Object Detection In Surveillance Video

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Abstract: Surveillance is a process to gather an information from the analysis. The surveillance can be applied in all applications like video, communication, data monitoring and in hospital. In all these field, the surveillance is performed to monitor the abnormal conditions in it. In this, the ship detection is performed in the marine surveillance videos. Because, the ships are easily crossed the other country border without knowing or with any intentional. In such a state, there is a risk of safety. To avoid this, the marine officers will routine check their area to find out any invasion of ships. It is possible during normal weather conditions. But, in abnormal conditions, it becomes a difficult process and time consuming is high for monitoring. In order to overcome such difficulties, the image processing technique were used to determine the ships in the sea. Most of the techniques were based on the YOLO processing which requires perfect threshold for detection. In order to eliminate the thresholding process, in this an optimized regional convolutional neural network is proposed. Here, the frames in the video will be subjected to firefly optimization based clustering process to separate the shore and sea area. Then, the sea area is subjected to regional convolutional neural network for different type of ship detection. Due to this optimized approach, it able to detect the ship effectively and in minimal time consumption of regional convolutional neural network by applying on the sea area alone. The ship detection process is implemented using MATLAB R 2018a version and evaluated in terms of accuracy, precision and Recall. The proposed optimized RCNN able to outperform saliency based YOLO function for ship detection.

Keywords: object detection, surveillance video, ship, YOLO, firefly, clustering, Regional CNN.

1. Introduction

The word surveillance means to watch from above i.e., it helps to observe the information from a longer distance. It helpful for monitoring the safety condition in normal civil and military borders to detect any abnormal activities. It is done with the help of camera by capturing the images in frame format to make a video of the conditions in a place. It can be done in any places like office, shopping complex, hospitals, national border and in common pathway.

The main motto of the surveillance is to find out an abnormal event or the person causing the actions by observing the video. The abnormal actions is determined through the image processing techniques and applications. Several algorithms were used to perform the following actions on the surveillance video like object detection, tracking and classification of the objects in the video. The discussion of those algorithms were is given in this and the following sections

A study of various algorithms and approaches used in the surveillance video is discussed in [1]. Here, first, the categories in the object detection in terms of detection and tracking. Then, in detection, it discussed about the similar type of object detection, fixed object detection and moving object detection. Then, it discussed about the subtraction of the background and techniques used in the detection and tracking process.

The detection of falling object in the video is proposed in [2]. Here, the object is the human falling from a building or any place. Because, it helps the security to initiate their safety process easily by monitoring their actions. To detect the human fall, various frames of human fall is trained with the help of PCA network. Then, the Support vector machine is used to classify the corresponding actions. This technique helps to increase the response rate for the falling action.

An algorithm for moving object in the footage of monitoring conditions is proposed in [3]. Here, first the motion is detected with the help of edge detection to segment the regions as stationary and non- stationary. Then, the optical flow algorithm Horn Schunck is used to estimate the motion of the object. This approach works faster in estimating the nature of motion due to the region separation process.

A max-coverage algorithm to define all the abnormal actions from various videos is proposed in [4]. Here, first the moving objects like pedestrians and vehicles are detected in the video. Then, it is processed with the max coverage algorithm to detect the abnormal actions in it. Finally, based on the trajectories information, the random classifier is used to summarize all those abnormal actions in a hierarchical manner. Due to this, the classifier is able to find out any abnormal events based on the motion of the objects in the video.

A moving object detection technique in a compressed video is proposed in [5]. Here, first the non-moving objects are considered as foreground. This foreground is determined with the help of connectivity with each other in four directions. Once the foreground, is clustered, then the moving objects like human and vehicles are determined with the help of codebook.

Most of the research works determined the objects based on the background or foreground subtraction in the video. It also able to detect one or two objects only. Due to this, it requires more processing time and new algorithm to detect the objects. This problem is overcome with the help of deep learning approach.

A deep convolution network is trained with various objects to detect the objects in the video [6]. Here, the objects are detected frame by frame with the trained network. It uses different types of layers for extracting the features and classification process. Due to this deep learning, it able to detect multiple objects at a time.

