Target Detection based on K-means Algorithm

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Abstract: In recent years, the application of deep learning to the safety of high-speed rail has been a hot research topic. In this paper, we have developed an improved yolov3 foreign body intrusion detection algorithm based on K-means++, which can realize accurate and fast identification of high-speed rail perimeter intrusion. In addition, we use K-means++ algorithm to improve yolov3 algorithm. After comparing the relevant precision indexes, we have obtained that the improved yolov3 algorithm with K++ is obviously better than the traditional image recognition algorithm, which can realize the precise prevention and control of high-speed rail perimeter intrusion.

1. Introduction

In recent years, China's high-speed railway industry has developed rapidly, but the problem of perimeter security has become increasingly prominent [1]. In order to realize the identification and detection of perimeter intrusion targets, video surveillance has been widely applied in our country.

At present, the application scale of video surveillance along the railway is getting larger and larger. [2] There are more than 1 million surveillance cameras on high-speed lines alone, and video data is showing explosive growth. Although the video surveillance equipment along the railway has greatly improved in function and performance, it still needs a lot of manual participation to complete various monitoring tasks. In most cases, video surveillance provides a large amount of redundant information, which makes it difficult for surveillance personnel to continuously concentrate on their work for a long time and to achieve seamless real-time surveillance [3]. It is often the case that important information is missed or misreported. Railway field demand not only requires fast processing of video data and automatic in-depth information analysis and mining of video content, but also requires low false alarm rate and is suitable for real-time field command [4]. Therefore, the research on intelligent video surveillance methods has become a research hot spot in the field of video surveillance.

2. Index improved yolov3 algorithm based on K-means++

2.1 Yolov3 network structure

In order to ensure the safety and order of EMU operation, to ensure the safety of passengers, to protect the safety of people's lives and property, and to enhance the image of high-speed rail operators, it has great social benefits. In view of this, this paper proposes a target detection method based on deep learning-an improved yolov3 foreign body intrusion detection algorithm based on K-means++. The algorithm is fast and simple. It has high efficiency for large data sets.

The main research ideas in this paper are shown in the following figure:

