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Detection of ships in inland river using high-resolution optical satellite imagery based on mixture of deformable part models☆

Pengfei Song [a,b,c], Lei Qi [a,d], Xueming Qian [b], Xiaoqiang Lu [a,*]

[a] Key Laboratory of Spectral Imaging Technology CAS, Xi'an Institute of Optics and Precision Mechanics, Chinese Academy of Science, Xi'an 710119, Shaanxi, China
[b] Xi'an Jiaotong University, Xi'an, 710049, China
[c] CCCC Railway Consultants Group Company Limited, Beijing, 100088, China
[d] University of Chinese Academy of Sciences, Beijing 100049, China

HIGHLIGHTS

- The Regions of Interest (ROIs) are firstly extracted based on water–land segmentation using multi-spectral information.
- Two kinds of ship candidates are extracted based on the panchromatic band.
- Backpropagation Neural Network (BPNN) is trained and used to classify the ship candidates using the multi-spectral bands.

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ABSTRACT

Ship detection using optical satellite imagery is of great significance in many applications such as traffic surveillance, pollution monitoring, etc. So far, a lot of ship detection methods have been developed for images covering open sea, offshore area and harbors. Compared to the ship detection in sea and offshore area, it is more difficult to detect ships in inland river due to several challenges. First of all, many ships in inland river are clustered together and hard to be separated from each other. Secondly, ships lying alongside the pier are very likely to be recognized as part of the pier. Thirdly, ships in inland river is usually smaller than those in the sea. A hierarchical method is proposed to detect the ships in inland river in this paper. The Regions of Interest (ROIs) are firstly extracted based on water–land segmentation using multi-spectral information. Then two kinds of ship candidates are extracted based on the panchromatic band. The isolated ships are detected by analyzing the shape of connected components and the clustered ships are detected by using mixtures multi-scale Deformable Part Models (DPM) and Histogram of Oriented Gradient (HOG). At last, a Back Propagation Neural Network (BPNN) is trained to classify the ship candidates using the multi-spectral bands. The experiments using Quickbird satellite images show that our approach is effective in ship detection and performs particularly well in separating the ships clustered together and staying alongside the pier.

1. Introduction

Ship detection using satellite imagery is of great significance and is widely applied in ship traffic service, fishery management, oil spills, etc. Optical satellites imagery is usually of high resolution and able to provide more detail information of object. Therefore, it has been adopted widely for ship detection, particularly the detection of small ships and the extraction of their detail information. An amount of related papers can be found in the open literatures [1,2,5,6,8,9,11,12]. In [2], a complete processing chain for ship detection in SPOT 5 images was proposed based on connected components analysis, wavelet transform, radon transform and a logistic regression model. A hierarchical method for ship detection based on shape and texture features was proposed in [12]. The ship candidates were extracted based on image segmentation and shape analysis. Then the texture features are extracted and the ship candidates were detected using a hierarchical classifier. [6] presented a Bayesian decision theory based small ship (about 5×5 pixels) detection method for SPOT 5 imagery. In [1], a visual search inspired model for ship detection was proposed. The ship candidates were extracted using visual attention mechanism and then local context and neighborhood

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* Corresponding author.
E-mail address: luxq666666@gmail.com (X. Lu).

