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Ship Tracking Identification Based on Darknet Network and YOLOv3 Algorithm

Haoxiang Gao

Merchant Marine College, Shanghai Maritime University, China

iblctw@gmail.com

Abstract: In order to solve the problems of low utilization rate, large error rate, no identification ability and manual participation in video surveillance processing in coastal and inland waters of China, a ship tracking and identification method based on Darknet network model combined with YOLOv3 algorithm is proposed to realize ship tracking and real-time detection and identification of ship types, which solves the problems of ship tracking and identification in important monitoring waters. The proposed Darknet network introduces the idea of residual network, adopts the cross-layer jumping connection mode to increase the network depth, constructs the ship depth feature matrix to extract advanced ship features for combinatorial learning, and obtains the ship feature map. On the above basis, YOLOv3 algorithm was introduced to realize target prediction based on image global information, and target region prediction and target class prediction were integrated into a single neural network model. Punishment mechanism was added to improve the ship feature difference between frames. By using logistic regression layer for binary classification prediction, target tracking and recognition was able to be realized quickly with high accuracy. The experimental results show that, the proposed algorithm achieves an average recognition accuracy of 89.5% with the speed of 30 frame /s; compared with traditional and deep learning algorithms, it not only has better real-time performance and accuracy, but also has better robustness to various environmental changes, and can recognize the types and important parts of various ships.
Keywords: Vessel monitoring; Vessel tracking; Vessel type recognition; Darknet network; YOLOv3 algorithm

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1. INTRODUCTION

In recent years, the number and scale of all kinds of sea-related and sea-using activities are increasing, and the number of various safety accidents, rule violations and illegal acts at sea are correspondingly increasing, making the monitoring of ships at sea increasingly heavy. At present the main monitoring method is the ship automatic identification system (Automatic Identification System, AIS) and the shore-based radar, but due to the existence of subjective error information in the AIS information, but the radar target exists information missing and so on, therefore in the harbor, the coast, as well as the

river coast all have arranged a large number of video cameras, to the existing AIS is supplemented with radar information to assist ship control, but the utilization of existing video surveillance is generally low, mainly because of the need to rely on manual observation.

To solve this problem, Yu Xin Huang [1] used OpenCV combined with an intelligent algorithm to monitor and track ship trajectories. Teng Fei et al [2] used the Tracking-Learning-Detection (TLD) framework to realize ship identification and tracking. In order to improve the accuracy of ship tracking, Zhu Guanghua [3] combined a BP (Back Propagation) neural network and a Kalman filtering algorithm to construct a dynamic ship tracking model. Jiang et al. [4] also proposed a ship type recognition method based on structural feature analysis.Currently, deep learning algorithms based on computer vision [5] have achieved good results in the field of target tracking and recognition, and Krizhevsky et al [6] proposed image classification for Deep Convolutional Neural Network (DCNN) based on deep learning theory. Szegedy et al. [7] treated the target detection problem as a regression problem for the target, and Erhan et al. [8] used deep convolutional neural networks to predict the target's bounding boxes in a regression. sermanet et al. [9] proposed a deep convolutional neural network (DCNN) based framework, OverFeat, which integrates identification, localization, and detection tasks. Simonyan et al [11] and Szegedy et al [12] designed a 22-layer deep convolutional neural network with a similar detection framework. He et al. [13] proposed a network layer that can be considered as a monolayer to improve the detection rate. In order to avoid the scenario where the extraction of candidate regions takes more time than the actual object detection, Girshick [14] proposed a fast regional convolutional neural network, and an end-to-end object detection model emerged. SSD) detection method.

