Research on X-ray welding image defect detection based on convolution neural network

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Abstract. In order to improve the efficiency of X-ray welding image defect recognition, it is proposed to use the deep learning network to identify welding defects. Based on the analysis of X-ray weld defect image characteristics, the convolutional neural network template and the number of layers are determined. By constructing a deep learning network structure that simulates the principle of visual perception, the steps of feature extraction of weld defect images are avoided. Also the deep learning network can directly determine whether the suspected defect image is a linear defect, circular defect or noise. The designed system can automatically learn the complex depth features in the X-ray weld defect image. The actual calculation shows that the proposed method is feasible and effective.

1. Introduction

The defect detection based on x-ray welding image is the most important method for sub-arc welding detection. More and more researchers pay their attention to auto x-ray welding image defect detection method, and get many research findings. Most of these findings are based on image processing. Zhang¹ and Tang² detect the defects by extracting the edges of welding and defects. The methods of ref [1,2] need different detection algorithms for defects in different positions, and the detection accuracy depends on defect region extraction. So, false X-ray image segmentation will cause false defect recognition. In order to dispel the influence of image segmentation error, ref [3,4] adopt compress sensor technology to recognize defect. Ref [5] reconstructs background area of welding image by fast independent component analysis, and let background area subtract original image. The threshold method is used to extract defect from subtracted image. Ref [6] adopts ultrasonic phased array to detect defect.

In recent years, intelligent recognition methods have been used in defect detection such as radial basis function(RBF) neural network⁷ and multilayer percutptron neural network⁸. Ref [9,10] descend dimensions of defect features firstly, and then compare recognition performance of support vector machine(SVM) and BP neural network. Ref [11] also adopts SVM to recognize defect. Based on the research of ref [11], ref [12] optimizes coefficients of kernel function and gets a better recognition result. Ref [13] summarizes 43 features of defect and verifies the defect recognition performance of three kinds of classifiers(neural network, SVM and K-nearest neighbor) by inputting these 43 features. Ref [14] adopts fuzzy neural network to detect defect and gets a high defect detection accuracy. But the classifier needs a large number of training samples to reach a high accuracy.

Since concept of deep learning is proposed, deep learning has been used in X-ray welding image defect detection. Of all the deep learning models, convolutional neural network(CNN) can reduce the
memory occupied by deep network and the parameters of network. Moreover, CNN can alleviate the over-fitting problem, so CNN is widely used in many recognition problems. This paper recognizes defect of X-ray welding image by using CNN. It does not need to segment X-ray image, and to extract any feature. The original images are inputted into CNN as models and CNN can automatically study complex features of images to realize defect detection.

2. X-ray Welding Image
A real X-ray welding image is shown in fig.1. It can be found that the X-ray welding image has low contrast, indistinct edge and great noise. Usually, segmented image has noise and true defect simultaneously as shown in fig.2. Such an image will cause false defect detection.

![Fig.1 X-ray weld defect original image](image1)

![Fig.2 X-ray weld image segmentation example](image2)

Traditional recognition methods need to calculate features of segmented noises and defects. But it’s difficulty to segment noise and defect precisely, which bears directly on getting accurate features. So we propose to make segmented small image as suspected defect region (SDR). A CNN is used to recognize these SDR images directly and no feature is needed in recognition. SDR is defined as an expanded 5 pixels rectangular area of circumscribed rectangular of suspected region, as shown in fig.3.

![Fig.3 Suspected Defect Region definition](image3)

There are two kinds of samples and testing data for CNN, one is original images as shown in fig.1, the other is SDR images as shown in fig.4–fig.6. No matter what kind of images, they are classified into linear defect, circular defect and noise according to the shape features. Usually, linear defect is more harmful than circular defect. So it’s essential to distinguish the type of defect not just defect or noise.

![Fig.4 27 circular defect SDR images](image4)

![Fig.5 27 linear defect SDR images](image5)

![Fig.6 27 noise SDR images](image6)

From fig.4–fig.6, we can find that the edge of circular defect is curve with some curvature, the edge of linear defect is line with slope of 125°~145°, the edge of noise is some short line that is out of order.
3. CNN Model for X-ray Image recognition

3.1. Structure of CNN

Deep learning is to construct a neural network that can mimic human brain to learn and analysis. CNN is one kind of deep learning model. Unlike traditional neural network, CNN is a locally connected network and has fewer weights. Thus the image can be inputted into CNN directly without feature extraction.

CNN includes some convolution layers, pooling layers and a fully connected layer. The parameters of CNN are optimized by studying the experimental data using the intelligent method of error reverse transform.

In convolution layer, image is processed by convolution operation that is auto self-learning. Then an activation function is used to get feature map. The number of convolution layers in CNN depends on many factors such as training data, activation function and gradient updating algorithm et al. But SDR image is not large, so it does not need a complex CNN model for recognition. We statistic 7 commonly used features of defect and noise as shown in fig.7.

![Figures showing various features of defect and noise](image-url)

Fig.7 features statistic of defect and noise
From fig.7 we can find that no feature can distinguish defect from noise directly. But there are 4 features that are the aspect ratio, length area ratio, circularity and rectangularity have a relatively large difference on defect and noise. And because the targets of convolution layer and pooling layer are to find some features of image, so the number of convolution layers should be 4.