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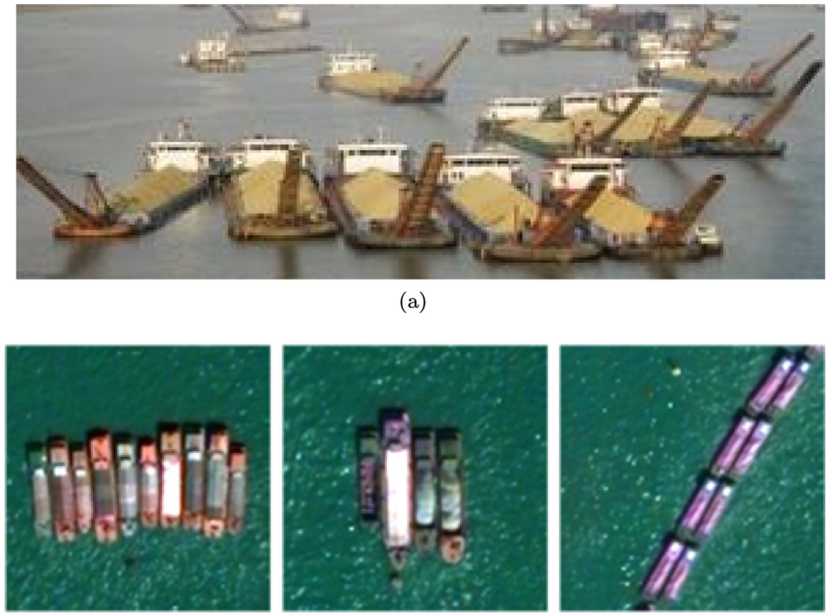
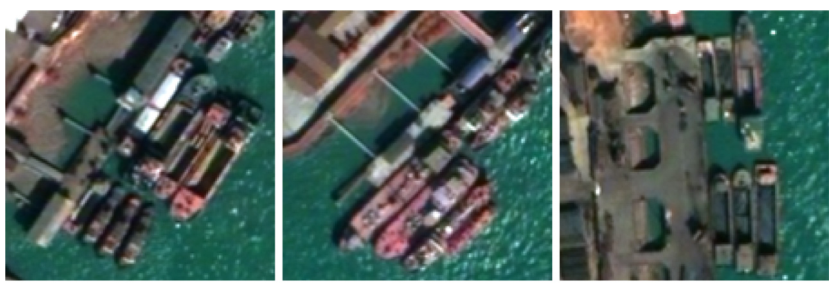


(a)

(b) (c) (d)

Fig. 1. Ships in inland river are tied up together, which makes it difficult to separate them from each other.



(a) (b) (c)

Fig. 2. Ships are lying along the pier. It is difficult to distinct the ships from pier.

similarity were employed to discriminate the ship candidates. [5] proposed a method employing Haar-like features and Adaboost. The method was tested using WorldView images in large area of 50 km^2. In [8], a method regarding the images as hyperspectral images was proposed. The ship candidates were preliminary extracted by regarding them as anomalies and the HOG and Adaboost were used to validate real ships out of the candidates.

Most of the above studies focus on the ship detection in the sea. Detecting ships in inland river also is very important for many applications such as traffic service, waterway management, and ship accident disposing. However, few publications on ship detection in inland river exist. Compared to the ship detection in the sea, several challenges are being faced when the regions of interest (ROI) of ship detection are the inland river.

The first and the greatest challenge is that a great portion of ships in inland river are tied up together. It is very difficult to separate them from each other. Fig. 1 shows the clustered ships.

This problem could be worse when the ships are lying alongside the pier and how to avoid recognizing ships as part of the pier is the second issue that must be addressed. Fig. 2 shows the ships are lying along the pier. Thirdly, the ships in inland river are usually smaller because the depth of the waterway is much less than that of the sea.

Moreover, the ships in the sea usually have the V shaped bows and most existing methods depend on this. However, unlike the ships in the sea, many ships in the inland river, for example, the sand carriers and small cargo ships do not have this kind of bow. Fig. 3 shows the comparison of ships with and without the V shaped bow. Therefore, a method that does not depend on the V bow is needed.

To address these above issues, a hierarchical method is proposed. The water and land are firstly segmented using Support Vector Machine (SVM) [10] to obtain the ROIs. The ROIs include the two narrow strips along the boundary between the water and land which covering the ships lying near to the shore and pier, and the connected components in the middle of the river that cover the clustered and isolated ships. The isolated ship candidates can be easily detected by simple shape analysis of the connected components. Then the clustered ship candidates near to the shore and in the middle of the river are extracted from the panchromatic band based on Histogram of Oriented Gradient (HOG) [3,7], Deformable Part Model (DPM) [4] and Latent-SVM. Then a Back propagation neural network [13] is trained to discriminate the real ships from the other candidates using the multi-spectral information. The Quickbird images with resolution of 0.6m are employed for the experiment and the results demonstrated that the proposed method is effective. The entire procedure of the proposed method is illustrated in Fig. 4.

The rest sections are organized as follows. Section 2 describes the proposed method. Section 3 describes the experiments and analyzes the result. Section 4 provides the conclusion.