To address the above problems, this paper proposes a ship tracking and recognition method based on the Darknet network model of the deep learning framework combined with the YOLOv3 algorithm [15]. The method improves the basic classification network structure and the bi-class prediction method of targets in traditional deep learning to achieve ship tracking and real-time detection to identify ship types. First of all, the deep network model constructed using the residual connection method on the input ship image sample data is convolutionally operated through the constructed ship feature matrix to extract the corresponding features, perform combinatorial learning, and train the feature map model of the object; and on this basis, a feature interaction layer is added, which is divided into three scales, and the local feature interaction of the feature map is realized by means of convolutional kernels within each scale, according to the data The standardized processing, dimensional clustering and fine-grained feature operation directly predict the central coordinates of the target ship; meanwhile, a penalty mechanism is introduced to improve the generalization ability of the model to better match the tracking ship, and a multi-label and multi-classification logistic regression layer is added on top of this to sub-classify each category and thus realize the classification identification of the target ship.

2. SHIP TRACKING IDENTIFICATION PRINCIPLE

Video-based vessel tracking and identification is one of the very important tasks in intelligent traffic monitoring at sea. Efficient ship tracking and identification algorithms are not only able to effectively track ships in the region of interest (ROI) in different application scenarios, but also identify multiple

ship types. Conventional processing methods are based on the combination of AIS systems and radar, and by using the Ship Tracker based on Multi-view learning and Sparse learning mechanism (STMS), it is possible to identify many types of ships.), Kalman filter, particle filter, meanshift and other algorithms [17-20], and achieved some results; but there is no good combination for tracking and identification, and it can't be well applied to the maritime intelligent traffic management.

3. VESSEL FEATURE EXTRACTION NETWORK

The ability of feature extraction network to extract and learn ship features is the key to ship tracking and type recognition. The Darknet network structure of the deep learning framework adopts the connection idea of the residual network and introduces the Residual structure, which can still converge even though the network structure is very deep. However, in the process of extracting ship features, since the space belonging to the ship belongs to the complex region of high sea state that changes dynamically, some of the ship type features extracted by the original basic network structure are low-level ship features, which not only have no significant difference between these low-level ship features, but also directly affect the calculation speed and the recognition accuracy of different types of ships. In order to be able to extract different ship depth feature expressions and generate more feature combinations to learn the feature map of the obtained object, the ship depth feature matrix is constructed in the original basic network structure to extract the high-level features of the ship, while adding the maximum pooling layer and introducing the local neuron activity to create a competition mechanism.

The YOLOv3 algorithm extracts features directly from the input image using regression ideas through the feature extraction network to obtain a feature map of a certain size, then divides the input image into grids of corresponding sizes, and directly matches and locates the bounding box predicted by the grid with the central coordinates of the target object in the real bounding box, and performs classification and recognition of the target object on this basis.

3.1 Ship tracking

For the spatial environment where the ships are located, the background similarity and the overlapping of the ship movement, the direct use of frame regression to predict the coordinates of the ship target and then match the positioning to track the ship, will result in the loss of the ship boundary frame. In order to effectively suppress background similarity objects to prevent tracking frame drift and to achieve a more robust effect on the movement of the target itself, a penalty mechanism is constructed to process the model features and to represent and learn these features in order to achieve the purpose of ship tracking in video sequences.

3.2 Vessel type identification

For the identification of maritime ship types, the spatial distribution of ships has the overlapping phenomenon, there will be the same box detection corresponds to two different ships, so that only one ship type can be identified, resulting in the identification rate down. In this paper, multi-label classification is used for target category prediction, and a logistic regression layer of multi-label and multi-classification is added to the network structure. The sigmoid function [21] is used as the logistic regression unit to bi-categorize each category.

