	67.8	67.8	57.6	51.6	65.0	94.5	**98.9**
Con.A	49.6	62.7	56.3	60.2	52.1	67.3	**72.8**
Nim.	44.6	59.3	65.0	64.6	68.0	**78.8**	67.2
Tar.	50.9	62.4	67.0	79.5	75.0	89.1	**96.5**
Mer.	12.8	27.4	18.2	**54.4**	22.0	10.0	17.9
Aus.	43.2	48.7	42.7	26.3	26.9	80.5	**86.3**
Com.A	57.1	50.5	38.4	17.0	33.2	85.2	**85.3**
Ent.	3.0	23.0	18.2	3.0	43.8	55.3	**55.7**
Per.	43.9	47.6	42.3	51.8	49.1	82.9	**91.9**
Tic.	57.4	48.6	49.8	69.4	66.6	84.2	**88.2**
Mean	45.2	51.0	43.7	40.5	43.5	71.0	**74.2**

during the imaging process reflects in the images, which has a great influence on the accuracy of ship detection. However, most of the methods collected in the literature collection cannot adapt to various environments. Among them, the relatively robust one is the detection methods taking advantage of the reflection signature of the target. Lacking the research in the analysis of the spectral reflection relationship between the target and background, none of these algorithms perform well under the influence of the target covered by cloud and shadow. Therefore, it is still a very challenging task that detects ships in remote sensing images under various environmental changes.

Second, as the remote sensing image covers a large area of the earth's surface, ship targets become relatively small and distribute sparsely on the image. In recent years, ship detection and classification methods based on CNN structure design become the mainstream applications. However, the neglected fact is that these methods require high-performance equipment and still cannot work efficiently. Efficiency has always been a difficult problem in the object detection field, so there is no exception in ship detection from remote sensing images.

Third, the aerial view perspective in remote sensing images causes the target distortion according to the imaging angle of the satellite sensors and the relative position of the target. With the changes in scale and partial occlusion, the difficulty of the detection task enhances due to the variations of the targets' appearance and structure. Therefore, research on comprehensive features description on ship target and the utilization of imaging property in remote sensing to improve the detection accuracy is still ongoing.

Last but not the least, the problem in ship classification is the lack of a unified classification criterion among different datasets. Besides, affected by cloud cover or surrounding environment, the difference inner the ship classes may be greater than the difference between different ship classes. Few studies perform research on ship classification. And those methods have strict requirements on the completeness of ship extraction

as they based on the feature descriptor of shape, texture, and size of ships. Therefore, there is an urgent need to study ship classification in remote sensing images with the continuous improvement of spatial resolution.

All in all, there is still a gap between the current ship detection and classification technology and the practical application.

The upsurge of research on CNN technology leads to massive studies on object detection in optical remote sensing images applied such technique.[141] Although it makes great progress in object detection tasks in natural scene images, there still are a lot of rooms for improvement when performing in remote sensing images. Structure design that saves time and computational cost are very important in ship detection and classification from optical remotes sensing images.

With the number of publicly available dataset increases, the access for fine-grained labeled ship classes becomes convenient for researchers. These datasets provide a foundation for study on ship classification in aerial view images.

Unlike synthetic aperture radar, optical remote sensing images cannot resist weather conditions. It is an effective way to realize target detection to apply fusion information from different types of sensors.[146] Research on ship detection and classification based on multi-sourced information is promising in practical application.

6. Conclusions

In this paper, we provided statistics of 153 papers on ship detection and classification from 1978 to July 2020 and introduced their commonly used detection scheme and workflow. In the image preprocessing procedure, sea-land segmentation and cloud filtering are introduced and the applied technologies in these two operations are analyzed. We classified the methods in these papers into two categories: the feature design based methods and the CNN structure design based methods. In the feature design based methods, six basic techniques were mainly adopted in the ship candidate extraction stage; the combination of classifiers with feature sets strategy was generally applied in the ship identification stage. In the CNN structure design based methods, designers usually made improvements in hidden layers while maintaining the backbone structure. There were two classic CNN backbone structures commonly applied in ship detection and classification from optical remote sensing images according to our literature collection. Finally, the detail information of nine public available datasets was listed, which can be applied to testify the ship detection and classification algorithms. Based on the analysis of the methods in these papers, we summarized the current problems and provided the possible future works on ship detection and classification methods for optical remote sensing images.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A.