An improved version of Gaussian mixture model is proposed to detect the moving objects in the CAVIAR video [7]. Here, the frames are resized first to speed up the process. Then, the GMM is applied on the resized frames to perform the background subtraction by having more than five values of GMM. Finally, the moving objects are detected by placing the bounding box on it.

The fastest approach to detect the objects in a video is proposed in [8]. Here, the GMM is used for the object detection but it update its value only if there is a change in the pixel. Otherwise, it doesn't update its value and keep it. Due to this, it able to speed up the background subtraction process efficiently as compared to other GMM methods.

Most of the detection algorithm is used to find or track the objects. But in [9] the recognition of human motion using machine learning is performed. Here, the face of the human is used for determine the emotions. The face image is processed to extract features from it. Then, those features are trained along with its motion labels using support vector machine and dynamic time warping and naïve bayes classifier for recognition process. Among the three approaches, the Dynamic time warping is best for detection of human motions.

A study of various algorithms and approaches for object detection and tracking is discussed in [10]. Here, first, the categories in the object detection in terms of detection and tracking. Then, in detection, it discussed about the similar type of object detection, fixed object detection and moving object detection. Then, it discussed about the subtraction of the background and techniques used in the detection and tracking process.

The organization of the paper is as follows. Recent survey of the object detections algorithms were discussed in section 2. Section 3 discussed about the existing approach and its short coming. Section 4 discussed about the proposed method working. Section 5 discussed about the implementation and the discussion of the results. Finally, the paper is concluded in section 6 and future work is given in section 7.

2. Related works

In this section, the recent techniques used in the ship detection process are discussed below:

Table 1: various techniques in ship detection

Author	Technique	Observations	shortcomings
Shaw et al., (2018)	Faster RCNN with different trained networks and YOLO Version 2	Faster RCNN with ResNet is best in terms of detection. YOLO is best for processing	Directly applied on the frame results in minimum frame rate detection in faster RCNN
Chen et al., (2018)	Gaussian mixture model	Locate the moving ship targets	Modelling of the background is important for better results
Kim et al., (2018)	Faster R-CNN Intersection over union Bayesian function for classification	Ship classification by region localization using RCNN and IoU	Threshold selection in IoU is important for detection of ships
Huo et al., (2018)	Contrast based technique for ship detection	• Synthetic Aperture Radar image is used. • Maximal extremely stable region for ship localization. • For exact detection, contrast based weighted	Area variation rate is responsible for the region separation.

		information entropy is used.	
Lin et al., (2018)	Faster RCNN with VG net	Squeeze and excitation mechanism is applied to the feature encoder block to improve performance	Performance is improved but time consumption is high.
Zhao et al., (2019)	Combined deep learning technique	Deep network for ship detection. Convolutional network for ship classification	Large time of processing using two deep learning approaches.
Liu et al., (2019)	Light spot detection and tracking	First, Light spots are detected through laplacian of Gaussian. Second, gray thresholding is applied to separate light regions Third, kalman filtering for the localization of ships	The detection rate is higher only in light tower region.
Li et al., (2019)	Saliency map based ship tracking	First, motion compensation between the frames. Second, the saliency map detection using Gaussian pyramid. Third, morphological process is applied to locate the ships	Tracking of particular ship only performed
Wawryzniak et al., (2019)	Ship detection and tracking in rivers	First, moving object is detected and its status is updated. Second, water detection is performed to locate the ships and track its position	Particular ship only can be analysed
Cao et al., (2019)	Segmentation and deep learning based ship detection	First, image is pre-processed with wavelet transform. Second, pre-processed is subject to segmentation process using morphological watershed algorithms Third, deep convolutional neural network for ship detection using Zemike moment	Large number of processing stages for ship detection
Chen et al., (2020)	Gaussian mixture model based YOLOV2	Hybrid combination of three techniques is used for ship detection. The three techniques are Gaussian mixture model Generative adversarial network YOLO version 2	Only small ships are trained and detected

