Based on the Second-stage Detection Networks to Realize Accurate Detection and Recognition For Anti-ship Missiles

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ABSTRACT

The target detection and recognition technology based on deep learning has high accuracy and speed of target recognition, which is a feasible way to realize the precise strike of anti-ship missiles and the essential way for the development of intelligent combat. Based on the development background of anti-ship missile precision strike and second-stage target detection networks, this paper proposed to achieve accurate detection and recognition of ship targets through Faster R-CNN network, and suggested to achieve maritime multi-targets through Mask R-CNN network. The detection method explored and find a feasible way to achieve the precise strike of anti-ship missiles.

KEYWORDS

Target Detection, Anti-ship Missile, Accurate, Deep Learning Network.

INTRODUCTION

Accurate strikes can not only achieve the purpose of deterring and containing the
enemy, but also directly destroy important military, political, and economic targets of the enemy through accurate selection of targets, paralyze the enemy's combat system, and thus influence and even determine the course and outcome of the war.

Anti-ship missiles, as the main combat weapons of current and future naval warfare, urgently need to find ways to improve the ability to select targets in complex environments, improve the effectiveness of anti-ship missiles in complex electromagnetic environments.

Applying target detection technology based on deep learning to target detection and identification of anti-ship missiles will greatly improve the accuracy in complex backgrounds, and can provide technical support and feasible technical approaches for anti-ship missiles to achieve precise strikes.

TARGET DETECTION NETWORKS

Classification of Detection Networks

After 2014, target detection technology based on deep learning has gradually become the mainstream in academia and industry, playing an important role in graphics processing; according to the different target positioning and classification methods, target detection is divided into one stage (one-stage) target detection algorithms: SSD, YOLO and two-stage (two-stage) target detection algorithms: R-CNN, Fast R-CNN, Faster R-CNN. [1-3]

The two-stage target detection algorithms belong to the target detection mode of first positioning and then classification. The second-order target detection algorithm, especially developed to Faster R-CNN, shows higher advantages in detection accuracy.

| Method       | Backbone | Training set | Testing Set | mAP  |
|--------------|----------|--------------|-------------|------|
| R-CNN        | VGG-16   | VOC2007      | VOC2007     | -    |
| Fast R-CNN   | VGG-16   | VOC2007      | VOC2007     | 66.9 |
| Faster R-CNN | VGG-16   | VOC2007      | VOC2007     | 69.9 |
Girshick et al.[4] proposed the Faster R-CNN network in 2016. Compared with the R-CNN and Fast R-CNN networks, it has truly realized the end-to-end training of the network and greatly improved the efficiency. The entire model can be divided into two modules: Region Proposal Network (RPN) and Fast R-CNN Detection Network.

The RPN network was first used in Faster R-CNN, compared with the original Selective search method, it has higher efficiency to extract candidates. Its loss function includes classification loss and regression loss.

\[
L(\{p_i\}, \{p'_i\}) = \frac{1}{N_{cls}} \sum_{i} L_{cls}(p_i, p'_i) + \frac{1}{N_{reg}} \sum_{i} p'_i L_{reg}(t_i, t'_i)
\]

\(L_{cls}\) is the classification loss, it is expressed as the following formula,

\[
L_{cls}(p_i, p'_i) = -\log(p_i p'_i + (1 - p_i)(1 - p'_i))
\]

\(L_{reg}\) is the regression loss, it is expressed as the following formula,

\[
L_{reg}(t_i, t'_i) = R(t_i - t'_i)
\]

RoI pooling layer conducts pooling operations, different sizes of interested regions will be solidified by RoI into the same size, and converted into 4096 dimensional feature vectors by two fully connected layers, and then obtain objects’ classes, confidence coefficient, positional information by classification and regression.
Figure 1. Schematic diagram of Faster R-CNN network.

