Research on Weld Defect Identification with X-ray Based on Convolutional Neural Network

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Abstract—In the process of X-ray weld defect detection, a deep learning network structure based on the principle of simulated visual perception is constructed. The size and number of layers of convolutional neural network template, and the influence of different activation functions, are analyzed with an improved method proposed, which may avoid the characteristic steps for the extraction of defect images, and can be used to directly determine the presence of any defect. Experiments on 200 images show that the proposed method for SDR images has an identification rate of more than 98%, which is better than other methods, and has highly practically in pipeline defect detection.

1. Introduction

Welding projects always involve weld defects\([1]\), which may lower the service life of pipeline, and even cause such issues as property losses and personal safety. There are many kinds of defect detection methods, and usually the non-destructive testing method\([2]\) is used to detect the defects inside the weld. Non-destructive testing technology includes radiographic testing and ultrasonic testing, and radiographic testing technology has a higher defect detection rate. X-ray testing technology has the advantages of intuitive and accurate detection results, permanent preservation and self-supervision, so it has become one of the most commonly used non-destructive testing methods for weld defects. Since “deep learning” \([4]\) was put forward, it has developed rapidly in academia and industry, enabling it to be applied to the field of weld defect detection with X-ray. Among the deep learning models, convolutional neural network (CNN) is the most widely used one, which can reduce the network memory and network parameters, and mitigate the excessive fitting issue of the model \([5]\). In this paper, CNN method is used to identify X-ray weld defect images, thereby reducing the workload and improving the accuracy of defect identification. With CNN, the original image samples are input to automatically learn the characteristics of defect images, thus realizing the defect classification automatically.
2. Selection of defect sample

The X-ray weld image in industrial production is shown in Fig. 1.

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

It can be found from Fig.1 that the less obvious contrast between defect and noise and more noise interference cause unclear defect perimeter. Therefore, the segmentation method is used for the segmentation processing of images. Conventional segmentation methods cannot accurately locate the defects. The defects segmented are mixed with noise together, making it difficult to distinguish them and imposing a great impact on defect identification, as shown in Fig.2.

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

In this paper with the Suspected Defect Region (SDR) for deep learning, the computer is used for image preprocessing and model training for the purpose of defect identification. In this way, it is possible to improve the calculation efficiency, save time and avoid the eigenvalue error.

Image samples are selected from the database. One is the original X-ray weld defect image, a circular defect, as shown in Figure 1; the other is the segmented SDR image, which can be classified into circular SDR and noise, as shown in Fig.3 and Fig.4.

![Fig.3 100 sets of circular defect images](image)

![Fig.4 100 sets of noise images](image)
By comparison of the circular defect with the noise map, it is found that there is a curve with certain arc at the edge of the circular defect, while the noise is an irregular line segment. Both defect and noise can be described with such eigenvalues as location G1, ratio of length to width G2, ratio of length to area ratio G3, ratio of area bounding rectangle G4, circularity G5, rectangularity G6 and Heywood diameter G7, etc, resulting in complex comparison and more calculation. Upon deep learning, it is unnecessary to consider the extraction of eigenvalues, because following the input of sample images, the CNN has included the defect eigenvalues in the calculation process.

3. Deep Learning Calculation Framework

3.1. Convolution layer
Convolution layer connects each input neuron with the local receptive region of the upper layer, and extracts the eigenvalues of this part.

\[ a_i^j = F(b_i^j) \]
\[ b_i^j = \sum_{j=0}^{m_i} a_j^{i-1} \times c_{ij} + n_i^j \]  

Where “*” is the convolution symbol, \( a_i^j \) is the output of Channel \( i \) of the convolution layer \( l \), \( b_i^j \) is the net activation of Channel \( i \) of the convolution layer \( l \), \( m_i \) is the subset of the input feature map used for the calculation of \( b_i^j \), \( a_j^{i-1} \) is the output feature map of Channel \( j \) of the previous layer of the convolution layer \( l \), \( c_{ij} \) is the convolution kernel matrix, \( n_i^j \) is the bias of the post-convolution feature map, and \( F() \) is the activation function. For an output feature map \( a_i^l \), the convolution kernel \( c_{ij} \) of each input feature map \( a_j^{i-1} \) may be different.

