Advances in Computer, Signals and Systems (2022)
Clausius Scientific Press, Canada

DOI: 10.23977/acss.2022.060111
ISSN 2371-8838 Vol. 6 Num. 1

Research on Image Recognition Algorithm of Weld Defect Based on Deep Learning

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Keywords: Deep learning, Weld defects, Image recognition, Algorithm research

Abstract: Aiming at the problem that the traditional deep learning model is not effective in detecting small defects, a weld defect detection algorithm based on the improved deep learning FasteRCNN model is proposed. The algorithm extracts multi-scale feature maps through multi-layer feature network and acts on the subsequent links of the model together, so as to make full use of the low-level features in the model and increase the detailed information. The area generation network of the model is improved, and a variety of sliding windows are added, so that the aspect ratio of the anchor point of the model is optimized and the detection ability is improved. Two different activation functions in the hidden layer of convolutional neural network are verified by experiments, and optimization methods are put forward. The deep learning neural network can avoid extracting the features of weld defect images and directly judge whether the suspected defect images are defects. Experiments on 580 images show that the recognition accuracy of SDR images by the proposed method is over 98%, which is superior to traditional methods. And that design system has the characteristics of automatically learn complex depth features in X-ray weld defect images, and has strong practicability.

1. Introduction

As a processing method to solve the problem of component connection in industrial production, welding is widely used in aerospace, machinery manufacturing, shipbuilding, nuclear industry, petrochemical industry and other fields, and plays an important role in modern industrial manufacturing[1]. During the welding process of weldments, due to the instability of welding parameters and the influence of external factors, different degrees and numbers of defects such as air holes, cracks, incomplete fusion and incomplete penetration are formed in the weld seam, and the service performance and service life of weldments will be affected to different degrees due to the existence of various defects, which will ultimately affect the quality and safety of the whole product, and even threaten the safety of property and life[2]. In order to ensure the reliability of welding quality, it is particularly important to detect, identify and evaluate the possible defects in welded joints. Because of the non-uniformity of the shape, position, direction and size of defects, it is a complicated task to analyze and evaluate the acquired inspection images. At present, manual film evaluation is still used in many cases. However, relying on manual evaluation is a timeconsuming and laborious task. It requires technicians to judge whether there are defects, the number, location and type of defects by experience[3].

This method has some disadvantages: subjective factors such as the physical or professional quality of technicians will cause inconsistent results. For example, when different technicians evaluate the same weld image, they may make different evaluation results due to the degree of care, working time and professional level. In addition, due to the great improvement of industrial production efficiency, a large number of weld images are produced every day, so the workload is huge. The fatigue of technicians may cause the defect to be missed and the unqualified products to enter the market, thus causing unpredictable losses. Aiming at the problem that the traditional Faster RCNN model is not ideal for detecting small targets in weld defects, an improved Faster RCNN weld defect algorithm is proposed[4]. The features extracted from the shallow network and the high-level network are used as the input of the subsequent links in the improved algorithm, so as to enhance the ability of features to describe the details of defects, optimize the anchor parameters to improve the accuracy of target frame positioning, improve the RPN structure and increase the sliding window to improve the detection ability of the model. Experiments verify the effectiveness of the algorithm[5].

2. Deep Learning Principle

2.1 Convolution Layer and Pool Layer

In the convolution layer, each SDR image is a digital matrix to the computer, and the convolution operation is to convolve the digital matrix of the image with a learnable convolution kernel. Then, through an activation function, the output characteristic graph can be obtained[6]. Each output feature map can combine and convolve the values of multiple feature maps:

$$x_j^l = F\left(u_j^l\right),$$
$$u_j^l = \sum_{i\mathrm{EM}_j} x_j^{l-1} * k_{ij}^l + b_j^l \quad (1)$$