Chen et al., (2020)	Ship detection based on spatio temporal properties	First, ship and other regions are separated using YOLO Second, ship area is segmented using K-means clustering Third, the spatio temporal properties is used for the ship detection	Multistage processing required
Feng et al., (2020)	Multi branch SVM based ship detection	First, region localization is performed using multi gradient features, Then, the ship is detected using the Multi branch SVM	Precision rate is minimum for four categories of ships
Zhang et al., (2020)	Feature fusion of CNN for ship detection using Google earth images	CNN features are get fused using different level for the better detection	The detection requires some pre-processing steps for improving the performance and detection
Huang et al., (2020)	Regressive convolutional neural network on USV ship images	First, YOLO version 2 for feature extraction Second, YOLO version 3 for multiple features. Third, clustering to group similar feature and classify using CNN	Time consumption is high due to repeated CNN processing

3. Existing system

In existing system, the ship detection in the surveillance video is performed through deep learning technique. Here, first the different types of ship images were collected. From the collected images, the features are extracted and its corresponding ship types is given as the label for the features. The feature extraction and labelling process is performed with the help of convolutional neural network. The image in the surveillance video is first processed with canny edge operator and Hough transform to detect the boundaries in the image. Then, the boundary detected image is processed with the YOLO operator to detect the coastal line area [26]. After the detection of salient regions, the frames will be processed with the help of convolutional neural network to determine the ships in the region. The CNN based approach is tested with six types of ship images. Among this, it able to detect five ships with coastline at accuracy of above 80%. Yet, it has better identification of the ships effectively with coastline, there are few infirmity in this method. It is as follows:

- It requires more memory space for processing the frames in the video.
- It uses YOLO functions for accurate coastline detection which works based on the threshold value.
- There is a chance for the coastline missing by using the minimal threshold.

This limitations are reduced with the help of the proposed method Region based convolutional neural network.

4. Proposed system

In this work, a single deep learning network is proposed to detect the ships in the frames of the surveillance video. Because, in existing system, it uses the Yolo operations for detecting the coastal region of the frames. But, in this, the threshold, is selected based on the optimization which is able to detect the coastline perfectly. Then, the salient region is further processed with Region based CNN for accurate detection of ships. In this, the negative value is given to the background area and the positive value to the ships by using the cluster based region based CNN. The flow chart for the proposed method is shown in the below figure 1.

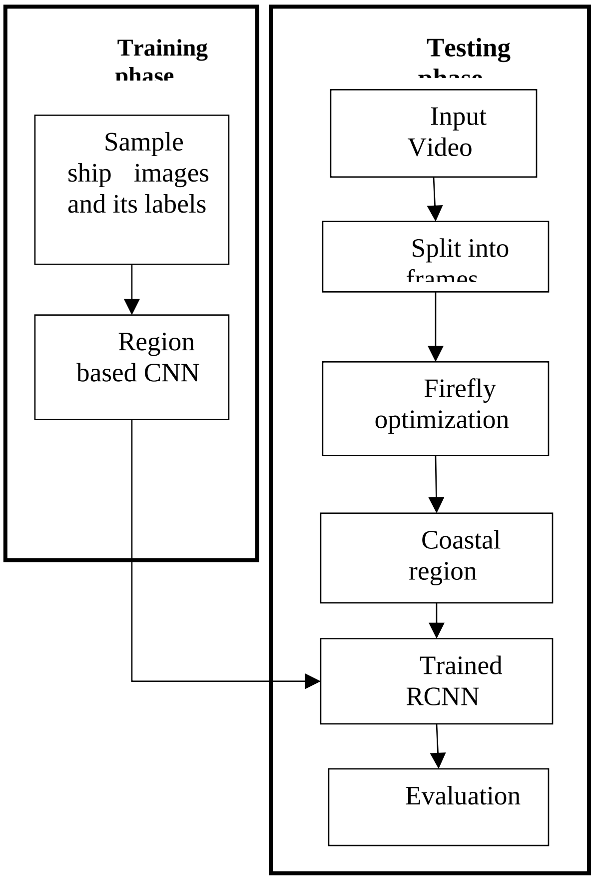

Figure 1. Proposed RCNN flow diagram

Figure 1 comprises the process in both the training and testing phase in the proposed method. In the training phases, the input images is directly processed with the Region based CNN for extracting the features. In the testing phase, the coastal line is extracted and then it is tested with the trained RCNN for the ship detection. The detail explanation of the proposed method is given below.

4.1 Training of ship detection using Region based CNN:

In this section, the training process of ship image detection using region based CNN.