3.2. Pooling layer
Pooling Layer, also known as Sub Sampling Layer, can save valuable information, reduce parameters and improve the training speed. The common pooling methods include maximum pooling, average pooling and random pooling. Amongst others, maximum pooling is also the most used method, which mainly selects the maximum as the pooling result of the region. In the pooling layer, each input feature map samples the output feature map through the equation (2):

\[ a_i^j = F[b_i^j] \]
\[ b_i^j = \delta_{ij} \text{down}(a_j^{i-1}) + n_i^j \]  

Where, \( b_i^j \) is the net activation of Channel \( j \) of the pooling layer \( l \), \( \delta \) is the weight coefficient of the pooling layer, \( n_i^j \) is the offset of the pooling layer, and the symbol \( \text{down}() \) represents the pooling function, which divides the input feature map into several non-overlapping \( n \times n \) image blocks by the window sliding method, and then calculates the maximum of the pixels in each image block, so that the output image is reduced by \( n \) times in two dimensions.

3.3. Fully connected layer
The fully connected layer is the last layer of the neural network. Each neuron in the fully connected layer is fully connected with each neuron in the previous layer. After the operation of the classifier, the probability of each tag is calculated

In the fully connected layer, the feature maps of two-dimensional images are spliced into one-dimensional features as the input of the fully connected layer. The input of the fully connected layer can be obtained by the weighting and sum of input and the response of activation function:
\[ a_i' = F(b_i') \]
\[ b_i' = w^i a^{i-1} + n_i' \]  \hspace{1cm} (3)

Where, \( n_i' \) is the net activation of the fully connected layer \( i \), \( w^i \) is the weight coefficient of the fully connected layer \( i \), and \( n_i' \) is the bias term of the fully connected layer \( i \).

### 3.4. Activation function

The commonly used activation functions include ReLU function, Sigmoid function and tanh function. Its function can be defined as follows:

\[ f(x) = \max(0, x) \]  \hspace{1cm} (4)

ReLU function graph is shown in Fig.5.

![ReLU function diagram](image)

Fig.5 ReLU function diagram

It can be seen from the graph that the value range of the function is \([0, \infty]\). Then its reciprocal is expressed as follows:

\[ f'(x) = \begin{cases} 
0 & x < 0 \\
1 & x \geq 0 
\end{cases} \]  \hspace{1cm} (5)

Sigmoid function graph is shown in Fig.6.

![Sigmoid function diagram](image)

Fig.6 Sigmoid function diagram

It can be seen from the graph that Sigmoid function is a nonlinear curve graph, with its definition as follows:

\[ f(x) = 1 / (1 + e^{-x}) \]  \hspace{1cm} (6)

By comparison of ReLU function with Sigmoid function, it can be found that ReLU function can make the output of some neurons 0, increase the sparsity of the network, greatly speed up the convergence speed, improve the performance of the algorithm, avoid the phenomenon of gradient disappearing, so it is more suitable for CNN neural network structure.
3.5. Loss function

The CNN model can be optimized by activation function and loss function to improve the training accuracy. The loss function used in this paper is the cross-entropy cost function, as show in equation (7):

\[ y = -\frac{1}{n} \sum_x [b \ln a + (1-b)\ln(1-a)] \]  

(7)

Where, \( y \) is the objective function, \( n \) is the total number of samples, \( x \) is the sample, \( B \) is the actual value, and \( a \) is the output value.