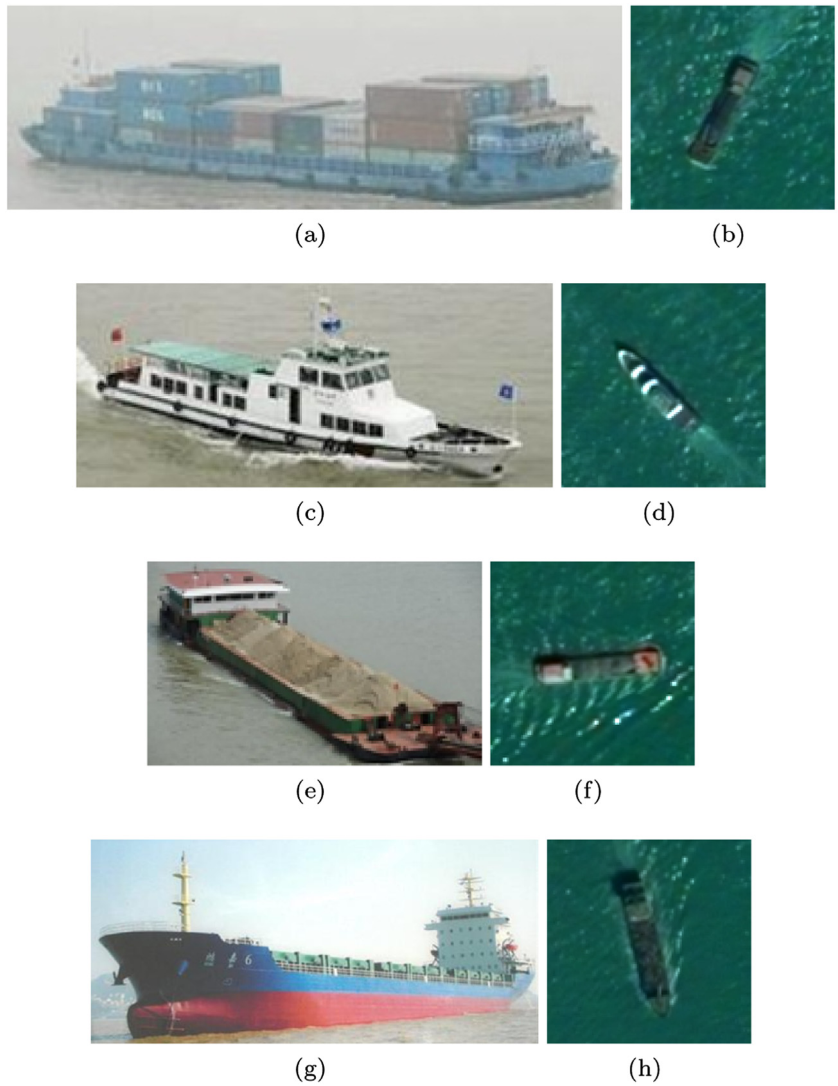


Fig. 3. Ships in the sea (c, d, g, h) usually have the V shaped bows and ships in the inland river (a, b, e, f) usually do not have this kind of bow.

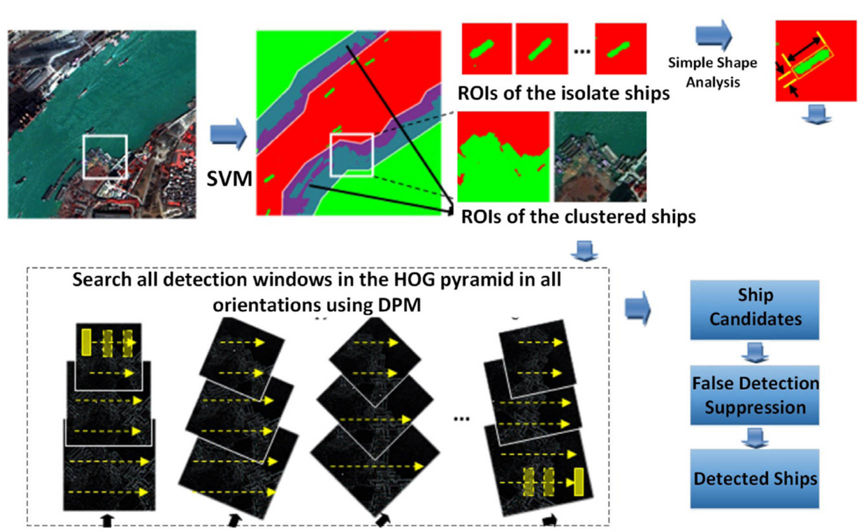


Fig. 4. Flow diagram of the proposed method.

