Research on Detection Method for Welding Seam Defects in Ultrasonic TOFD Image Based on Mask R-CNN

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Abstract. In this paper, the technology of ultrasonic TOFD was used in the welding seam inspection of construction steel structure. 162 ultrasonic TOFD scanning images including five kinds of common defects were obtained through field test. The five kinds of common welding defects include stoma, slag inclusion, lack of fusion, incomplete penetration and crackle. Combined with artificial intelligence image recognition technology, an automatic detection algorithm of welding seam defects in ultrasonic TOFD scanning images based on Mask R-CNN was developed. By comparing the effects of automatic location and classification of welding seam defects based on Mask R-CNN after the same number of iterative training under different parameter configurations, the results show that Mask R-CNN can automatically locate and classify welding seam defects and the recognition effect is the best when epoch is 667, steps_per_epoch is 15 and learning rate is 0.001. Under this parameter configuration, the recognition and classification of five kinds of common defects such as stoma, slag inclusion, lack of fusion, incomplete penetration and crackle are correct. The correct recognition confidence of all five kinds of defects can reach more than 0.9, and the location is precise.

Keywords: Welding defects; TOFD scanning image; Mask R-CNN; Image recognition.

1. Introduction

Welding is one of the main methods of member connection in steel structure construction. When steel members are welded, the defects inside or outside the steel in the welded base metal or nearby the area affected by high temperature are called welding defects. Common welding seam defects include stoma, slag inclusion, incomplete penetration, lack of fusion and crackle, etc. [1]. The bearing capacity of building steel structure is greatly affected by welding seam defects, so it is necessary to inspect the welding seam quality of steel structure.

Ultrasonic TOFD (time of flight diffraction) method is a kind of method to detect and characterize welding seam defects by obtaining diffraction ultrasonic energy from the end of the internal defects of the test pieces. Ultrasonic TOFD method has the advantages of high one-time detection rate, wide application range, no need of calibration, high detection accuracy, and the image data stored in the computer for a long time. At present, the ultrasonic TOFD method has been widely used in the welding seam inspection of various pressure equipment, but it is rarely used in industrial and civil steel structure buildings, lacking complete and mature specifications. It still needs to rely on manual analysis and judgment of welding seam defects in the ultrasonic TOFD scanning images, which requires the inspectors to have certain experience. In addition, there is still a lack of corresponding standards for ultrasonic TOFD detection of building steel structure weld, so it is a complex task to analyze and evaluate the weld defects in the ultrasonic TOFD scanning images[2]. In recent years, artificial intelligence has gradually penetrated into all walks of life. It is also a new idea and an important direction
to study the defect image automatic recognition system based on artificial intelligence which can be realized on the computer.

Some scholars have done a series of researches on the automatic recognition of welding seam defects in ultrasonic TOFD scanning image. Cruz et al.[3] used a series of methods such as cosine transform to extract the feature signals of weld ultrasonic testing signals from the idea of extracting image features first and then automatic recognition, and he constructed a neural network based on multi-layer perceptron to recognize the extracted feature signals. Liu et al.[4] used BP neural network to train and recognize the multiple reflected wave signal of spot welding decomposed by the wavelet packet technique, and completed the automatic recognition of failed weld, stick weld, good weld, and defective weld with gas pore. In order to improve the resolution and readability of TOFD scanning images of welding defects, Chi Dazhao and Sheng Chaoyang et al.[5-6] adopted the corresponding image processing technique. In the aspect of automatic recognition of welding defects in ultrasonic TOFD scanning images, Chen Zhenhua et al.[7] used BP neural network and straight through wave to realize automatic detection and recognition of defects near the weld surface. Lin Naichang et al.[8] used Gabor wavelet to extract the characteristic signal of ultrasonic TOFD scanning image, and automatically identified the defect signal to realize the detection of welding quality. Huang Huandong et al.[9] analyzed the image features of welding defects in ultrasonic TOFD scanning images, and summarized the features of various welding seam defects in ultrasonic TOFD scanning images; Faster R-CNN neural network was constructed to automatically recognize the welding seam defects in ultrasonic TOFD scanning images. Although the traditional artificial neural network can automatically identify the defects in the ultrasonic TOFD scanning images by combining with feature extraction, feature extraction is a complex process, and there are some difficulties in operation[10].