Table A1 Literature collection of ship detection and classification methods published from 1978 to July 2020.(Literature collection from 1978 to 2016 partially source from Ref.[147]).

Year	Satellite sensor	Applied band	Resolution (m)		Minimum detection target (m)	Application purpose
			PAN	MS		
1978[45]	Landsat-2 MSS	G,NIR	–	80	112	Ship detection
1993[32]	SPOT XS	G,NIR	–	20	63	Ship detection
	Landsat TM	R,NIR	–	30	108	
2003[3]	IKONOS	PAN,B,G,R,NIR	1	4	8	Ship detection
2005[64]	SPOT-5	PAN	2.5	-	100	Ship detection
2005[148]	IKONOS	PAN	1	-	10	Ship detection
	QuickBird		0.61	-		
2007[28]	QuickBird	PAN	0.61	-	n/a	Ship detection and classification
2007[149]	Google Earth	PAN	7	–	n/a	Ship detection
2007[150]	IKONOS	PAN,NIR	1	4	2	Ship detection
2008[23]	QuickBird	PAN	0.61	-	n/a	Ship detection
2008[25]	SPOT-5	PAN	5	–	14	Ship detection and classification
2008[24]	SPOT-5	PAN	5	–	n/a	Ship detection
2009[7]	Landsat-7 ETM +	PAN,B,G,R,NIR,SWIR, MWIR,TIRS1,TIRS2	15	30	50	Ship detection
2009[151]	QuickBird	n/a	-	2.5	n/a	Ship detection
2009[152]	HJ-1	B	-	30	n/a	Ship detection
2009[65]	VHR satellite images	B,G,R	-	1	n/a	Ship detection and calssification
2009[13]	Landsat-5 TM	SWIR1,SWIR2	–	30	n/a	Ship detection

(*continued on next page*)

Table A1 (*continued*)

Year	Satellite sensor	Applied band	Resolution (m)		Minimum detection target (m)	Application purpose
			PAN	MS		
2010[4]	SPOT-5	PAN	5	–	20	Ship detection
2010[14]	QuickBird	PAN	0.61	–	n/a	Ship detection
2010[15]	Google Earth	B,G,R	n/a	n/a	150	Ship detection
2010[16]	SPOT-5	PAN	5	–	15	Ship detection
2010[11]	CBERS	G,R,NIR	–	20	n/a	Ship detection
	SPOT-2	PAN	10	–		
	SPOT-4		10			
	SPOT-5		5			
2011[5]	MODIS	B,G,SWIR1,SWIR2,SWIR3	–	500	150	Ship detection
2011[153]	SPOT-5	PAN	5	–	n/a	Ship detection
	QuickBird		0.61			
	Google Earth		10			
2011[46]	SPOT-5	PAN	2.50	–	n/a	Ship detection
2011[154]	Google Earth	B,G,R	–	0.5	10	Ship detection
2011[155]	RapidEye	G	–	6.5	n/a	Ship detection
2011[18]	GeoEye-1	PAN,B,G,R	0.41	1.65	n/a	Ship detection
2011[156]	Google Earth	B,G,R	0.6	–	n/a	Ship detection
2011[122]	Electro-Optical satellite	PAN	n/a	–	n/a	Ship classification
2012[123]	Electro-Optical satellite	PAN	n/a	–	n/a	Ship classification
2012[17]	SPOT-5	PAN	5	–	50	Ship detection
2012[52]	Landsat-7 ETM +	B,G,R,NIR,SWIR1,SWIR2	30	–	n/a	Ship detection
2013[60]	GeoEye-1	PAN,B,G,R,NIR	0.41	1.65	n/a	Ship detection
2013[26]	WorldView-2	C,B,G,Y,R,RE,NIR1,NIR2	–	2.0	n/a	Ship detection
2014[47]	GeoEye-1	B,G,R,NIR	0.41	1.65	4	Ship detection
	WorldView-2		0.5	2.0		
	IKONOS		1	4		
	QuickBird		0.61	2.5		
2014[66]	QuickBird	PAN	0.61	–	n/a	Ship detection
2014[67]	ASTER	G,R,NIR	–	15	15	Ship detection
2014[12]	Google Earth	PAN	1	–	40	Ship detection
2014[68]	Google Earth	PAN	0.5	–	n/a	Ship detection
2014[157]	Google Earth	PAN	0.6	–	n/a	Ship detection
2014[56]	SPOT-5	PAN	5	–	n/a	Ship detection
	Google Earth					
2015[69]	IKONOS	PAN	1	–	n/a	Ship classification
	GeoEye-1		0.41			
	QuickBird		0.61			
	WorldView		0.5			
2015[158]	Google Earth	PAN	≥4	–	n/a	Ship detection and calssification
2015[27]	GeoEye-1	PAN	0.41	–	n/a	Ship detection
2015[159]	Google Earth	PAN	0.61	–	n/a	Ship detection
2015[61]	GaoFen-1	PAN	2	–	n/a	Ship detection
2015[19]	SPOT-5	PAN	5	–	50	Ship detection
2015[75]	WorldView-2	PAN,B,G,R,NIR	0.5	1.8	n/a	Ship detection
	QuickBird-2		0.61	2.8		
	GeoEye-1		0.41	1.65		
	RapidEye		–	6.5		
	Formosat-2		2	8		
2015[160]	Landsat-5 TM	SWIR2	–	30	n/a	Ship detection
	Landsat-7 ETM +					
2015[30]	SPOT-5	PAN	0.5	–	n/a	Ship detection
2015[161]	WorldView-2	PAN	0.5	–	n/a	Ship detection
2015[126]	Electro-Optical satellite	PAN	n/a	–	n/a	Ship classification
2015[128]	Electro-Optical satellite	PAN	n/a	–	n/a	Ship classification
2015[37]	Electro-Optical satellite	PAN	n/a	–	n/a	Ship classification
2016[162]	Sentinel-2	B,G,R,NIR	–	10	n/a	Ship detection
2016[163]	Google Earth	B,G,R	–	0.12–0.25	n/a	Ship detection
2016[164]	WorldView-1	PAN	0.5	–	n/a	Ship classification
	WorldView-2					
2016[165]	Google Earth	B,G,R	–	0.4–2	n/a	Ship candidate extraction