2. Proposed method

2.1. ROIS extraction

To detect the ships in the satellite imagery, the ROIs that contain the candidate ships must be extracted firstly. In this paper, the ROIs are extracted based on the segmentation of the water and land.

The spectral intensity of the water is very different from that of the land. Therefore, it is easy to segment the water and land based on the pixel intensity. In this paper, a SVM based classifier is used to accomplish this. The segmentation result is a binary image and two types of ROIs can be extracted from it.

The first type of ROIs are two narrow strips along the boundary between the water and land. The ships lying near to the shore are covered by these two strips. The second type of ROIs are the connected components in the middle of the river. The clustered and isolated ships are covered by this type of ROIs.

2.2. Detection of the isolated ship candidates

The detection of the isolated ships is based on the analysis of the shape and area of the second type of the ROIs, i.e. the connected components in the middle of the river.

The thresholds of the ratio of length to width and the area are firstly given according to the image resolution and the knowledge of ships. Then the isolated ships are selected from those connected components using the thresholds.

2.3. Detection of the clustered ship candidates

For the clustered ships, how to separate ships from each other is the most challenging task. In this paper, a method based on mixtures of multi-scale DPMs is adopted.

The DPM is proposed to detect multi-scale objects in images with complicated background. It is proved that it can perform very well on PASCAL Visual Object Classes (PASCAL VOC) dataset [7] in detecting objects such as pedestrian, car, dog, bottle, and others.

The object detection method based on the DPM uses a scanning window. A model for an object consists of a group of filters, including a root filter and several part filters. Each filter is scored by computing the dot product of between the weights and HOG features of a window. The score of a detection window is the score of the root filter plus the score of the part filters on the resulting sub-window minus the deformation cost. The DPM is defined in a fixed scale and the objects in different scales can be detected by searching over an image pyramid.

In DPM, the score of a detection window is sum of filter scores minus deformation costs. Filter scores $Score_f$ can be computed by dot product of filters parameters F and HOG feature of root position and part position H as follows:

$$Score_f = \sum_{i=0}^{n} \langle F_i, H_i \rangle \, , \tag{1}$$

where F_i is parameter of ith part filter and H_i is the HOG feature vector of ith part. Here 0th part means root. Similarly, deformation costs $Cost$ can be computed by the dot product of deformation parameters and displacements as follows:

$$Cost = \sum_{i=1}^{n} \langle (a_i, b_i), (dx_i, dy_i) \rangle \, , \tag{2}$$

where (a_i, b_i) is the deformation parameters corresponding to ith part and (dx_i, dy_i) means the displacement between ith part and root. (dx_i, dy_i) can be computed as follows:

$$(dx_i, dy_i) = (x_i, y_i) - 2(x_0, y_0) + v_i, \tag{3}$$

where (x_i, y_i) is the location of the ith part and 0th part means root. v_i is a two-dimensional vector specifying an anchor position for ith part relative to the root position. Given the filter scores and deformation cost, the score of a detection window can be obtained as follows:

$$Score = Scores_f - Cost. \tag{4}$$

More details about DPM and latent SVM can be found in [4].

The DPM model can capture the variations in appearance of the objects. Different kinds of ships vary greatly in the length, the distance between the bow and the stern and the spatial relationship between key parts. Therefore, the DPM can perform better than the method that are not based on part model in ship detection.

Besides the variations that can be captured by DPM, there are more significant variations in appearance of the ships. For example, the yacht usually has a V shaped bow which could be used as a very important discriminative feature for ship detection. But the bow of sand carrier and some cargo ships are not V shaped and the shape of the bow is the same as their stern. Thus, a single DPM is not expressive enough to represent the ships. In [4], this problem was solved by using mixture of the multiple DPMs. In this paper, multiple DPMs are used for the ships with different shapes.

Another advantage of DPM in ship detection is the ability of suppressing "hard negative" examples i.e. the objects that are similar to ships data-mining the hard negative examples. This is of great significance for detecting ships lying alongside the pier. The object such as the pier that looks like ships can be suppressed by labeling these training samples as the hard negative ones.