In 2018, He Kaiming et al.[11] proposed a new target detection algorithm called Mask R-CNN (mask regions with convolutional neural network features) on the basis of Faster R-CNN (faster regions with convolutional neural network features). The semantic segmentation branch is added to Mask R-CNN, and the algorithm structure is more complex. Therefore, the training and testing speed is slower. However, it can describe the size and location of welding seam defects in the images in the form of mask, and can mark multiple welding seam defects in one TOFD scanning image, which can improve the detection efficiency of a single image. Fang Luping, et al.[12] ordered the development and current situation of target detection algorithm, summarized the development, improvement and deficiency of traditional algorithm and target detection algorithm with deep learning, and made a comparison. The conclusion is that Mask R-CNN has reached a high level in detection accuracy and instance segmentation. Peng Qiuchen et al.[13] used Mask R-CNN to process the binocular images of the robots, recognized the objects and segmented the shapes in the images, and then used neural network features to match the same objects in the binocular images. The experimental results showed that this method can recognize and locate the objects at a quasi real-time speed. Compared with the traditional method relying on the calculation of global disparity map, the speed and accuracy were improved.

In earlier works, the artificial intelligence image recognition technology was applied to the automatic recognition of weld defects in building steel structures, and training and automatic recognition system for the ultrasonic TOFD scanning image of weld defect was established. The computer automatic recognition without manualpretreatment has been realized. The follow-up research needs to call different algorithms and adjust parameters for the automatic recognition system, so as to obtain an automatic recognition system with higher accuracy suitable for ultrasonic TOFD scanning image recognition. In this paper, the ultrasonic TOFD method will be used for the welding seam detection of building steel structure. According to the principle and characteristics of the artificial intelligence image recognition algorithm Mask R-CNN, the automatic location and recognition algorithm of welding seam defects in ultrasonic TOFD scanning images based on Mask R-CNN will be proposed. By comparing the recognition effect of the algorithm under different parameter configurations, the algorithm with high recognition confidence will be obtained.
2. Ultrasonic TOFD Method and Its Application in Welding Seam Detection of Building Steel Structure

2.1. Working Principle of the Ultrasonic TOFD Method

Different types and sizes of defects have different forms and intensities of diffraction. Based on the differential diffractive phenomenon, the ultrasonic TOFD method can be used to detect the welding seam\(^{[14]}\).

As shown in figure 1, the welding seam defects cause tips inside the test piece which will produce wave diffraction phenomenon in the detection range. The ultrasonic wave emitted by the transmitting probe can propagate in the base metal and weld, and can divide into several parts when it reaches the receiving probe. The ultrasonic wave divide into the straight through wave, the bottom reflection wave and the diffraction wave if defects exists. By receiving and detecting the diffraction wave, the relevant information of the defects in the weld can be gotten. When scanning, the position and size of welding defects can be quantitatively calculated according to the geometric relationship such as probe spacing, probe angle and the propagation speed of ultrasonic wave in the testing piece.

![Figure 1. A sketch map of the ultrasonic TOFD testing principle.](image)

2.2. Ultrasonic TOFD Scanning Image Test Process

In this paper, the ultrasonic TOFD method is used to detect the welding seam in the construction site of a large-scale building steel structure. 162 typical scanning images including five common kinds of welding seam defects are obtained, which include stoma, slag inclusion, incomplete penetration, lack of fusion and crackle. Before scanning, a series of preparations are needed to ensure the detection effect. Firstly, it is necessary to inspect the testing piece in advance, which can help to understand the relevant information of the welding seam. After that, we need to set the appropriate probe spacing to ensure a large enough detection range and a good enough acoustic beam resolution. In order to select the appropriate PCS by calculating, it is necessary to ensure that it is the center line of the acoustic beam of the transmitting probe and the center line of the acoustic beam of the receiving probe intersect at 2/3 of the thickness of the specimen in the case that the probe angle is set as \( \theta \). The value of PCS can be calculated according to the relevant formula. In addition, in order to make the defect characteristics more
obvious in the ultrasonic TOFD scanning images, the gain should be set, which is usually set by grass echo and grain noise or diffraction signal of the groove at one open end.