Pooling is an important step in CNN, which can reduce the number of features while keeping the local invariance of features. There are three commonly used pooling methods, namely maximum pooling, average pooling and random pooling[7]. Maximum pooling refers to selecting the maximum value in a region as the pool result of the region. The CNN structure designed in this paper is to maximize the pool by calling the max_pool function of Tensor Flow[8]. The pool layer passes each input characteristic map through the formula:

$$x_j^l = F\left(u_j^l\right), u_j^l = \beta_j^l down\left(x_j^{l-1}\right) + b_j^l \quad (2)$$

In recent years, the digital radiographic weld images have been taken as the research object, mainly aiming at the segmentation, location and classification of weld defects in digital radiographic weld images[9]. The research is carried out from three aspects. Firstly, because there is a large area of non-weld area in the X-ray weld image, in order to reduce the calculation amount of weld segmentation, the weld area in the weld image is accurately located and the weld area is trimmed. The second is to mark the defects existing in the extracted weld, find a suitable segmentation network according to the characteristics of the weld image itself, and then improve the network according to the characteristics of the weld image, so that it can better adapt to the segmentation of weld defects. The third is to locate the defects after welding seam segmentation, obtain the key characteristic values, extract the segmented defects accurately, label the extracted defects in categories, and build a suitable classification network for the marked defects, so as to accurately predict the types of defects[10].

Since the quality of welded workpieces has an important influence on the service life and safety of product components, the automatic detection technology of welding defects has been studied abroad since 1960s. With the deepening of research, the methods of automatic detection and identification of weld defects are also expanding. However, according to the results of existing literature research, the methods used in the process of weld defect identification are mainly divided into three stages, namely image segmentation, feature extraction and defect classification. Image segmentation is to enhance the contrast of the image by image enhancement, image filtering and other methods at first, and to separate the regions of interest such as welds and defects from the background by using relevant algorithms, and extract the relevant weld or defect regions to form a binary gray image; Feature extraction is to measure and calculate the weld defect area after image segmentation, extract the artificially designed and selected features, use the calculated data instead of the two-digit image, and often use machine learning method to classify different types of defects in the weld. The image features manually extracted by researchers are used as input samples to train the classifier, and then the defect feature data is fitted by nonlinear functional relationship, so as to complete the defect classification and recognition.

2.2 Improve Fastercnn Model Defect Detection

The shallow network of convolutional neural network can provide more detailed information, which belongs to the detailed characteristics, but the semantic information provided by it is sparse; On the contrary, the features provided by the deep network have been downsampled for many times, and the whole information is retained while the detailed information is ignored, so the semantic information is very rich, which is an integrated feature. The process of convolution kernel convolution is the process of edge detection of the image, so the appropriate convolution kernel size should be selected according to the area of SDR image. Small convolution kernel size and tiny features will be extracted, but it is easy to cause over-fitting, and large convolution kernel size will lead to insufficient feature extraction, which will lead to misjudgment of defect types. Because the convolution layers and the depth of convolution kernel are enough to extract the features of defective SDR images, the convolution kernel should be smaller, which can reduce the complexity of each operation. For the 4-layer CNN model designed in this paper, 3×3 and 5×5 convolution kernels can be selected, 5×5 convolution kernel can be selected when the depth of convolution kernel is low, and 3×3 convolution kernel can be selected when the depth is high, which not only reduces the complexity of the network, reduces the operation time, but also can fully extract the image features and improve the classification accuracy.

The size of the image quality gauge wire number depends on the thickness of the measured piece. The larger the image quality gauge wire number, the smaller the wire diameter, and the stronger its ability to find the smallest defect. Generally, a ruler type is attached to the bottom of the weld seam, and the weld seam is generally long. When a defect is found in the radiographic image, the defect can be accurately located according to the ruler. By putting the size type of the inspected piece into the weld image, the information such as the diameter and thickness of the inspected piece can be clearly seen. The pipe slogan in the weld image can realize the accurate positioning of the detected workpiece. The color information in the weld image increases the complexity of the image processing model, but it does not play a key role in tasks such as weld defect identification. For the weld gray map, each pixel needs to provide less information, and the gray map only contains black, white and gray. The gray map usually represents the gray value of the pixel by the combination of eight binary numbers, which ranges from 0 to 255. Although there is little information in the gray scale image, it can clearly describe the brightness, contrast, edge, shape, outline, texture, perspective, shadow and other information, which is enough for the identification of weld defects.