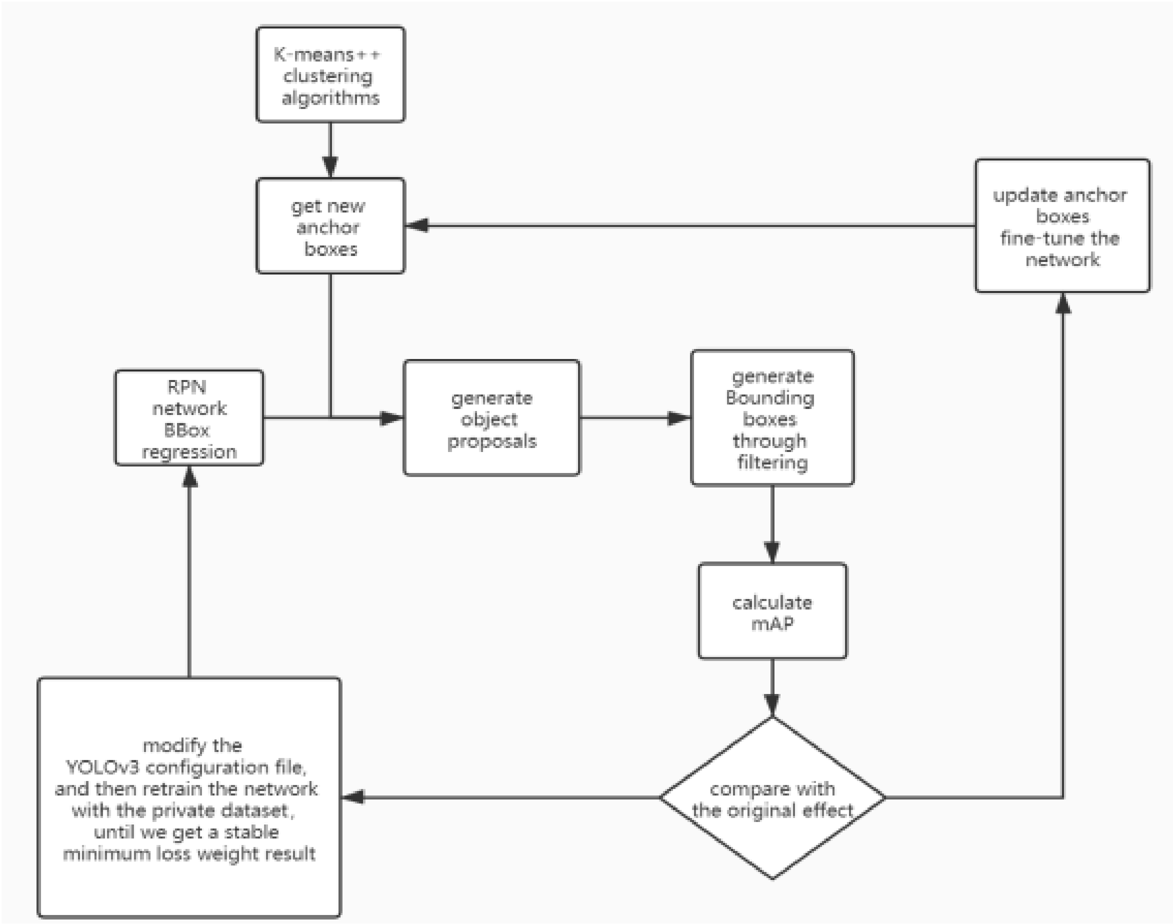

Figure 1. Algorithm flowchart

Yolov3 algorithm is a real-time object detection algorithm, which applies a single neural network to a complete image. It divides the image into several regions and predicts the bounding box and probability of each region respectively. It has the characteristics of fast running speed and high precision.

In order to improve the prediction accuracy of Yolov3 algorithm, we have improved the existing network structure on this basis. The size in Darknet53 in the original network is trained on the picture classification training set, so the input image size is 256x256, and the following figure is drawn based on YOLO v3 416 model, so the input size is 416x416, and the predicted three feature layer sizes are 52, 26, and 13 respectively.

In addition to adding three feature layers for prediction, we also abandoned the full connection layer in DarkNet53 and adopted the convolution layer instead. Therefore, it is also called full volume network. Note that Convolutional (convolution layer) refers to Conv2d+BN+LeakyReLU, the same as that in Darknet53, while the last three layers that generate prediction results are only Conv2d.Through the following figure, we can more easily build the network framework of YOLOv3.

