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Fine Crack Detection Algorithm Based on Improved SSD

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Abstract: The fine cracks on the workpiece surface are the significant potential hazard to safety of industrial production process. In order to identify fine cracks on the workpiece surface, an improved SSD (Single Shot MultiBox Detector) algorithm is built in this paper and applied to detect fine cracks. Based on the SSD network, the dilated convolution module is proposed in the convolutional operation to ensure access to global feature and by reducing the pooling layer treatment. In order to achieve the effective cracks detection, the cracks images are divided into two cases: obvious bold cracks and vague fine cracks, and mark them respectively. The obvious bold cracks are marked as "neg" and detected by SSD network framework, while the vague fine cracks are marked as "crack" and detected by SSD network with reduced pooling layer. This improvement is helpful to increase the detection accuracy of fine cracks. In this paper, the actual crack images are used to verify the improved algorithm. Results show that under the training and testing with workpiece crack data set, the improved algorithm can effectively detect fine cracks such that the detection precision toward the number of cracks in the image is higher than 80%. The aforementioned algorithms present potential application for the detection of fine cracks.

Keywords: Fine Crack, SSD Network, Dilated Convolution, Crack Detection

1. Introduction

As age advances and with the development of science and technology, the requirement for high-quality industrial devices also rises. In the practical production and utilization process, the appearance of crack damage is inevitable due to some adverse factors such as internal material corrosion and external natural hazards, which may lead to workpiece quality reduction and even serious safety accidents. To prevent the destructive effect of crack damage, it is necessary to detect the crack of the workpiece in the production process. Through computer vision, the crack detection methodology is mainly to judge the crack existence on the workpiece surface and then to detect the specific location of the crack, which plays an important role in ensuring safety in use and prolonging the service life of the workpiece.

The traditional crack detection method is usually manual detection, but this method is not effective for crack detection in complex cases. And it dissipates a large amount of manpower and material resources, which seriously delays the risk control measure. Hinton et al. proposed the concept of deep learning [1], and since then object recognition algorithms based on deep learning have developed rapidly and replaced traditional object recognition methods in more and more application scenarios. At present, the deep learning based object recognition algorithms are mainly divided into two categories: the recommendation -based region and regression-based region. The former algorithms mainly include R-CNN [2], Fast R-CNN [3], Faster R-CNN [4] and SPP-Net [5], etc., and it has high accuracy and recall rate but slow detection speed; while the latter one mainly includes Yolo [6-8], SSD [9-12], etc., and it has relatively low accuracy but fast detection speed.

Aiming at the problem of recognizing difficulty during the fine cracks detection on the workpiece surface with a traditional deep learning algorithm, a detection algorithm based on improved SSD is presented in this article. Section 2 briefly describes the principle of SSD algorithm. The following Section 3 shows that the SSD is improved for detection accuracy of fine cracks. Then in Section 4, the original SSD and the improved SSD are trained respectively, and their performances are tested on the workpiece surface crack data set to see the improvement.

2. Principle of the SSD Algorithm

The SSD algorithm, short for single shot multi-box detector, belongs to one-stage detection algorithm. The detection speed and precision of the SSD has a certain boost against the same stage detection algorithm, YOLO series. YOLO implements detection by means of the full connection layer at the end, while SSD directly uses conventional neural network to extract the detection results, and multi-scale feature map to extract the features of the target such that SSD has excellent results during the detection of small objects with more accurate positioning results of detecting targets. The comparison of network structure is shown in Figure 1.