Therefore, there is no need to use more complicated and more difficult color images. By converting the original weld image into an 8-bit gray image, the redundant information in the weld image can be removed, thus improving the speed of image processing.

3. The Basis of Image Recognition

3.1 Feature Extraction of Image Based on

Image features are the raw materials for subsequent image recognition and machine learning. The quality of features is directly related to the execution of subsequent tasks, so it is very important in the model. High-quality features are considered to convey the information of data well, and have strong distinguishability. According to the granularity of features, features can be classified into two categories, namely, shallow primary features and hierarchical high-level abstract features. Then, at what granularity can the learning algorithm be represented? As far as the image is concerned, the information of the image can't be obtained at the pixel level, and the image can be further identified or classified. Brunoolhausen and David Field found that a series of simple basic structures can be combined to form complex content. The biggest difference between man and machine is that man can think. The reason why human beings can think lies in the work of human neural network. Stimulated by the outside world, the human neural network will make corresponding response according to the cognition of the brain, and the research direction of artificial intelligence is to simulate this situation. Therefore, we need to recognize the neural network of human body first.The sensory organ model is shown in Figure 1.

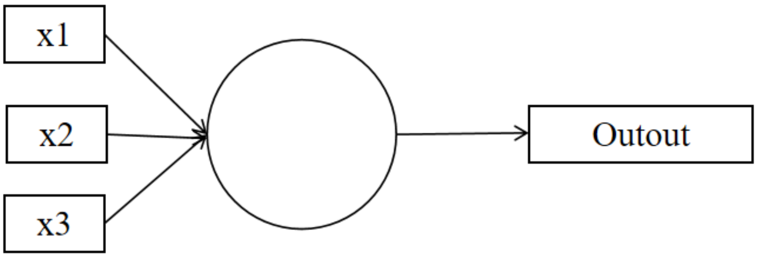

Fig.1 Perceptron Model

The reason why CONV1 layer and CONV2 layer are selected in the shallow layer network is that their extracted features pay more attention to preserving the details such as edges and textures of images, which is conducive to the detection of tiny defects such as small pores and short cracks. Feature maps extracted from different layers are sent to their corresponding RPNs. Because the receptive fields of neurons in each layer are different, the anchor box size parameters of each RPN need to be set separately. See Table 1 for specific parameters. Table 1 Anchor size parameters of different RPN.

Table 1 Anchor Size Parameters of Different RPN

Extraction layer	Parameter
CONV1	(2 4)
CONV2	(4 8)
CONV5	(4 8 16 32)

Because the output feature map of CONV5 layer contains small defect targets, the anchor parameter of size 4 is added to generate a number of small-area anchor boxes to detect small-size defect targets. In order to describe and detect the elongated defect target more accurately, the length-width ratio of the anchor point in the RPN corresponding to CONV5 layer is set to (1： 3, 1： 1, 3： 1). At the same time, on the basis of the original 3 × 3 sliding window in RPN network, 1 × 1 and 5 × 5 sliding windows are added, and three different sliding windows are convolved before feature fusion. The improved RPN structure is shown in Figure 2.