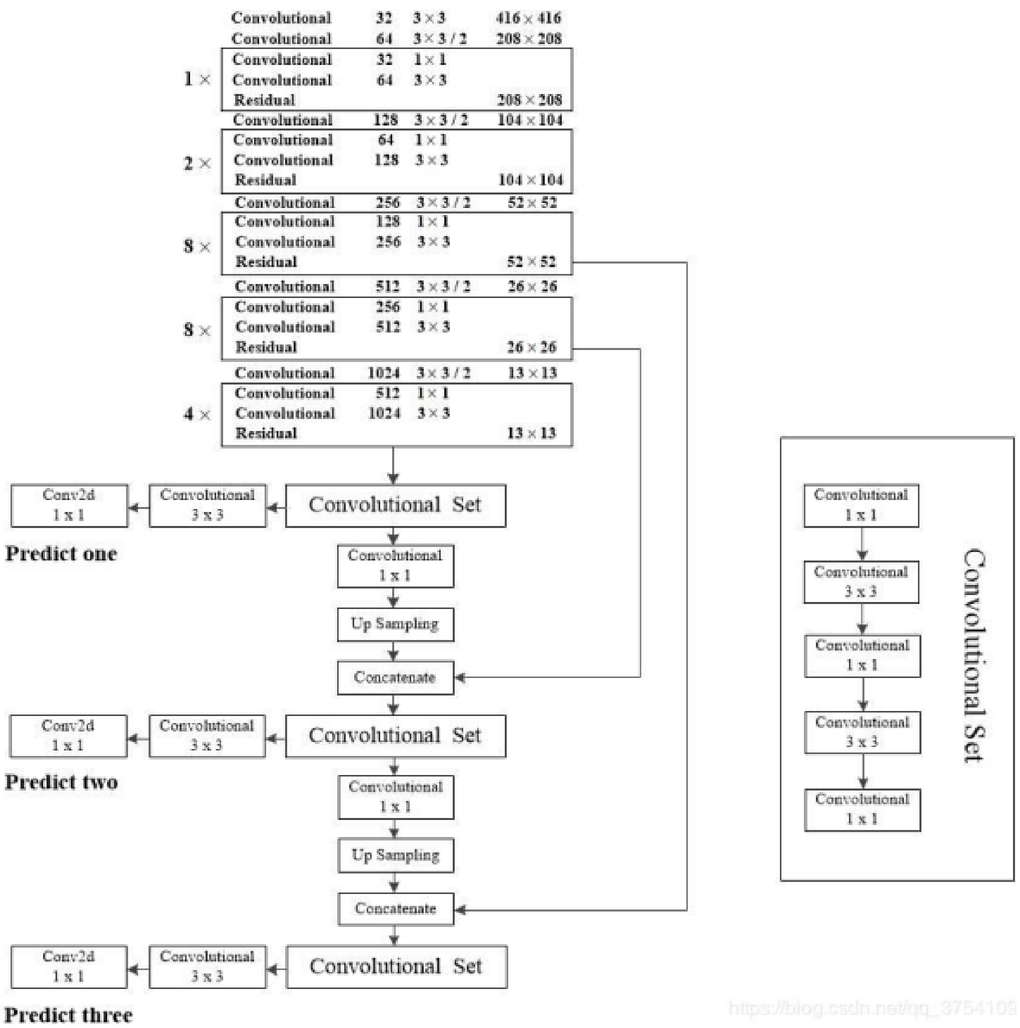

Figure 2. Yolov3 network structure

2.2 Anchor boxes settings based on k-means++

We use K-means algorithm to cluster dimensions on voc data set, in order to obtain the most ideal K anchors to replace the artificial anchors in the original algorithm. Anchor boxes have influence on object proposals, and the quality of object proposals directly affects the accuracy of bounding box. Therefore, we have made an improvement on anchor boxes based on the idea of k-means++ algorithm, and verified and adjusted the preset position effect of anchor boxes obtained by the improved clustering algorithm.

In k-means algorithm, Euclidean distance, Manhattan distance and Chebyshev distance are usually used as distance measures to calculate the distance between two points. If Euclidean distance is used according to traditional k-means algorithm, obviously large boxes will produce more loss errors than small boxes. However, what we really want is boxes that produce good IOU scores (regardless of box size).Therefore, the following distance measurement is adopted. K-means++ is calculated as follows:

(1) Randomly select a data point in the data set and set it as the first clustering center.

(2) Count the distances of all data points, calculate the distance D(x) from its nearest clustering center and accumulate to obtain Sum (D(x)).

(3) Try to update the data points. The selection criteria are: the probability of being selected as the new clustering center for the points containing more data should be higher, and a threshold value is randomly taken out. If the accumulated seed point distance is higher than the threshold value, it is set as the next "seed point".

(4) Repeat steps 2 and 3 until K cluster centers are selected.

(5) Initialize k clustering centers and run k-means algorithm.

The specific implementation of K-means++ is as follows:

(1) Select K points far enough from each other as the centroid:

(2) When the cluster allocation result of any point changes, for each data point in the data set, for each centroid, calculate the distance between the centroid and the data point, and allocate the data point to the cluster nearest to it. For each cluster: find the mean value and update it to the centroid.