4. EXPERIMENTS AND ANALYSIS OF RESULTS

4.1 Ship tracking

The port of Shanghai has become one of the most important ports in the world, with container throughput exceeding 36 million TEU (Twenty-foot Equivalent Unit) in 2016. The huge container throughput of the Shanghai port has resulted in the shipping lanes within the hinterland of the port being one of the busiest inland waterways in China. Therefore, it is of practical significance to use the proposed ship tracking identification model to detect the ships in the surveillance video of Shanghai port. The collected maritime surveillance videos are divided into two groups in order to evaluate the performance of the ship detection algorithm. The first group of vessel surveillance videos is based on the good navigational environment and is used to evaluate the detection performance of the vessel detection model under different traffic states. The second group of ship monitoring videos is based on foggy navigational environment and is used to test the robustness and accuracy of the ship inspection model under very low visibility conditions. The experimental platform for this study is Windows 10 operating system, 16 GB RAM, CPU processor at 3.2 GHz, GPU is GTX 2070, and the experimental platform is PyCharm (version 2020).

4.2 Analysis of experimental results

In order to verify the validity and reliability of the detection, the average loss curve based on the number of iterations of the training process shown in Figure 3(a) reveals that after 400 training iterations, the value of the average loss function remains almost constant and stabilizes as the number of iterations increases, indicating that the algorithm has a fast convergence in the training process. Precision-Recall curve is used to measure the performance of the classifier. Take container ship as an example, there are A container ships in the test image, and the trained model detects B container ships, of which C container ships are detected correctly, then Precision-Recall is defined as follows: Recall (R The maximum number of seconds per second is C/A for ecall and C/B for precision.

4.3 Comparison of results

The keyframes are extracted from the vessel surveillance video under different environments and traffic flow to evaluate the detection performance of the algorithm, respectively. The ships of the video sequence are detected by the proposed YOLOv3 algorithm; in addition, the ships of the video sequence are also detected using the Kalman and Meanshift tracking algorithms based on traditional algorithms and the ship tracking operator (STMS) model based on Multi-view learning and sparse learning mechanisms, respectively, to Comparing the detection performance of different algorithms in different scenarios [22]. Based on the traditional algorithm, it shows good tracking performance in the early ship tracking process; however, in frames 168 and 372, the tracking frame is far away from the real target ship, and even in frame 450, the target ship is not tracked correctly. Moreover, the above algorithm can only mark one class of ship targets, but cannot track multiple targets and has no identification function. In this paper, the proposed YOLOv3 algorithm can track and identify almost all the ships in this frame, and can detect the ships in real time. The detection performance of this algorithm remains basically unchanged in the case of large maritime traffic, while the traditional algorithm has a certain false detection rate.

In order to verify the robustness and accuracy of YOLOv3 in this paper, a ship detection experiment is conducted on the maritime surveillance video of a ship navigating in foggy weather, based on the fact that the traditional algorithm has lost the ship target during the ship navigation, which greatly challenges the robustness and accuracy of the ship tracking algorithm. Identify the ship. The algorithm in this paper effectively overcomes the effects of foggy weather and lighting changes, and tracks and identifies ships even in very low visibility conditions. The YOLOv3 algorithm in this paper accurately identifies various ship types and important parts of the ships.

5. CONCLUSION

The proposed method based on Darknet network and YOLOv3 algorithm in this paper effectively overcomes the shortcomings of various sea conditions such as different lighting, different weather and wind conditions as well as human involvement in the problem of ship tracking recognition oriented to the visual perception task of intelligent navigation. Comparative experiments with traditional algorithms show that the algorithm is able to detect ships in fast and real-time, yet with good accuracy and robustness. This study is based on ship tracking and ship type recognition studies with good visibility conditions and does not carry out studies related to ship detection, tracking and ship type recognition studies with poor visibility conditions, such as ship detection, ship tracking and ship type recognition studies based on night vision conditions. The follow-up work will integrate radar, infrared, AIS and other maritime traffic data to conduct in-depth research on issues such as ship tracking and identification in poor visual conditions.

Rotary kiln is also used in the production of saloon with production capacity by burning specific clay soil that possesses adequate quantity of silica, alumina, and iron oxides. The external diameter of the kiln is.

The main purpose of a rotary kiln hydrolyser is to convert olive pits into char fated to the production of activated char. The capacity of plant is about of wet olive pit, distribution of pyrolysis products as function of the process temperature

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