4.1.1 Input images:

Here, the input images are taken from the openly available dataset from google images [27]. In this, totally eight types of ship images are used for detection. The sample ship images and its name are mentioned in the table 2.

Table 2. Sample ship images and its types

Image	Type	Image	Type
	Ore carrier		passenger

	Bulk carrier		container
	Cargo		Oil tanker
	Fishing		Aircraft carrier

The sample ship images for each type is shown in the table 1. The database is formed with total 500 images by collecting images from each types.

4.1.2 Pre-processing:

Here, the input images are converted into gray scale image using the following formula in 1.

$$\text{Gray image} = 30\% \text{ of } R + 59\% \text{ of } G + 11\% \text{ of } B \qquad (1)$$

The terms R, G and B are the red, green and blue channels of image. Then the pre-processed image is processed with RCNN for the identification of ships in the video

4.1.3 Region based CNN:

Here, the pre-processed image is given as the input image for the network. The working of the Region based CNN for the detection process is shown in the figure 2.

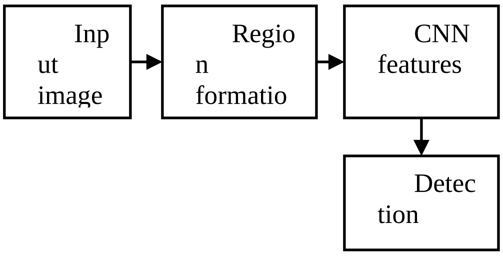

Figure 2. Steps in RCNN

4.1.3.1 Input image:

Here, the input image is the pre-processed ship images from the previous step.

4.1.3.2 Region formation

In this, the region formation is performed to separate the background and the object of interest region. It is performed with the help of selective search algorithm. In selective search algorithm which converts smaller similar region into a larger region. Here, the background region is indicated with the negative value and the ship region is indicated with the positive value.

The steps in the region formation is as follows:

Step 1: Input image

Step 2: Perform Initial segmentation of the images

Step 3: Apply greedy algorithm to combine the similar region. It uses the following formula for segmenting similar regions (SSR).

$\mathrm{SSR} = \mathrm{CS} + \mathrm{TS} + \mathrm{FS} + \mathrm{SS}$	2
$\text{Color similarity (CS)} = \sum_{1}^{n} \min \text{(histogram bins in rows and columns)}$	3
$\text{Texture similarity (TS)} = \sum_{1}^{n} \min \text{(texture of image)}$	4
$\text{fill similarity (FS)} = 1 - \frac{\text{size of bounding box} - \text{size of rows} - \text{size of column)}}{\text{size of image}}$	5
$\text{Size similarity (FS)} = 1 - \frac{\text{size of rows} + \text{size of column)}}{\text{size of image}}$	6

Step 4: segment the regions based on the similarity level using equations 2 to 6.

Step 5: Region based segmented image

4.1.3.3 CNN Features:

Then, the segmented regions are subjected to the convolutional neural network for feature extraction process. In general, the soft-max and classification layer will be present in the convolutional neural network. This layers are not available for this work, in order to extract the features alone. The working of CNN for feature extraction is as follows:

Step 1: Segmented image from the region formation as input to the input layer of size [128 128].

Step 2: Convolve the input with the convolution layer with each region separately. The size of convolution filter is [48 48 96]

Step 3: Then, the max-pooling layer is used to group the pixel values.

Step 4: Then, three convolution layers are used with size [24 24 256] for one layer and [13 13 4096] for the remaining two layers.

Step 5: The max-pooling layer will be available between two convolutional layers.

Step 6: By processing of image with all the layers, the output feature is obtained as bounding box.

4.1.3.4 Detection

The detection process takes place in the testing phase. It is performed using support vector machine based on the bounding box values obtained from CNN for each region.

4.2 Ship detection using Firefly based R_CNN:

In this section, the testing of the proposed algorithm is performed on the ship video.

4.2.1 Input video:

The input video is formed with the help of images taken from [27].

4.2.2 Frame conversion

Then, the input video is processed as frames for the object detection.