Faster R-CNN network includes 4 steps: (1) Extract the image’s feature map through CNN; (2) Extract the feature information of the candidate region through the RPN network; (3) Through the RoI Pooling layer The feature maps are converted into fixed-length feature vectors; (4) The feature vectors are sent to the fully connected layer for classification and regression.

EXPERIMENTS AND RESULTS ANALYSIS

Data Sets

At present, there is no open source data sets for visible light warship target images. In this paper, a data set containing some classes of ships is artificially constructed for the purpose of ship target detection. In this paper, according to the needs of the experiment, the more common and richer samples in different classifications were selected. The data set was classified into 7 categories including: various types of warships, aircraft carriers, hovercrafts, passenger ships, cargo ships, sailing ships, and fishing boats. However, in the actual sampling process, it was difficult to collect some types of samples, which may easily caused the uneven number of various types to affect the experimental results. Therefore, the samples were changed to three representative types: aircraft carriers, warships, and sailboats.
The obvious characteristics can better verify the effect of the target monitoring network on the detection and recognition of ship targets.

This paper set a VOC2007 format data set, some sample data images are as follows:

![Figure 2. Part of the data set images.](image1)

**Experimental Environment**

This experiment was conducted under ubuntu16.04 operating system, using deep learning framework Tensorflow, hardware environment: Intel Xeon (R) CPU, Nvidia Gforce GT705, using python language to achieve programming operations.

**Evaluation Indexes**

(1) Precision represents the proportion of all samples detected as positive categories that really belong to the target category.
\[
\text{Precision} = \frac{TP}{TP + FP}
\]  \hspace{1cm} (4)

(2) Recall also known as the detection rate, that is the proportion of the number of targets detected as positive classes to the total number of all detected classes as targets.

\[
\text{Recall} = \frac{TP}{TP + FN}
\]  \hspace{1cm} (5)

(3) \( mAP \) is the average of all APs.

\[
mAP = \frac{\sum_{q=1}^{Q} AP(q)}{Q}
\]  \hspace{1cm} (6)

\( Q \) is the total number of queries, TP means True Positive, TN means True Negative, FP means False Positive, FN means False Negative.

**Results Analysis**

The network was trained through the self-built ship target data set, the weight model obtained by the training was tested on the samples in the test set, and the detection box probability threshold was set to 0.5. The test effects after 20,000 times of network training were as follows:
It can be seen from the experimental results that the Faster R-CNN network had a better detection effects on ship targets in the self-built data set and can distinguish the types of ships, but the detection effects on small targets were not good and there exited omissions.
Mask R-CNN achieves more accurate ship targets’ detection.

Facing the complex natural environment at sea and multi-target situation, the region of interest can be extracted from the image through instance segmentation to achieve more accurate target detection. In 2017, Mask R-CNN network [5] proposed by Kaiming He can achieve instance segmentation of pixel-level images.

Mask R-CNN network added Fully Convolutional Network (FCN) and RoI Align to Faster R-CNN. On the one hand, the Faster R-CNN network is used to predict the category and location information; on the other hand, the FCN network is used to perform pixel-level segmentation and generate masks.

Figure 5. Mask R-CNN network structure.
The Mask R-CNN network can be used for the detection and identification of marine ship targets, which can accurately distinguish the adjacent, close and formation targets of various types of ships, suppress background interference, effectively avoid the complex marine electromagnetic environment and the impact of the natural environment, given a feasible theoretical approach for improving precise attack of anti-ship missiles on targets.

CONCLUSION

The application of artificial intelligence technology to the anti-ship missile accords with the future trend of intelligent combat development. The second-stage target detection algorithms have excellent characteristics in detection accuracy applied the detection networks to the anti-ship missiles’ target detection and recognition link, compared with traditional methods, it can improve the ability of anti-ship missiles to detect and recognize targets in complex environments, and the recognition accuracy and speed can be greatly improved. It is less affected by environmental factors and has strong anti-jamming capabilities. It is accurate for achieving anti-ship missiles. It has great significance for realizing the precise strike of anti-ship missiles.

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