Table A1 (*continued*)

Year	Satellite sensor	Applied band	Resolution (m)		Minimum detection target (m)	Application purpose
			PAN	MS		
2016[20]	Google Earth	PAN	–	1	n/a	Inshore ship detection
2016[166]	WorldView-2 QuickBird-2 GeoEye-1	B,G,R,NIR	–	10 (downsampled)	20	Ship detection
2016[6]	Sentinel-2	B,G,R,NIR	–	10	30	Ship motion detection
2016[167]	Google Earth	n/a	–	–	n/a	Ship detection
2016[54]	SkySat-1	PAN	1.1	–	n/a	Ship detection in video
2016[168]	WorldView-1	PAN	0.5	–	25	Ship detection
2016[169]	CBERS-02B	PAN	2.36	–	n/a	Ship detection
2016[170]	Landsat-8	PAN, NIR,SWIR1,SWIR2, TIRS1,TIRS2	15	30	n/a	Ship detection
2016[171]	WorldView-2 QuickBird-2 GeoEye-1 RapidEye Formosat-2 Sentinel-2	PAN,B,G,R,NIR	0.5 0.61 0.41 – 2 –	1.8 2.8 1.65 6.5 8 10	15	Ship detection
2016[48]	OrbView-3	PAN	1	–	n/a	Ship detection
2016[51]	Google Earth	PAN	–	–	n/a	Ship detection
2016[21]	GaoFen-1 VRSS-1	PAN	2 2.5	–	10 320	Ship detection
2017[57]	VNREDSat-1	PAN	2.5	–	n/a	Ship detection
2017[73]	GaoFen-1	PAN,B,G,R,NIR	2	8	n/a	Ship detection on inland rivers
2017[172]	Google Earth	PAN	2	–	n/a	Ship detection
2017[55]	Google Earth	B,G,R	–	–	n/a	Ship detection
2017[53]	Google Earth	PAN	2	–	n/a	Ship detection
2017[173]	Google Earth	B,G,R	–	1	n/a	Ship detection
2017[174]	GaoFen-4	PAN,B,G,R,NIR	50	50	n/a	Ship motion detection
2017[175]	Google Earth	PAN	–	2	n/a	Ship detection
2017[58]	Google Earth	B,G,R	–	n/a	n/a	Ship detection
2017[176]	Google Earth	B,G,R	–	1	n/a	Ship detection
2017[62]	n/a	B,G,R	–	n/a	n/a	Ship detection
2017[31]	GaoFen-2	B,G,R	–	4	100	Ship detection
2017[177]	WorldView-2	PAN,B,G,R,NIR	0.5	1.8	20	Ship detection
2017[63]	Google Earth	B,G,R	–	0.5	n/a	Ship detection and calssification
2017[99]	Google Earth	B,G,R	–	0.54	n/a	Ship detection
2017[178]	Google Earth	B,G,R	–	2	n/a	Ship detection
2017[179]	GaoFen-1 Google Map	PAN B,G,R	2 –	– 1	n/a	Sea-land-ship segmentation
2017[180]	RapidEye	B,G,R,RE,NIR	–	5	n/a	Ship detection and direction prediction
2017[131]	QuickBird	PAN	0.61	–	n/a	Inshore ship detection and classification
2017[114]	Google Earth	B,G,R	–	0.4–2	n/a	Ship detection and classification
2017[108]	Google Earth	PAN	1	–	20	Ship detection
2017[130]	Google Earth	B,G,R	–	0.5	n/a	Ship detection and calssification
2017[49]	Chinese agile remote sensing satellite	PAN	n/a	–	n/a	Ship detection in video
2017[74]	Sentinel-2	B,G,R,NIR,SWIR1,SWIR2	–	10	n/a	Ship detection
2018[83]	Google Earth	B,G,R	–	n/a	n/a	Ship detection
2018[181]	Google Earth	B,G,R	–	1	n/a	Ship detection
2018[115]	GaoFen-2 Google Earth	PAN	1 0.3	–	n/a	Ship detection
2018[182]	Google Earth	PAN	n/a	–	2-30pixel	Ship detection
2018[183]	CBERS-02B ZY3	PAN	2.36 2	–	n/a	Ship detection
2018[119]	GaoFen-2	PAN	0.81	–	n/a	Ship detection