In the process of scanning, water, paste and butter are often used to ensure that the probe can fit well with the testing piece. It is also necessary to ensure that the scanning device can be well fixed to ensure that the PCS can remain unchanged during the scanning process, and line between the probes is always perpendicular to the centerline of the weld.

3. Mask R-CNN Algorithm

3.1. Frame Structure

As shown in figure 2, the Mask R-CNN algorithm is mainly composed of the convolutional neural network (CNN), the region proposal network (RPN), the region of interest alignment (RoIAlign), fully connected layers and the mask branch. When an image is input into the algorithm, the image firstly passes through CNN. CNN extracts the features from the input image, and the regional proposal network generates proposal windows, which are then mapped to the output feature map of the last convolution layer in CNN. RoIAlign generates feature maps of fixed size from feature maps in these windows. The full connection layers classify and locate the detection targets in these fixed size feature images, and the mask branch mark the outlines of them.

![Figure 2. The frame structure diagram of Mask R-CNN.](image)

When using Mask R-CNN to train and test the ultrasonic TOFD scanning images, what people need to do is to mark the defects in the images directly. In the process of training, the learned information will be fed back to the neural network. After thousands of times of training, if the test data is input into the algorithm, the algorithm will automatically locate and classify the defects in the images according to the specific neural network model formed by training.

3.2. Feature Extraction Network, Full Convolution Network and Region of Interest Alignment

The feature extraction network used by Mask R-CNN is the deep residual network Resnet101\(^{[15]}\), and its framework is shown in figure 3.

![Figure 3. The frame structure diagram of Resnet101.](image)

The deep residual network is composed of convolution layers, channel feature layers and the activation function. In order to ensure the integrity of information and strengthen the network, a channel is established in Resnet101 to connect the input and the output directly. In the mask branch, Mask R-CNN adopts full convolutional networks (FCN). FCN is a kind of semantic segmentation algorithm, which can classify every pixel in the image and segment the instances in the images accurately. RoIAlign uses the double line interpolation method to obtain the pixel values of the images in the floating-point coordinates. In this way, the instances in the feature map can be aligned with the instances in the original image, which ensures the accuracy of training and testing.
4. Mask R-CNN Algorithm for Welding Seam Defect Recognition

In the early stage, about 40 ultrasonic TOFD images including 5 kinds of typical welding defects were obtained through field measurement, and there are some problems in the process of training and testing.

4.1. The Problems of Mask R-CNN Training and Testing

4.1.1. Underfitting. Machine learning needs enough iterative training to make the artificial neural network model ‘remember’ the characteristics of the detected object. If the iterative training is not enough, the artificial neural network can not recognize new data and the data used for training can not be well recognized either. This phenomenon is called underfitting.

4.1.2. Overfitting. Mask R-CNN can be used to train and test the dataset. The neural network can ‘remember’ the characteristics reflected by the training set in training. Then in the test, the test results reflect the automatic recognition effect of the artificial neural network after machine learning.

In the training process, there is a phenomenon that the artificial neural network has a good performance in the training set, but the recognition result is poor when identifying the data that does not exist in the training set. This phenomenon is called overfitting. The reasons for overfitting are following:

(1) The amount of training set data is too small, which can’t reflect all the characteristics of the recognition object. No matter how many iterative training times is, once encountering the new data containing the features that don’t exist in the training set, the accuracy of machine recognition will be greatly reduced;
(2) The feature distribution of the new data used in training and testing is inconsistent. No matter how large the training set is, if these data do not contain all the features of the recognition objects, the trained artificial neural network can not recognize the same kind of objects with new features;
(3) There is noise in the ultrasonic TOFD scanning image data of the training set. During the training process, the artificial neural network may mistakenly take the noise as the feature of the detection object, or even ‘remember’ the noise features and ignore the real object features;
(4) Because of too many iterative training times, the characteristics of the data in the training set are fitted, but the representative characteristics are not fitted.