The improved k-means++ algorithm initializes the centroid randomly, which is completely different from the traditional k-means algorithm. Applying the changed IoU as the distance and setting distance thresh is to screen the next initialization center far enough from the previous initialization center, thus making clustering more successful. Then the total distance is calculated after the classification is completed, and the centroid position is updated when a new centroid can obtain a smaller distance sum. In addition, the improved k-means++ algorithm is fast and simple, and has high efficiency for large data sets, which is conducive to improving the speed and accuracy of the algorithm.

3. Algorithm Implementation and Experimental Analysis

3.1 Experimental Process

In order to improve the accuracy and precision of algorithm recognition, sample collection was carried out on the railway site, collecting 800 positive samples (pedestrians) and 1000 negative samples (snow, branches, stones, etc.).80% of the data in the sample database are trained as training sets, and the remaining 20% are tested as test sets.

We have also set up corresponding platforms for testing, mainly based on QT platform testing and python--SQL--java Java platform testing.

The basic framework is as follows: SQL is responsible for storing the data set collected earlier. Python provides the core code and java is the interface. The three transmit data interactively to realize image recognition. In this process we used regular expressions and opencv libraries, jython and jPype.

3.2 Analysis of Experimental Results

The experimental original drawing and the algorithm recognition effect drawing are as follows:

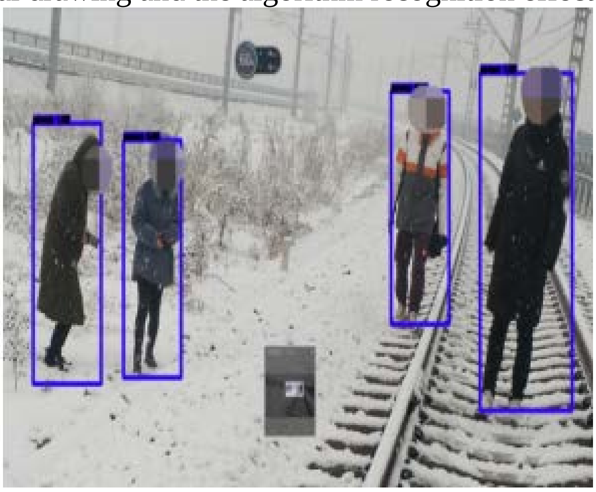

Figure 3. Shows the recognition effect

The following are the performance indicators of the algorithm.

1. AP measures the quality of the learned model in each category. We take the average value of AP in all categories to obtain mAP, which can measure the quality of the trained model in all categories.

2. We also plotted the horizontal axis of recall, which indicates recall rate, and the vertical axis of precision, which indicates precision and precision. The recall rate is for our original sample. It

indicates how many positive cases in the sample have been predicted correctly. There are two possibilities: one is to predict the original positive class as positive class (TP) and the other is to predict the original positive class as negative class (FN).The accuracy rate is based on our prediction results. It indicates how many of the samples predicted as positive true positive samples are. Then there are two possibilities to predict positive, one is to predict positive class as positive class (TP) and the other is to predict negative class as positive class (FP).

The formula for calculating the accuracy rate and recall rate is as follows: The loss curves of this algorithm is shown in fig.4 and the P-R graph is shown in fig.5.