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Table A1 (*continued*)

Year	Satellite sensor	Applied band	Resolution (m)		Minimum detection target (m)	Application purpose
			PAN	MS		
	WorldView-2		0.5			
	EROS-B		0.7			
2018[84]	Google Earth	B,G,R	–	0.5	n/a	Ship detection and direction prediction
2018[85]	Google Earth	B,G,R	–	1–5	n/a	Ship detection
2018[113]	Google Earth	B,G,R	–	1	n/a	Ship detection
2018[101]	Google Earth	B,G,R	–	0.2–1	n/a	Ship detection
2018[184]	VNREDSat-1	B,G,R,NIR,PAN	2.5	2.5(pan-sharpened)	n/a	Ship candidate extraction
2018[127]	Electro-Optical satellite	PAN	n/a	–	n/a	Ship classification
2018[185]	GaoFen-4	B,G,R,NIR,PAN	50	50	2 pixel	Ship tracking
2018[124]	Electro-Optical satellite	PAN	n/a	–	n/a	Ship classification
2018[100]	Google Earth	B,G,R	–	0.4–2	n/a	Ship detection
2018[121]	Microsoft Bing maps	B,G,R	–	n/a	4 pixels	Ship detection and classification
2018[125]	Electro-Optical satellite	PAN	n/a	–	n/a	Ship classification
2018[96]	Google Earth	B,G,R	–	1	n/a	Ship detection
2018[71]	SPOT-5	PAN	5	–	n/a	Ship detection
	GaoFen-1		2			
2018[186]	JiLin-1	B,G,R	–	0.72	n/a	Ship detection
	Google Earth			1		
2018[86]	Google Earth	B,G,R	–	0.4–2	n/a	Ship detection and classification
2018[87]	Google Earth	B,G,R	–	1	8 pixel width, 11 pixel length	Ship detection
2019[88]	GaoFen-1	PAN	2	–	n/a	Ship detection
	GaoFen-2		0.81			
	JiLin-1		0.72			
2019[120]	n/a	PAN	2.6	–	n/a	Ship detection and classificaiotn
2019[59]	GaoFen-1	PAN	2	–	n/a	Ship detection
	GaoFen-2		0.81			
2019[109]	GaoFen-2	B,G,R,NIR,PAN	1	1(pan-sharpened)	n/a	Ship detection
2019[187]	Sentinel-2	B,G,R,NIR	–	10	20	Ship detection
		SWIR		20		
2019[35]	Electro-Optical satellite	PAN	n/a	–	n/a	Ship classification
2019[89]	Google Earth	B,G,R	–	3	n/a	Ship detection
2019[29]	Google Earth	B,G,R	–	n/a	n/a	Ship candidate extraction
2019[129]	Sentinel-2	B,G,R,NIR	–	10	n/a	Ship detection and classification
2019[90]	n/a	PAN	0.2–3	–	n/a	Ship detection
2019[36]	Electro-Optical satellite	PAN	n/a	–	n/a	Ship classification
2019[97]	Google Earth	B,G,R	–	0.4–2	n/a	Ship detection and classification
	QuickBird	PAN	0.61	–		
2019[132]	Google Earth	B,G,R	–	0.4–2	n/a	Ship classification
2019[188]	GO-3S	PAN	n/a	–	n/a	Ship detection in video
2019[107]	Google Earth	B,G,R	–	0.4–2	n/a	Ship detection
2019[189]	Google Earth	B,G,R	–	0.5	n/a	Ship detection
2019[111]	SPOT-6	PAN, B,G,R,NIR	1.5	6	22	Ship detection
2019[91]	Google Earth	B,G,R	–	0.4–2	n/a	Ship detection
2019[190]	n/a*	B,G,R	–	n/a	n/a	Ship detection
2020[92]	n/a*	B,G,R	–	n/a	n/a	Ship detection
2020[95]	Google Earth	B,G,R	–	n/a	n/a	Ship detection
2020[34]	Google Earth	B,G,R	–	0.4–2	n/a	Ship classification
	GaoFen-1	PAN	2	–		
2020[72]	GaoFen-2	PAN	0.81	–	n/a	Ship detection
	ZY-3		2.1			
2020[102]	Google Earth	B,G,R	–	0.5	20 × 20	Ship detection
2020[103]	Google Earth	B,G,R	–	1	80	Ship detection

