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Research on target detection of carrier-based aircraft based on deep convolutional neural network

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Abstract. Aiming at the problem that the aircraft carrier deck carrier is dense and easy to block, the carrier aircraft target is difficult to detect, and the detection effect is easily affected by the illumination condition and target scale. Based on the YOLO v3 target detection model, the loss function weighted and linear attenuation NMS strategy is proposed. The experimental results show that the proposed improved method can automatically and comprehensively extract the target characteristics of the carrier aircraft. Compared with the original YOLO v3 detection model, the improved model has a good detection effect on the occlusion aircraft target, the detection accuracy and speed can meet the actual needs, and the adaptability is strong under different illumination conditions and target scales, and the model is highly robust.

Keywords. carrier-based aircraft detection; convolutional neural network; YOLO v3 model

1. Introduction

At present, computer vision technology is developing rapidly, and image target detection has been widely used in the military field. Vigorously developing image recognition technology is of vital importance to improving our combat effectiveness and the safety of our personnel equipment. Aircraft carrier deck target detection is of great significance for ensuring the safety of deck aircraft equipment and improving the efficiency of aircraft transportation [1]. Due to the relatively small deck space of the aircraft carrier, the area of the aircraft usually has a large occlusion area. The occlusion of a large area often causes a serious loss of the target image information to the aircraft target, and the target cannot be accurately detected. Aiming at the problem that YOLO v3 target detection algorithm has low precision and difficult to detect occlusion target in detecting carrier aircraft targets, a loss function weighting and linear attenuation NMS (Non-Maximum Suppression) improvement strategy is proposed to detect the carrier aircraft carrier target on the carrier deck[2,3,4]. Experiments prove that this method Good results have been achieved in occluding carrier aircraft target detection.

2. Improvement method

2.1. Loss function weighting

If the true value of each cell is \( p^* \) and the predicted value is \( \hat{p}^* \), the loss can be expressed as the difference between the predicted value and the true value, ie \( \hat{p}^* - p^* \). In the YOLO v3 training
process, the loss is the mean square error between the predicted and true values of all cells. The loss function \( l \) consists of three parts, namely the bounding box loss \( l_{\text{coordinate}} \), the confidence loss \( l_{\text{confidence}} \) and the classification loss \( l_{\text{class}} \), which can be expressed as

\[
l = l_{\text{coordinate}} + l_{\text{confidence}} + l_{\text{class}}
\]

(1)

The bounding box loss consists of the error of the central coordinate and the error of the bounding box width and height, which can be described as

\[
l_{\text{confidence}} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} \text{Pr}_{\text{obj}}(i, j) \left[ (\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2 \right] + \sum_{i=0}^{S^2} \sum_{j=0}^{B} \text{Pr}_{\text{obj}}(i, j) \left[ (\sqrt{\hat{w}_i} - \sqrt{w_i})^2 + (\sqrt{\hat{h}_i} - \sqrt{h_i})^2 \right]
\]

(2)

Where \((\hat{x}_i, \hat{y}_i)\) denotes the coordinates of the prediction boxes; \(\hat{w}_i\) and \(\hat{h}_i\) denote the width and height of the prediction boxes respectively; \((x, y)\) denotes the coordinates of the calibration boxes, \(w_i\) and \(h_i\) denote the width and height, respectively; \(\text{Pr}_{\text{obj}}(i, j)\) denotes the presence of the target in cell \(i\), and The j-th anchor box is responsible for prediction. The calculation formulas for confidence loss and classification loss can be described as

\[
l_{\text{confidence}} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} \text{Pr}_{\text{obj}}(i, j) \left[ (C - \hat{C}_i)^2 \right] + \sum_{i=0}^{S^2} \sum_{j=0}^{B} \text{Pr}_{\text{obj}}(i, j) \left[ C - \hat{C}_i \right],
\]

(3)

\[
l_{\text{class}} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} \text{Pr}_{\text{obj}}(i, j) \sum_{c \in \text{classes}} \left[ p_i(c) - \hat{p}_i(c) \right]^2,
\]

(4)

Where \(\hat{C}_i\) is the confidence of the prediction box; \(C_i\) is the confidence of the calibration box. The classification labels are all-hot encoded, \(\hat{p}_i(c)\) is the encoded prediction category, \(p_i(c)\) is the encoded real category; \(c\) is the current detection target category; classes represent all target categories in the data set; \(\text{Pr}_{\text{obj}}(i, j)\) indicates that there is no target in the cell \(i\).

If the loss is calculated directly using (1), then the weights of the three types of losses are all 1. The weighted loss function \(a\) is

\[
l_w = (\alpha_{\text{xy}} l_{\text{xy}} + \alpha_{\text{wh}} l_{\text{wh}}) + (\beta_{\text{obj}} l_{\text{conf}} \text{obj} + \beta_{\text{no-obj}} l_{\text{conf-noobj}}) + \lambda_{\text{class}} l_{\text{class}}
\]

(5)

Where \(\alpha_{\text{xy}}\) is the bounding box center coordinate loss weight, \(\alpha_{\text{wh}}\) is the bounding box width and height loss weight, \(\beta_{\text{obj}}\) is the confidence loss weight of the target in the cell, \(\beta_{\text{no-obj}}\) is the confidence loss weight of the target in the cell, \(\lambda_{\text{class}}\) is the classification Loss weight.