4. CNN Model

The number of convolution layers in the CNN model is determined based on the training data and activation function. Due to the large difference of SDR images, making them easy to be distinguished, a complex network structure is not required. A lot of training shows that the 2-level model produces better effect, so we can design a two-level convolution layer. The model designed in this paper consists of 6 layers: 1 input layer, 2-level convolution, 2 fully connected layers and 1 output layer. The specific structure of CNN is shown in Fig.8, where C1 and C3 are convolution layers, S2 and S4 are pooling layers, F5 and F6 are fully connected layers.

The dimension of C1 convolution kernel is set to 3 × 3 with depth of 8; the dimension of C3 convolution kernel is also set to 3 × 3 with depth of 64; for S2 and S4 as pooling layers, the dimension of convolution kernel is set to 3 × 3 with the moving step of 1.

In CNN model, zero padding operation is adopted for the convolution layer to keep the input sample length and width unchanged and increase the depth; while zero padding operation is not adopted for the pooling layer since after pooling, the depth of the sample remains unchanged and the length and width decrease.

4.1. CNN training and forecast

CNN training involves the learning of convolution kernel parameters and the network parameters between layers, and then the update of weight according to the gradient descent formula. The specific steps are as follows:

a) The output value of each neuron is calculated forward;

b) The sensitivity of each neuron is calculated reversely;

c) The gradient of weights among neurons is calculated;

d) The weight is updated.

In this paper, the training and forecast of the model is carried out in Python language under TensorFlow framework. The number of forecast samples of CNN model is 30% of the training samples. In the training of CNN model, the overall learning rate (\( \alpha \)) is set to 0.01, and the batch size is set to 64. After 20 times of training, the accuracy of the model is increased by almost zero, so the number of epoch is set to 20. The optimizer adopts the adaptive moment estimation algorithm (Adam).
5. Analysis on the Experiment Results

200 SDR images of circles and noise are selected to form samples. Training and testing experiments show that CNN training is featured by fast training speed, obvious classification, and training accuracy of more than 90%. The identification results are shown in Fig.8.

![CNN recognition result](image)

In order to further verify the classification algorithm of CNN model, the SDR images of circular defects, linear defects and noise in the database are grouped into a group of 20 images, with each group taken as a sample for test. The test results are shown in Table 1.

| Test Number | Training set | Verification set |
|-------------|--------------|------------------|
|             | Loss value   | Accuracy         | Loss value   | Accuracy         |
| 1           | 3.889632     | 0.983264         | 4.320854     | 0.967480         |
| 2           | 3.936737     | 0.978739         | 4.879305     | 0.985536         |
| 3           | 4.895203     | 0.975846         | 5.280532     | 0.985536         |
| 4           | 4.776521     | 0.975846         | 5.61731     | 0.997631         |
| 5           | 3.280716     | 0.986456         | 4.48350      | 0.998631         |
| 6           | 2.892156     | 0.989466         | 6.520386     | 0.967480         |
| 7           | 3.887412     | 0.983264         | 1.260341     | 1.000000         |
| 8           | 1.820365     | 0.993167         | 7.003178     | 0.985536         |
| 9           | 3.493206     | 0.987732         | 7.910251     | 0.997480         |
| 10          | 4.798865     | 0.976582         | 3.340928     | 1.000000         |

It can be seen from table 1 that there is no big difference between the accuracy of training set and that of verification set, which also shows that CNN has a stable structure of CNN. Through image comparison, it is found that the accuracy rate of SDR image is higher than that of the original image, and the identification rate reaches more than 98%. Because the defect features of the original image are not obvious with many interference factors, it shows that CNN model has more identification function, in addition to high identification speed and high identification efficiency.

6. Conclusion

In this paper, the CNN algorithm selected for identification adopts a 6-layer CNN structure. Convolution kernel size and moving step of convolution layer and pooling layer are set and ReLU function is used for activation. Finally, the training of SDR image and original image in CNN model is compared. SDR image is selected as the best input sample. The experiment shows that CNN network structure model has fast training speed and high accuracy, making it more suitable for the identification and detection of X-ray weld defect images with an accuracy rate of more than 98%.

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