Finally, the ships in satellite images are of different orientations. To train the DPM, the positive training samples are normalized by rotating them to make sure that the bow is at the top and the stern is at the bottom. In order to detect the ships in all orientations, the detection windows are rotated from 0 to 360 degree and the scores in all orientations are computed.

2.4. False detection suppression

The detection using DPMs is mainly based on the gradients of image and some objects which are recognized as ships because of similar gradients with ships. In order to suppress this kind of false detection, the spectral density of remote sensing imagery is adopted to compute extra features to refine the ship detection result. In this paper, the number of pixels of water is counted. The ratio of water-pixels and the area of the bounding box are used to suppress the false detections.

3. Experiments

3.1. Dataset

The proposed method is tested on a database that consists of 10 Quickbird panchromatic and multi-spectral images with the resolution of 0.6 m and 2.4 m respectively. The size of images is 3000 by 3000.

The images cover Huangpu river which is the largest river in Shanghai, China. The length is 113 km and the average width and depth are 400 m and 9 m. Most kinds of inland river ships can be found in this river.

The database is divided into two groups. The first group includes 4 images and is used to select training examples and learn the mixtures of the DPMs. 183 positive examples (ships) are selected by visual checking and bounding boxes. The negative examples are iteratively selected using the algorithm of data mining "hard negative" examples. 204 negative examples are selected after three iterations.

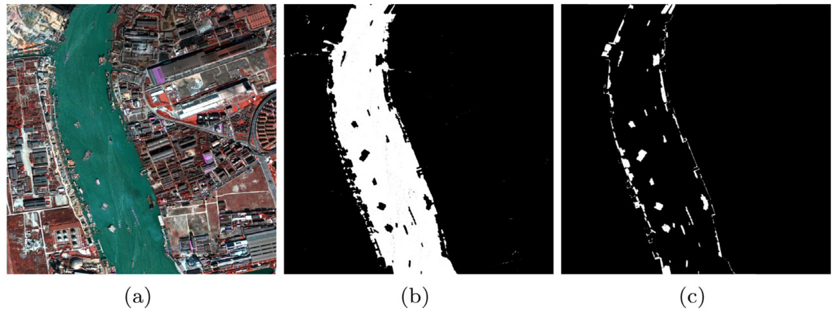


Fig. 5. Result of segmentation and the ROIs. (a) Quick Bird Image; (b) Segmentation using SVM; (c) ROI for ship detection.

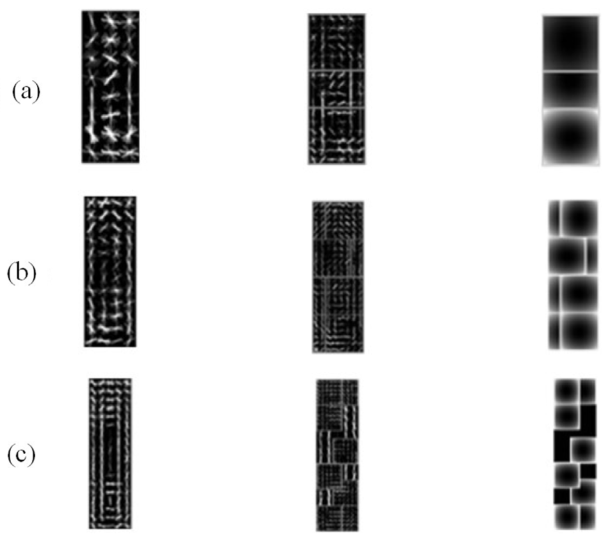


Fig. 6. Three components of the DPMs. The first and the second columns of (a), (b) and (c) show the positive weights of the root filters and the part filters, the third column of (a), (b) and (c) show the spatial models that reflect the cost of placing the center of a part at different locations relative to the root.

The second group consists of 6 images and is used to evaluate the performance of the proposed method.

3.2. Image segmentation and ROIs

The segmentation of the water and land is conducted by using a SVM with radial basis function kernel. The penalty factor is set to 1.0. The pixel intensity of multi-spectral bands is employed as the feature. 2021 and 2034 pixels are used as the training examples of the water and land respectively. The connected components in the river are treated as the ROIs for the isolated ships and clustered ships. In each side of the boundary, a narrow band with the width of 30 pixels is defined as the ROIs for the ships lying next to the riverbank. Fig. 5 shows a result of segmentation and the ROIs.