Figure 1. Two mutually obscured aircraft.
2.2. Linear attenuation NMS algorithm
As shown in Figure 1, the two aircraft parked on the ship's surface, the A plane in the red box, the confidence score of the prediction box is 0.8, and the blue box is the B plane. The confidence score of the prediction box is 0.6, B. The aircraft severely obscures the A aircraft, and the crossover ratio of the predicted frames of the two aircrafts A and B is greater than 0.5. When using the NMS algorithm to process the excess prediction box, the IOU (Intersection-Over-Union) of the A and B aircraft prediction frames is higher than 0.5 (the YOLO v3 setting threshold is 0.5), and the A aircraft with a higher confidence score is retained, and the confidence score of the prediction frame of the B aircraft is set to 0, causing the B aircraft to be undetectable. This paper attempts to solve the problem that the occlusion aircraft cannot be accurately detected by NMS in YOLO v3 by using the linear attenuation NMS algorithm. When the IOU $I_{bi}^M$ is higher than the suppression threshold $N$, the confidence score $P_{class_i}$ in equation is linearly smoothed, and the optimized NMS algorithm is

$$P'_{class_i} = \begin{cases} 
P_{class_i}, & I_{bi}^M < N \\
Q_{class_i} \left(1 - I_{bi}^M\right), & I_{bi}^M \geq N 
\end{cases}$$

(6)

Where $P'_{class_i}$ is the confidence score after linear smoothing.

Optimized NMS algorithm processing flow chart, as shown in Figure 2.

**Figure 2.** Flow chart of NMS processing

This method adopts the IOU value linear attenuation confidence score method to avoid accidentally deleting the prediction frame of the occlusion target and improving the detection ability of the occlusion target.

3. Experiment and analysis

3.1. Dataset
The data set allocation is shown in Table 1.
Table 1. Experimental dataset

| Category                          | Train | Test | Sum |
|----------------------------------|-------|------|-----|
| Wing folding                     | 350   | 100  | 1200|
| Wing expansion                   | 366   |      |     |
| Wing folding + Wing expansion    | 384   |      |     |

3.2. Experimental results and analysis

Comparison of detection performance of two models of the same picture. The parameters are shown in Table 2, and the detection effect is shown in Figure 3.

Table 2. Detection performance of two algorithms of the same picture

| Detection algorithm      | Detection | False detection | Missed inspection | Recall/% | Precision/% | Detecting a single picture time /s |
|--------------------------|-----------|-----------------|-------------------|----------|-------------|-----------------------------------|
| Original YOLO v3         | 351       | 59              | 81                | 81.25    | 85.61       | 0.059                             |
| Improved YOLO v3         | 387       | 36              | 45                | 89.58    | 91.49       | 0.067                             |

Figure 3. Compared with the original image, the detection effect of the algorithm before and after the improvement

Figures 3(b) and (c) show the original YOLO v3 algorithm and the improved algorithm proposed in this paper. Combined with Table 2 and Figure 3, it can be concluded that the improved algorithm is higher than the original YOLO v3 in terms of accuracy and recall. The algorithm also has a good detection effect on targets with a large degree of occlusion. Compared with the original YOLO v3 algorithm, the proposed algorithm improves the recall rate by about 8%, the accuracy rate by about 6%, and the detection speed to meet the real-time requirements.

Table 3. Different algorithms deal with the detection effect of the same picture

| Detection method    | Precision/% | Detecting a single picture time /s |
|---------------------|-------------|-----------------------------------|
| Improved YOLO v3    | 91.49       | 0.067                             |
| YOLO v3             | 85.61       | 0.059                             |
| SSD                 | 87.34       | 0.074                             |
| Faster R-CNN        | 93.58       | 0.116                             |
Different algorithms deal with the detection effect of the same picture. The SSD, Faster R-CNN, the original YOLO v3 algorithm and the improved method of this paper are used to detect the images in the test set. The accuracy and detection rate of the test are shown in the table. It can be seen that the proposed method has better performance in terms of detection speed and accuracy, and the accuracy is slightly worse than the Faster R-CNN algorithm. Considering this, the method is an effective and feasible carrier-based machine detection method. The test results are shown in Table 3.

Improve YOLO v3 detection effect under different illumination. From the above 100 test set test results, the pictures with different illumination conditions are selected for comparison, and the test results are shown in FIG. 4. In the figure, (a) is the detection effect with strong illumination, and (b) is the detection effect with weak illumination. It can be seen that for different illumination conditions, the improved model can effectively detect the aircraft and has high robustness.

Figure 4. Detection effect under different lighting conditions

4. Conclusion
In this paper, based on the original YOLO v3 detection model, the loss function weighting and linear attenuation NMS strategy is added to solve the problem of aircraft carrier occlusion aircraft target detection accuracy and difficulty. It has good detection effect on different illumination conditions, and the robustness of the model is high. The detection accuracy and real-time performance can meet the actual needs.

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