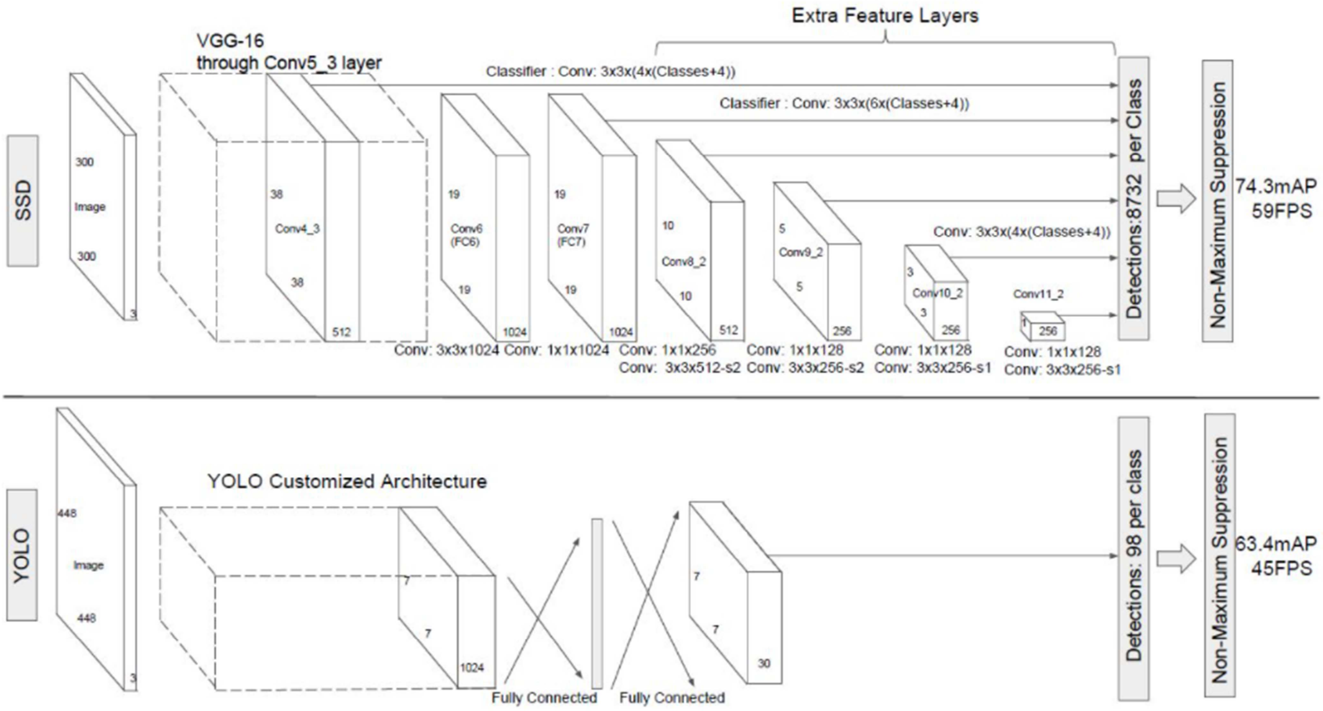


Figure 1. *Comparison of SSD and YOLO network structure [9].*

The basic network of SSD is VGG-16 [12], consisting of 13 convolution layers, 3 full connection layers and 5 pooling layers. The convolution layer and the full connection layer have weight coefficients. On the basis of VGG-16, SSD converts the fully connected layers of FC6 and FC7 into two convolution layers and adds four convolution layers after FC7. So as to obtain more feature maps for detection. In the prediction process, Conv4-3, FC7, and additional four convolution layers produce six feature maps with different scales. After that, SSD selects candidate boxes of different sizes on the feature maps to achieve multi-scale prediction.

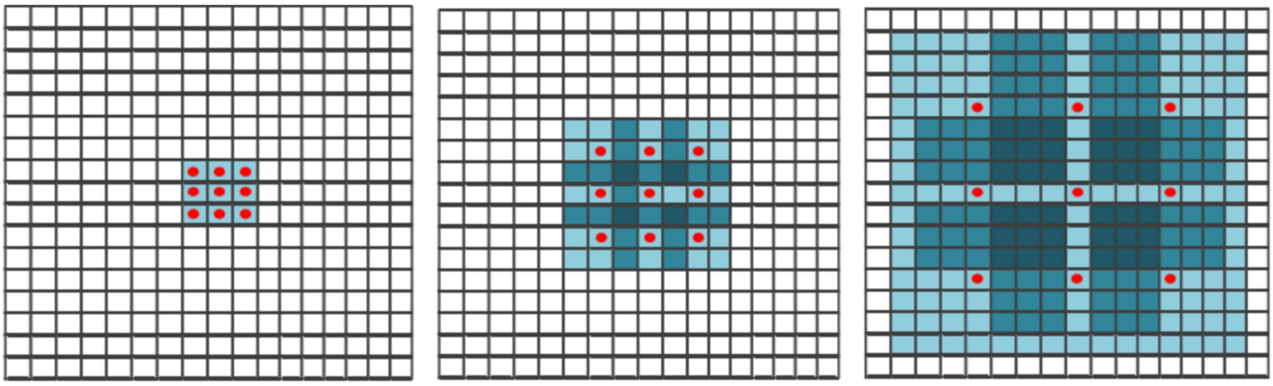
The core of SSD algorithm is multi-scale feature mapping. The original picture is transformed to feature map after multiple convolutions, as the mechanism tells that SSD algorithm detects the original image information through the feature map of multiple convolution layers [13]. However, SSD is poor in characterizing low-level feature maps and in accuracy when detecting fine cracks. In order to ensure the acquisition of global features and enhance the ability of image characterization, we present a potential improving method in the following sections.