3.3. Ship detection

To distinguish the isolated ships and other isolated connected components ROIs. The length to width ratio R of the enclosing rectangle is computed and a threshold TR = 1.8 is given. The isolated connected components with R larger than TR are labeled as ships.

The ships clustered in the middle of the river and the next to the riverbank are searched by using DPM in a group of rotated 5-level HOG pyramids. The difference of rotation angle between two pyramids is 5 degrees. The size of cell and block of HOG is 8 and 16.

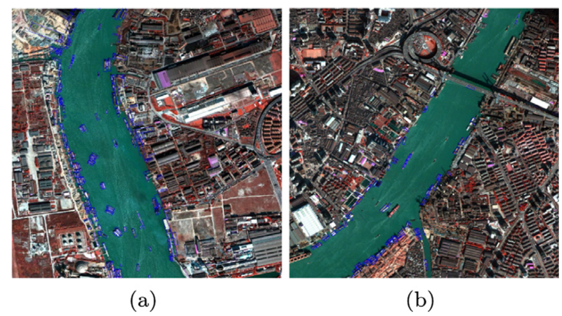


Fig. 7. Result of ship detection using two 3000 × 3000 images.

The DPMs employed in the experiment consists of three components. The three components correspond to three parts respectively. Fig. 6 shows the three components of the DPMs.

Fig. 7 shows two results of ship detection using two images. The bounding boxes of the detected ships are shown using blue rectangles.

Fig. 8 shows detection result for ships connected side by side. This is the most common scenario for clustered ships in the test images. Although the bounding boxes of each ship are overlapped, the center of the box shows the accurate position of each ship.

Fig. 9 shows the detection result for ships connected head to tail. For the ships staying this way, there is little overlap between detection bounding boxes.

Fig. 10 shows detection result for ships staying next to the river bank and docks. The river is detected and separated from the riverbank and pier.

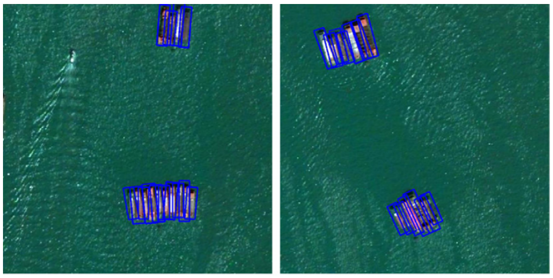
Fig. 11 shows the detection result for isolated ships and the ships with different size and shapes. The ships differing in size and shape can all be detected. The precision–recall graph [13] is used to show the performance of the proposed method. Precision and Recall are defined as

Precision = true positives/(true positives + false positives)

Recall = true positives/(true positives + false negatives)

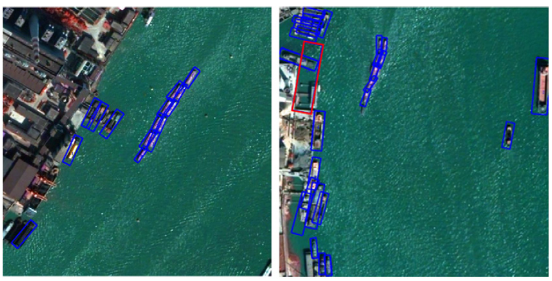
Fig. 12 shows the precision–recall curve. The mean average of precision is 0.824.

Based on the detection result of DPMs, a portion of false alarms are removed using the ratio of water pixels and area of bounding box for each detected ships. The detections with a ratio larger than 0.3 are removed. Finally, the best precision and recall of the proposed method are 0.88 and 0.92.



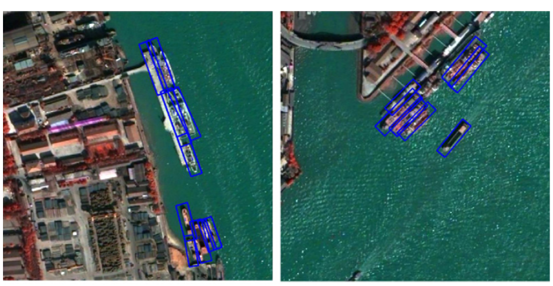
(a) (b)

Fig. 8. Detection result for ships connected side by side.