Table A1 (*continued*)

Year	Satellite sensor	Applied band	Resolution (m)		Minimum detection target (m)	Application purpose
			PAN	MS		
2020[33]	n/a	B,G,R	–	n/a	n/a	Ship detection and calssification
2020[191]	Google Earth	B,G,R	–	0.4–2	Average 150 pixels	Ship detection
2020[192]	Google Earth	PAN	n/a	–	n/a	Ship detection and classification
2020[93]	Google Earth	B,G,R	–	0.2–30	n/a	Ship detection and segmentation
2020[104]	Google Earth	B,G,R	–	0.4–2	n/a	Ship detection
2020[193]	n/a	B,G,R	–	n/a	n/a	Ship detection
2020[22]	GaoFen-1	B,G,R,NIR	–	8	80	Ship detection
	SJ9			10	50	
	ZY3			6	30	
	CB04			20	100	
2020[94]	Google Earth	B,G,R	–	n/a	n/a	Ship detection
	JiLin-1			≤2.88		
	GaoFen-2			3.2		
2020[116]	Google Earth	B,G,R	–	0.27–2.15	n/a	Ship detection
2020[105]	Google Earth	B,G,R	–	n/a	n/a	Ship detection
2020[194]	Google Earth	B,G,R	–	1–5	n/a	Ship detection
	GaoFen-2		–	3.2		
2020[76]	Google Earth	B,G,R	–	0.4–2	n/a	Ship detection
	JiLin-1			≤2.88		
	GaoFen-2			3.2		

* Performed on Airbus Ship Detection dataset.

Table A2 Detail information of datasets that can be applied to ship detection.

Dataset abbreviation	Resolution (m)	Image source	Image amount	Application purpose	Image size (pixel)
NWPU VHR-10	0.5–2	Google Earth	715	Object classification	956 × 554–1073 × 704
	0.08	Vaihingen dataset[195]	85		
NWPU-RESISC45	0.2–30	Google Earth	31,500 (700 each class)	Scene classification	256 × 256
HRSC 2016	0.4–2	Google Earth	1061	Ship detection and classification	300 × 300–1500 × 900
Airbus Ship Detection	n/a	n/a	208,162	Ship detection	768 × 768
xView	0.3	WorldView-3	1413	Object classificaiton	2772 × 2678–5121 × 3023
DOTA v1.5	n/a	Google Earth	2806	Object classificaiton	800 × 800–4000 × 4000
	≤2.88	JiLin-1			
	3.2	GaoFen-2			
HRRSD	0.15–1.2	Google Earth	21,761	Object classificaiton	493 × 402–2077 × 2606
	0.6–1.2	Baidu Map	4961		
DIOR	0.5–30	Google Earth	23,463	Object classificaiton	800 × 800
FGSD	0.12–1.93	Google Earth	4736	Ship detection and classification	930 × 930

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