Here, we construct a CNN with 10 layers that are 1 input layer, 4 convolution layers, 2 fully connected neural networks and 1 output layer as shown in fig.8. SDR is inputted into input layer directly. After operation of 4 convolution and pooling layers, the in-deep feature matrixes will be extracted. These feature matrixes are rearranged as a vector by line scanning. The vector is inputted into fully connected layer and is classified as line defect, circular defect and noise lastly.

The size of convolution kernel can be 3×3, 5×5 and 7×7. The size of SDR is not large, so 3×3 and 5×5 convolution kernels may get better performance in recognition. The depth of the convolution kernel increases by 16 folds layer by layer. The SDR recognition accuracies for different sizes of convolution kernel is shown in fig.9.

From fig.9, we can find that the size of 5×5 suitable for low depth convolution kernel and the size of 3×3 is suitable for high depth convolution kernel. By this way, it can decrease the complexity of CNN meanwhile fully extracting image features and increase recognition accuracy.

The detailed structure of CNN for defect classifying is shown in fig.10. In fig.10, C1, C3, C5 and C7 are convolution layers; S2, S4, S6 and S8 are pooling layers; F9 and F10 are fully connected networks; it's dropout layer after fully connected networks. The dropout layer can improve the generalization of CNN and reduce the degree of over-fitting and under-fitting.

The detailed coefficients of convolution layer is shown in table 1. The initial weight of convolution kernel is set to truncated normal distribution random number with average number 0 and standard deviation 0.1. In S2, S4, S6 and S8, the size of pooling window is 2×2, moving step length is 2. The number of nodes in F9 is 1024, and in F10 is 512. The constructed CNN is to classify linear defect, circular defect and noise, so the number of nodes in output layer is 3.

| Table 1 coefficients of convolution layer |
|-----------------|----------------|----------------|----------------|
| Size of kernel  | depth          | Step length    | Activation function |
| C1              | 5×5            | 64             | 1               | ReLU            |
| C3              | 5×5            | 64             | 1               | ReLU            |
| C5              | 3×3            | 128            | 1               | ReLU            |
| C7              | 3×3            | 128            | 1               | ReLU            |
In table 1, the activation function adopts ReLU because it can make outputs of some neurons be 0 and increase sparsity of the network. ReLU can also speed up the convergence speed, improve the performance of the algorithm and avoid the disappearance of gradient.

This paper does SDR image recognition tests by using ReLU activation function and Sigmoid activation function separately. Other things being equal, the SDR image recognition accuracies of CNN with ReLU and Sigmoid activation function are shown in fig.11.

Obviously, the performance of ReLU is better than Sigmoid for SDR image recognition. So this paper adopts ReLU activation function.

The training of CNN is to get convolution kernel and the weights between layers etc by learning. The training algorithm is back propagation algorithm. In this work, the training and prediction CNN model is based on open source in-depth learning framework – TensorFlow. The number of predicted samples is 20% of the training samples. Coefficient of regularization is 0.0001, global learning rate is 0.001, iterative step size is 64, the number of iteration is 20, optimization algorithm adopts adaptive moment estimation algorithm (Adam).

4. Examination

Here we select 580 circular, linear and noise SDR as testing samples to train and verify designed CNN model. The curve of accuracy to number of iteration is shown in fig.12, and the loss to the number of iteration is shown in fig.13.

From fig.12 and fig.13, we can find that the recognition accuracy increases and tends to be stable with number of iteration increasing. Also, testing accuracy and training accuracy tend to be same. It prove that there are no over fitting or under fitting for the designed CNN model. Also, it can be found that the loss value decreases with iteration progress. The recognition result is shown in fig.14.
In order to verify classifying performance of CNN model, the circular defects, linear defects and noise SDR images are grouped into groups, each group has 580 SDR images. Each group is taken as a sample to carry out experiments, and the results are shown in table 2. It can be found that the loss of training set is small, meanwhile the accuracy is high and stable.

### Table 2 Examination results of changing models

| Serial Number of experiment | Training set | Validation set |
|----------------------------|--------------|----------------|
|                            | loss          | Accuracy       | loss          | Accuracy       |
| 1                          | 2.940071      | 0.988839       | 6.298004      | 0.968750       |
| 2                          | 3.284623      | 0.982143       | 7.006881      | 0.984375       |
| 3                          | 1.790114      | 0.991071       | 7.874317      | 0.968750       |
| 4                          | 3.403730      | 0.988839       | 1.155796      | 1.000000       |
| 5                          | 3.080518      | 0.988839       | 3.406974      | 0.984375       |
| 6                          | 3.895833      | 0.984375       | 4.113029      | 0.968750       |
| 7                          | 3.951737      | 0.977679       | 4.770255      | 0.984375       |
| 8                          | 4.960793      | 0.977679       | 5.296495      | 0.984375       |
| 9                          | 4.737175      | 0.982143       | 3.471354      | 0.984375       |
| 10                         | 4.842976      | 0.977679       | 4.423430      | 1.000000       |

5. **Conclusion**

(1) This paper analyses features of X-ray welding image, and designs a CNN model with 10 layers that belong to 6 grade for defect detection. The size of convolution kernel should be $5 \times 5$ and $3 \times 3$.

(2) For X-ray welding image recognition, the classifying accuracy can reach 98.8% if CNN adopts ReLU activation function. Such a successful ratio is higher than that of CNN with sigmoid active function.

(3) Recognition tests show that classifying accuracy can be more than 90% only after 5 times of iteration, and the accuracy tends to be stable only after 20 times of iteration.

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