3. Improvement of SSD

Considering the problems arising in detecting fine cracks on the surface of workpieces with SSD algorithm, this paper improves it by introducing dilated convolution and reducing pooling layers.

3.1. Dilated Convolution

Although SSD adopts multi-scale feature mapping, its ability to characterize the underlying image is poor, which is adverse to the detection of fine cracks, but fortunately dilated convolution [14] can exactly make up for this defect. Dilated convolution is to expand the receptive field of ordinary convolution on the premise that the parameters remain unchanged, so the output of each convolution contains a larger range of information. The schematic diagram of dilated convolution is given in Figure 2.



(a) 3×3 convolution (b) 3×3 dilated convolution (c) 3×3 dilated convolution response

Figure 2. *Schematic diagram of dilated convolution [15].*

For a convolution of 3×3 with an expansion rate of 2, the receptive field expands to 5×5 through dilated convolution, on the premise of keeping the network parameters and calculation unchanged. The computational methods of dilated convolution kernel and receptive field are as follows:

$$f_n = f_k + (f_k - 1)(D_r - 1) \tag{1}$$

$$l_m = l_{m-1} + [(f_n - 1)\prod_{i-1}^{m-1} S_i] \tag{2}$$

where f_n is the size of dilated convolution kernel, f_k is the size of the original convolution kernel, D_r is the coefficient of expansion, l_m is the size of receptive field in layer m after dilated convolution, l_{m-1} is the size of the receptive field of layer m-1, S_i is the stride of layer i.

3.2. Reduce Pooling Layer

In neural networks, the function of pooling layer is to accelerate the calculation speed of the network without affecting the original characteristics. More pooling layers make SSD have faster detection speed, but at the same time fail to achieve accurate detection when dealing with fine cracks with unclear characteristics identical to the background. Therefore, this article aims to reduce the pooling layer of SSD network, which may increase the machine-learning characteristic parameters and improve the detection accuracy of fine cracks by the network.

In order to achieve the effective detection of workpiece surface cracks as much as possible, the workpiece cracks are divided into two cases: obvious bold cracks and vague fine cracks, then mark them respectively. The obvious bold cracks are marked as "neg" and detected by SSD network framework, while the vague fine cracks are marked as "crack" and detected by SSD network with reduced pooling layer. In this way, the detection accuracy of fine cracks is improved while ensuring the detection speed of SSD network. The specific situation is illustrated in Figure 3.