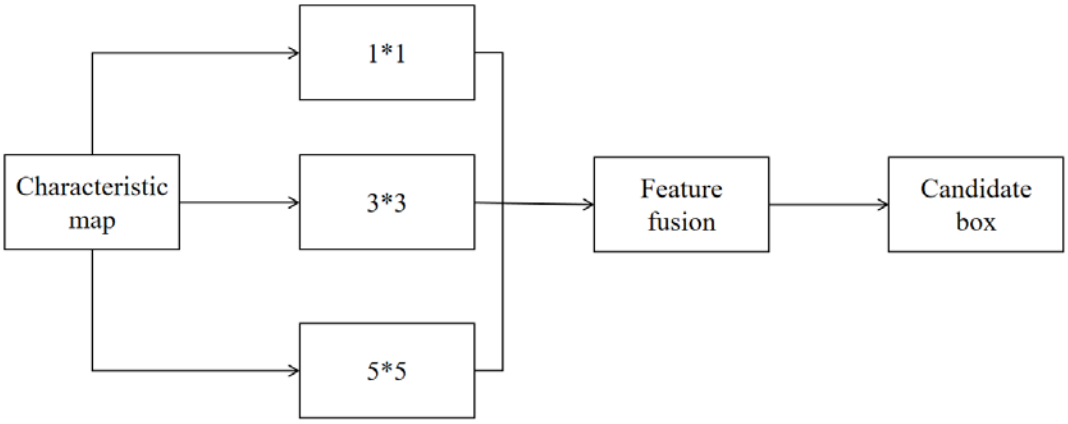

Fig.2 Structure Diagram of RPN in the Improved Model

The model designed in this paper can achieve an average recognition rate of 93. 4% for the original images of weld defects, and 98.8% for SDR images. Although the recognition rate of the original defect image is lower than that based on SDR image, the defect features of the original weld image are not obvious and there are many interferences, which further proves that CNN model has excellent defect feature recognition performance. Because the improved model mainly improves the detection accuracy of small defect targets and different size defect targets by introducing lower-level extraction features and adding sliding windows in the subsequent links of the model to preserve the details of image edges and textures, and optimizing the length-width ratio setting of the anchor points of the model, the subsequent links of the original model remain unchanged, so the computational complexity and defect detection time of the improved algorithm are basically unchanged compared with the original network model, thus maintaining the running efficiency of the original network model and improving the detection ability of microwave welding defect targets.

3.2 Experimental Analysis of Modified Faster RCNN Model

The size and quality of data sets directly affect the performance of e-learning. In this paper, GDXray, a nondestructive testing X-ray image data set published by Catholic University of Chile, is used in the experiment. The pixel size of its weld X-ray images is 500× 5,000. The images are cropped, rotated and flipped at 500×500, and mixed with the images collected in the laboratory to form an experimental data set of 2,340 images, which are divided into training set and testing set according to the ratio of 8:2. The batch size of training images is set at 64. The forward propagation formula of the model is:

$$Y = s_n\left(\ldots(s_2(s_1(X_{\omega 1}+b_1)\omega_2+b_2)\ldots)\omega+b_n\right) \quad (3)$$

After grayscale processing, the weld area is dark and the contrast between the weld area and the target area is not strong, which is not conducive to the extraction of the weld area. The histogram of the processed weld image and the corresponding cumulative distribution function are shown in the figure, in which the X axis represents the gray value of the weld image. For gray images, there is only one histogram, which greatly improves the image processing speed. The y-axis of the histogram is used to indicate the frequency of a certain gray value in the whole image. It can be seen from the figure that the gray values of most pixels in the histogram of weld seam range from 0 to 10, and there is no gray value of any pixel in the middle area. The cumulative distribution function corresponding to the gray image is a curve, which indicates that the contrast of the gray weld image is poor, and the whole image is dark. The histogram of the processed weld image and the corresponding cumulative distribution function are shown in Figure 3.