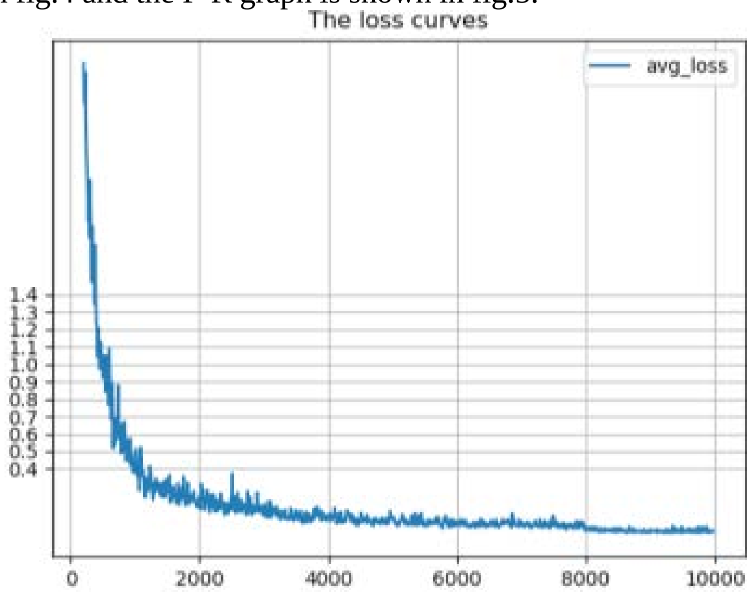

Figure 4. Loss graph

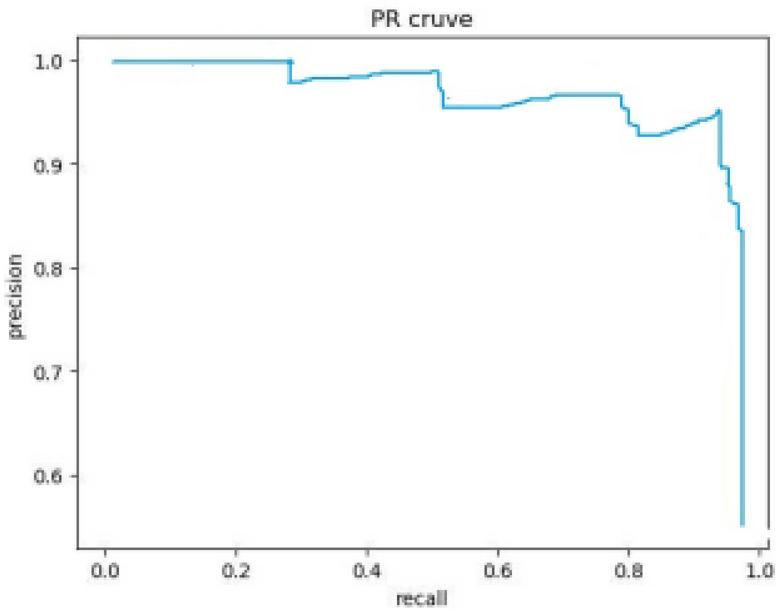

Figure 5. PR graph

4. Conclusion

The research on the theory and method of intelligent identification and detection of high-speed railway intelligent video surveillance is conducive to the timely detection and early warning of high-speed railway perimeter intrusion, effectively avoiding large-area delays caused by disruption of transportation order due to perimeter intrusion, and even causing heavy casualties and economic losses, with great economic benefits. In order to ensure the safety and order of EMU operation, to ensure the safety of passengers, to protect the safety of people's lives and property, and to enhance the image of high-speed rail operators, it has great social benefits. In view of this, this paper proposes a target detection method based on depth learning-an improved yolov3 foreign body intrusion detection algorithm based on K-means++. The algorithm is fast and simple. It has high efficiency for large data sets.

This paper proposes an improved yolov3 foreign body intrusion detection algorithm based on K-means++. This paper mainly applies the k-means algorithm to the anchor improvement of yolov3 network and tests it in the railway perimeter scene. The traditional yolov3 recognition rate is low, especially for small objects. After improvement, the accuracy rate reached 90%.This paper not only improves the accuracy, but also reduces the classification time. It can quickly and accurately complete the re-classification of railway intruding pedestrians and improve the alarm accuracy. It can be seen from the average accuracy of evaluation indexes that this algorithm has better detection performance. It can be seen from the experimental effect diagram that the detection effect of this algorithm on railway perimeter intrusion objects is greatly improved.

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