4.2.3 Firefly optimization

In this, the optimization process is applied to detect the threshold for the coastal line separation using YOLO. Here, first five frames will be processed with the optimization technique to detect the threshold. Then, by averaging those thresholds, the overall threshold for the YOLO process is determined. The steps in the firefly algorithm is as follows:

Step 1: Initialization

In this, the number of fireflies, firefly position, number of iterations and the parameter for updating the position of fireflies are given.

Step 2: Make all the fireflies attracted towards the light. Here, the light indicates the best solution for the fitness function. Here, the fitness function is to segment the coastal region effectively.

Step 3: As the fireflies are attracted towards the light, the intensity of the light is get affected. This affecting rate is mentioned as α.

Step 4: Due to the attraction of light, the fireflies also glows and it attracts other fireflies, this attractiveness of the firefly is indicated as β. It is given in equation.

$\beta = \beta_0 e^{-\gamma R^2}$	7

The term R and γ is the distance between the two fireflies, the distance is calculated using Euclidean distance and intensity of the light.

Step 5: The attraction of firefly to another firefly based on the above parameters is given in equation 8.

$M_i = M_i + \beta_0 e^{-\gamma R^2}(M_j - M_i) + \alpha \in_i$	8

Step 6: Based on the equation 8, the fireflies are attracted to other fireflies.

Step 7: The whole process is repeated till it reaches the maximum iteration from step 2 by updating new α, β and γ.

Step 8: The optimal threshold is determined for the one frame.

Step 9: The same process is repeated for five frames, then the average threshold from five frames will be calculated.

4.2.4 Coastal line extraction

Then, the calculated threshold will be applied to K-Means clustering and thresholding operations is performed on the image is to extract the coastal regions.

4.2.5 R_CNN for ship detection

Then, the coastal region extracted frame will be subjected to the trained R_CNN to detect the different types of ships. This approach is able to detect the ships effectively.

In many works, the R_CNN is addressed as time consuming process. But, this problem is overcome by applying the actual region location. Due to this actual region, the ship detection is performed accurately due to the double region detection process.

4.3 Evaluation Metrics:

The proposed firefly based R_CNN is evaluated using the following three parameters:

Accuracy: It indicates the number of ships identified correctly in the video. The formula 9 is used for the calculation.

$\text{accuracy} = \dfrac{\text{overall no of ships correctly identifed}}{\text{Number of frames in video}}$	9

Precision:Precision is to identify the particular ship classes correctly in it. The following formula 10 is used for the calculation.

$\text{precision} = \dfrac{\text{Correctly identified ships in a class}}{\text{total number of ships identified in that class}}$	10

Recall:Recall is similar to precision but it gives the exact result of ship class identification rate using the formula 11.

$\text{Recall} = \dfrac{\text{Correctly identified ships in a class}}{\text{total number of ships in that class}}$	11

In the next section, the discussion on the results of proposed method implementation is explained.

5. Implementation and discussion

In this, the proposed method is implemented with the help of simulation software called MATLAB under windows 10 environment.

The input images are processed with the firefly optimization to determine the optimal cluster value. The number of iterations required to determine the optimal cluster value is denoted using the convergence curve. It is shown in the figure 3.

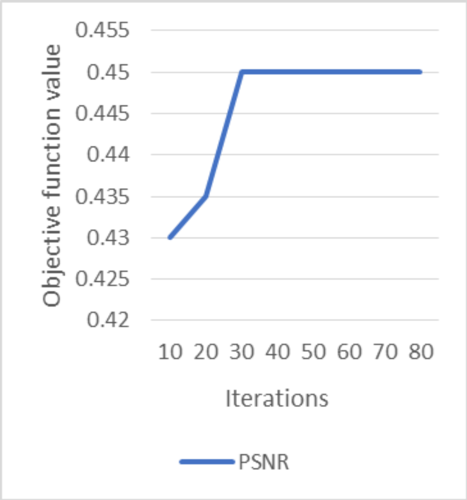

Figure 3. Firefly convergence curve for optimal cluster

Firefly optimization requires only thirty iterations to determine the optimal cluster for separating the coastal and water area using K-means clustering algorithm.

Then, the water area of the frames or images is subjected to regional based convolutional neural network. The classification of ship categories are evaluated using the metrics in 4.3 and compared with the existing technique.

First, the accuracy of each ship type is compared with the existing and proposed technique is shown in table 4.