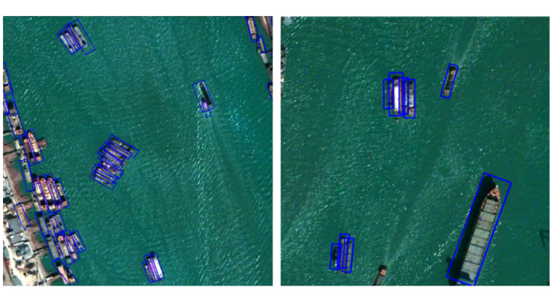
(a) (b)

Fig. 9. Detection result for ships connected head to tail.



(a) (b)

Fig. 10. Detection result for ships staying next to the pier and riverbank.



(a) (b)

Fig. 11. Detection result for ships differing in size and shape.

4. Conclusions

Detecting ships in inland river is facing challenges such as some ships are connected to side by side or head to tail, and some ships are staying next to the piers and docks, ships are highly differing in size and shape.

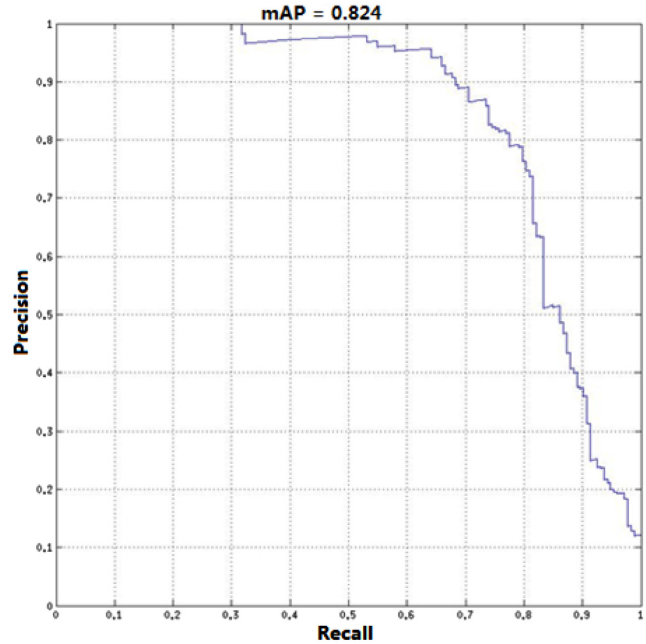


Fig. 12. Precision–recall curve.

In this paper, a hierarchical method is applied to detect ships. The regions of interest are located using image segmentation. The ship is detected in the ROIs using DPMs. Thank to the multiple components and deformable parts of the DPMs, the proposed method can detect ships with different size and shape and separate them from the riverbank and piers. For the clustered ships staying side by side or head to tail, the proposed method also is capable to detect them and separate them from each other. The spectral density is added to the detecting procedure and suppressed a portion of false detections.

Declaration of competing interest

No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work. For full disclosure statements refer to https://doi.org/10.1016/j.jpdc.2019.04.013.

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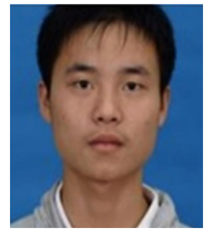
Pengfei Song is currently pursuing the Ph.D. degree Key Laboratory of Spectral Imaging Technology CAS, Xi'an Institute of Optics and Precision Mechanics, Chinese Academy of Sciences, Xi'an 710119, Shaanxi, P. R. China and with Xi'an Jiaotong University, Xi'an, China, 710049. His main research interests are pattern recognition and machine learning.



Lei Qi is currently pursuing the Ph.D. degree Key Laboratory of Spectral Imaging Technology CAS, Xi'an Institute of Optics and Precision Mechanics, Chinese Academy of Sciences, Xi'an 710119, Shaanxi, P. R. China and with University of Chinese Academy of Sciences, Beijing 100049, P. R. China. His main research interests are pattern recognition, machine learning, and computer vision.

Xueming Qian is full professor with Xi'an Jiaotong University, Xi'an, China, 710049. His research interests include social media big data mining and search.

Xiaoqiang Lu is a full professor with Key Laboratory of Spectral Imaging Technology CAS, Xi'an Institute of Optics and Precision Mechanics, Chinese Academy of Sciences, Xi'an 710119, Shaanxi, P. R. China. His current research interests include pattern recognition, machine learning, hyperspectral image analysis, cellular automata, and medical imaging.