4.2. The Solutions of Training and Testing Problems of Mask R-CNN

In view of the above problems, corresponding solutions can be adopted, and the solutions are as follows.

4.2.1. Ensure enough iterative training times. Aiming at the problem of underfitting, it can be avoided by increasing the number of iterative training times, but the number of iteration training times should not be too many, otherwise it is easy to produce overfitting phenomenon. In the pre-experiment, after 1000 times of iterative training, the test effect of artificial neural network is poor, and the machine recognition effect of training data set and test data set is poor; When the number of iterative training times is increased to 10000, the test effect of artificial neural network is better, the machine recognition effect of training data set and test data set is better. Therefore, in this paper, the artificial neural networks with different parameters are trained by 10000 iterations.

4.2.2. Increase the data volume and the data quality. In this paper, the training samples were increased by expanding the data set. The data set was added to 162 images by the accumulated weld ultrasonic TOFD scanning images in engineering practice. More ultrasonic TOFD scanning image data could be gotten from different samples from increasing field detection. In order to ensure the quality of the detected images, multiple detection was carried out to minimize the impact of noise. At the same time, the detection results were screened, and the data which were fuzzy or affected by noise were eliminated to ensure the quality of the images. In addition, when making the training data set, the defects in the picture need to be marked and labeled. The marked position and classification information is the content that the artificial neural network needs to ‘remember’ in training. The marked and labeled information had a very important impact on the training and recognition effect, so it was very important to ensure
the quality of the marked and labeled information, and it is necessary to avoid unimportant defect features and ensure that important defect features within the scope of marking and labeling.

4.2.3. Pre-training with COCO dataset. When training, we can use COCO pre-training weight mask_rccn_coco.h5, the pre-training weight is the result of training with COCO dataset. COCO dataset is a large object detection dataset including 91 kinds of object instances, about 330000 images and 2.5 million labeled data, which contains pixel segmentation. The neural network model after pre-training has a good ability in the image edge contour recognition. The possibility of underfitting of the pre-trained artificial neural network will be greatly reduced, and the ability of extracting feature map will be improved. Using the neural network model directly can improve the work efficiency and effectively avoid underfitting. The neural network model after pre-training only has the preliminary ability of image feature extraction, but it can not recognize the defects in ultrasonic TOFD scanning images. The artificial neural network model also needs fine-tuning, and the fine-tuning process is the process of training with ultrasonic TOFD scanning images. The weight after pre-training is input into the Mask R-CNN framework as the initial model, and 149 ultrasonic TOFD scanning images of the welding seam are used to train the neural network model. The neural network model obtained by the above method can effectively avoid underfitting, enhance the robustness of the recognition algorithm, and effectively make up for the lack of data.

4.2.4. Adjustment of Mask R-CNN parameters. There are many parameters in Mask R-CNN code that need to be used in training and recognition. It is very important to select the appropriate parameters to ensure the effect of training and recognition. In the training and recognition process, the parameters steps_per_epoch, epoch and learning rate are mainly adjusted. Among them, the parameter epoch represents the number of iterations, and one epoch represents the Mask R-CNN algorithm to complete a complete training of all samples in the training data set. The parameter steps_per_epoch represents the number of steps in a complete training for all samples in the training dataset. In addition, how much error is used in each update of parameters needs to be controlled by a parameter, which is learning rate.