Table 4. Detection rate of different ship types

Ship types	Existing Salient based YOLO	Proposed Firefly based RCNN
Ore carrier	0.881	0.895
Bulk carrier	0.876	0.897
Cargo	0.917	0.93
container	0.903	0.919
fishing	0.783	0.82
Passenger	0.886	0.90
Oil tanker	-	0.88
Aircraft carrier	-	0.87

Table 4 shows that it able to detect all the ship types effectively using the proposed method as compared to the existing method. It also able to classify additional two ships as compared to the Salient based YOLO method.

The precision and recall value comparison of each ship type between the existing Salient based YOLO method and proposed firefly based RCNN is shown in the following figures 4-5

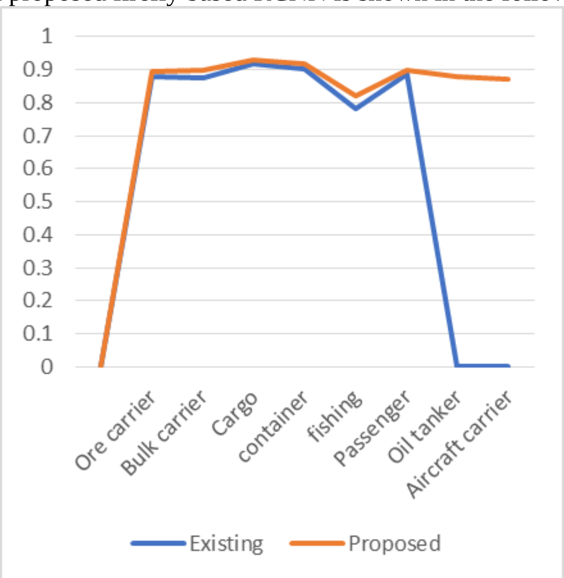

Figure 4. Precision comparison curve

Figure 4 shows that the proposed firefly based RCNN is able to detect the individual ships types effectively as compared to the existing YOLO based detection with 80% above for all the ship types.

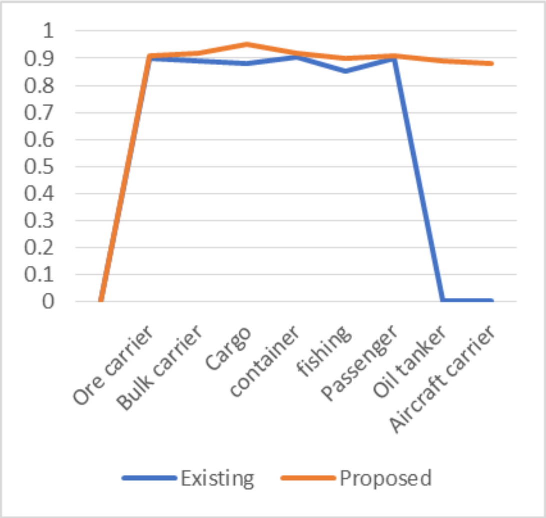

Figure 5. Recall comparison

The proposed Firefly based RCNN able to identify the individual ships effectively with minimum false calling of other ship names by having higher percentage of recall value of 90% for all the ship types as compared to the existing method depicted from the figure 5.

Therefore, the proposed firefly based RCNN is best in terms of detecting all the ship types as compared to the existing method. It also shows that it able to detect the coastal region automatically by using optimization algorithm instead of thresholding technique as in the existing method. Due to this, it able to work faster for all the ship types with region based convolution neural network.

6.Conclusion

Ship detection is one of the important type of object detection in the surveillance video. Because, the ship detection in the marine field helps the officers from invasion of other ships to our border and invading our ships to other border. In the existing, the YOLO based ship detection is performed on the coastal area separated frame. The detection is good with better choice of threshold. To avoid this, here the firefly optimization is used to cluster the sea area and costal area. Then, the RCNN is applied on the sea area to detect the various types of ships. With the proposed method application on a surveillance video, it is observed that it able to detect the ships accurately with lesser time period and it outperform the existing method with higher detection rate and lower recall rate. Therefore, the proposed optimized Regional CNN is best for the ship detection.

7. Future Scope

In future, the proposed method can be extended by applying faster RCNN to improve its performance and speed.

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