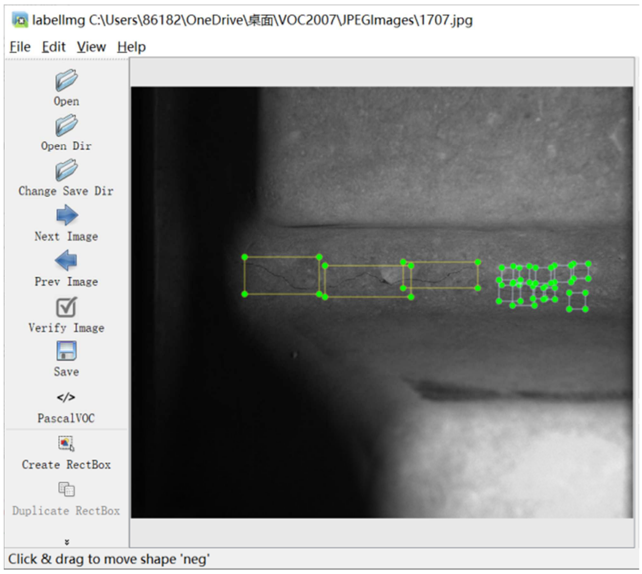


Figure 3. *Schematic diagram of crack marking.*

4. Results and Discussion

4.1. Experimental Environment

The experiment in this article requires high hardware device, especially GPU for operation. The specific experimental configuration is demonstrated in Table 1.

Table 1. *Specific experimental configuration.*

software and hardware	**environment**
system	WIN 10
processor	Intel Core i7 10875H
memory	6GB
graphics card	GTX 3060
programing language	Python 3.6
Carrying environment platform	Tensorflow-gpu

4.2. Dataset and Annotation

This article selects the public crack data set of workpiece, including totally 14010 pictures with and without crack, respectively. The crack data are divided to training set and testing set at the ratio of 9:1. 12609 of them are used for training set and the rest 1401 for test set. However, due to the large size of data set, the original annotation is not accurate such as the missing annotation of crack. This leads to gradient explosion during training, which seriously imposes bad effect on the results to be obtained. Therefore, this article relabels the data set.

When marking the crack in the picture, too slender label border hinders the network from learning features because SSD algorithm adopts 3 * 3 convolution. Hence in this article, the slender workpiece crack is divided into multiple labels for annotation, and the border of the label is as small as possible to guarantee the convergence of features. The specific annotation format is shown in Figure 4.

Figure 4. *Schematic diagram of crack label.*

4.3. Evaluating Indicator

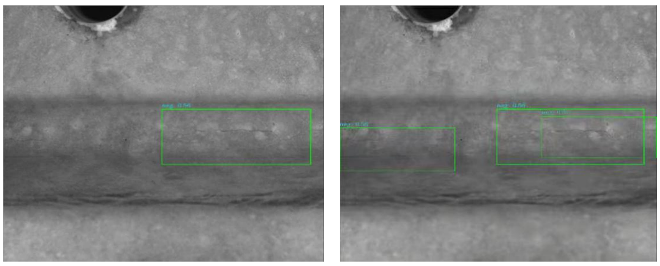
In order to comprehensively evaluate the improved network performance, this paper selects the following two indicators: overall accuracy and single sheet accuracy.

$$overall\ accuracy = \frac{\text{number of samples with cracks detected}}{\text{total number of samples}} \quad (3)$$

$$single\ sheet\ accuracy = \frac{\text{number of cracks detected in single picture}}{\text{total number of cracks in single picture}} \quad (4)$$

4.4. Results Analysis

The SSD network and the improved SSD network are trained respectively, and their performance is tested on the crack data set of the workpiece. Some test results are shown in Figure 5. Comparing Figure 5 (a) with Figure 5 (b), it can be seen that the improved SSD successfully detected fine cracks that could not be identified before the improvement. To further compare the performance of SSD with the improved SSD, we calculate the overall accuracy and single sheet precision of the improved SSD, and derive that the improved SSD can reach an overall accuracy of 100% and a single sheet precision higher than 80%. In summary, the improved SSD in this article exhibits better performance during the detection of fine cracks on the workpiece surface.



(a) test results before improvement (b) test results after improvement

Figure 5. *Comparison of test results before and after improvement.*

5. Conclusions

In order to detect fine cracks on the workpiece surface that is difficult to be identified by the traditional deep learning, this paper improves the SSD algorithm and sets up a new detection algorithm based on improved SSD. By introducing dilated convolution module and reducing pooling layer, the improved SSD is helpful to increase the precision of fine crack detection by means of confirming the global feature access. Using the improved SSD algorithm, we train the SSD before and after improvement respectively and test their performance on crack data set of the workpiece. The results show that the improved SSD can successfully detect fine cracks that cannot be identified before improvement. The improvement SSD based detection algorithm given in this paper can be used to detect fine cracks in workpiece surface as well as cracks in petrochemical and other equipment.

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