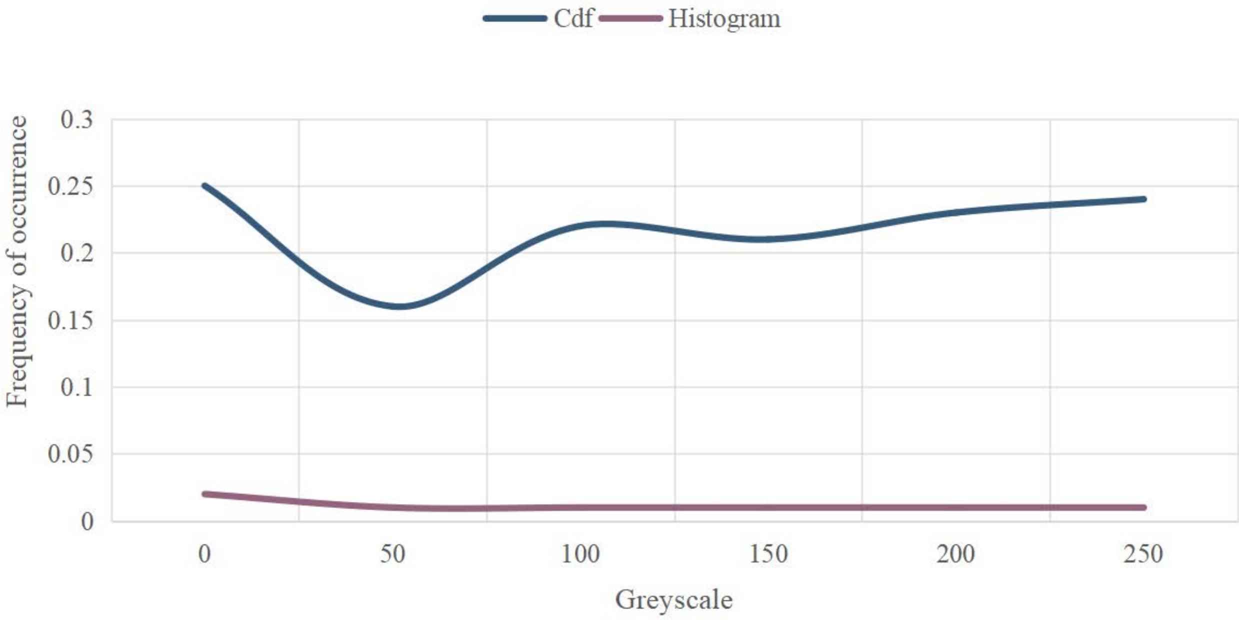

Fig.3 Histogram of Weld Image after Gray Processing and the Corresponding Cumulative Distribution Function.

In many tasks related to image classification and recognition, the changes of image contrast, brightness, saturation, hue and image flipping will not affect the recognition result of the neural network model. Therefore, for the diversity problem of the training images in the training process of the neural network model, these features of the images can be randomly changed, thus making the model more robust in the training process. However, the amount of image data obtained through the network and enterprises is far from enough in deep learning training. In the task of X-ray weld flaw detection image recognition based on deep learning, in order to fully and effectively extract and learn the image features and improve the generalization ability of the model in the process of image recognition, the common method is to expand the first collected image, and increase the sample diversity of weld flaw detection image by randomly flipping the image, shifting the angle, changing the contrast and changing the hue, so as to prevent the under-fitting phenomenon caused by insufficient training data in the process of model training.

4. Conclusions

To solve the problem that the traditional FasterCNN model is not ideal for detecting small defects in welding seam defects, an improved FasterCNN model is designed, which extracts feature maps of different scales through multi-layer feature networks and acts on the subsequent links of the model together, thus increasing the detailed information input by the model and improving the detection effect of small defects. The category of the extracted defect images is marked, the classification network is constructed based on the existing classification network, and the classification of defect images is studied. Construction and open source of seam inspection image database. In actual industrial production, each production unit can accumulate a large amount of raw data, which can only be used in a limited range due to some conditions. However, in the field of deep learning, a large amount of high-quality data is often needed as training samples. If we can obtain these data, increase the types and quantity of samples, and build a high-quality database of weld defect samples, then we can comprehensively train and learn various types of defects that may occur, such as pores, cracks, incomplete fusion, incomplete penetration, etc., by building a deeper convolutional neural network model, so as to better realize the accurate identification of various defects. Because the distribution of the types of defects in welding is inconsistent, aiming at this unbalanced classification problem, this paper introduces three basic strategies including synthetic minority oversampling technique (SMOTE) to obtain a balanced data set. Smote algorithm artificially synthesized new minority samples, and increased the data set in order to improve learning. This paper introduces the extraction of classic traditional manual features, including texture features and HOG features.

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