4.3. Test Results of the Mask R-CNN Parameter Configuration
In this paper, nine kinds of parameter configurations shown in table 1 are selected to test the effect of Mask R-CNN algorithm training. The above nine kinds of parameter configurations are tested in the case of 10000 iterations of training.

| No. | steps_per_epoch | epoch | learning rate |
|-----|-----------------|-------|---------------|
| 1   | 15              | 667   | 0.001         |
| 2   | 15              | 667   | 0.0001        |
| 3   | 15              | 667   | 0.00001       |
| 4   | 2               | 5333  | 0.001         |
| 5   | 2               | 5333  | 0.0001        |
| 6   | 2               | 5333  | 0.00001       |
| 7   | 1               | 10000 | 0.001         |
| 8   | 1               | 10000 | 0.0001        |
| 9   | 1               | 10000 | 0.00001       |

Table 2 lists the recognition effect of the Mask R-CNN algorithm under the above nine parameter configurations after 10000 iterations of training.
Table 2. The test effect of Mask R-CNN after 10000 iterations of training under different parameters.

| No. | Parameter configurations | defect types | whether correct recognition results exist | whether the location is accurate | whether the missing recognition exists | whether the wrong recognition exists | confidence of correct recognition |
|-----|--------------------------|--------------|------------------------------------------|---------------------------------|--------------------------------------|------------------------------------|----------------------------------|
| 1   | epoch=667, steps_per_epoch=15, learning rate=0.001  | stoma        | yes                                      | yes                             | no                                   | no                                 | 1.000                            |
|     |                                          | slag inclusion | yes                                      | yes                             | no                                   | no                                 | 0.999                            |
|     |                                          | crackle       | yes                                      | yes                             | no                                   | no                                 | 0.971                            |
|     |                                          | lack of fusion | yes                                      | yes                             | no                                   | no                                 | 0.997                            |
| 2   | epoch=667, steps_per_epoch=15, learning rate=0.0001 | stoma        | yes                                      | yes                             | yes                                  | no                                 | 0.985                            |
|     |                                          | slag inclusion | yes                                      | yes                             | yes                                  | no                                 | 0.999                            |
|     |                                          | crackle       | yes                                      | no                              | yes                                  | yes                                | 0.776                            |
|     |                                          | lack of fusion | yes                                      | yes                             | no                                   | no                                 | 0.740                            |
|     |                                          | incomplete penetration | yes                                   | yes                             | no                                   | no                                 | 0.988                            |
| 3   | epoch=5333, steps_per_epoch=2, learning rate=0.001 | stoma        | yes                                      | yes                             | no                                   | no                                 | 1.000                            |
|     |                                          | slag inclusion | yes                                      | yes                             | no                                   | no                                 | 0.999                            |
|     |                                          | crackle       | yes                                      | yes                             | no                                   | no                                 | 0.942                            |
|     |                                          | lack of fusion | no                                       | yes                             | no                                   | yes                                | -                                |
|     |                                          | incomplete penetration | no                                    | no                              | yes                                  | yes                                | -                                |
| 4   | epoch=5333, steps_per_epoch=2, learning rate=0.0001 | stoma        | yes                                      | yes                             | yes                                  | no                                 | 0.994                            |
|     |                                          | slag inclusion | yes                                      | yes                             | no                                   | no                                 | 0.961                            |
|     |                                          | crackle       | yes                                      | yes                             | yes                                  | yes                                | 0.992                            |
|     |                                          | lack of fusion | no                                       | yes                             | no                                   | yes                                | -                                |
|     |                                          | incomplete penetration | yes                                   | yes                             | no                                   | no                                 | 0.991                            |
| 5   | epoch=10000, steps_per_epoch=1, learning rate=0.0001 | stoma        | yes                                      | yes                             | no                                   | no                                 | 0.997                            |
|     |                                          | slag inclusion | yes                                      | yes                             | no                                   | no                                 | 0.986                            |
|     |                                          | crackle       | yes                                      | yes                             | no                                   | yes                                | 0.989                            |
|     |                                          | lack of fusion | yes                                      | yes                             | no                                   | no                                 | 0.790                            |
|     |                                          | incomplete penetration | yes                                   | yes                             | no                                   | no                                 | 0.986                            |
| 6   | epoch=10000, steps_per_epoch=1, learning rate=0.0001 | stoma        | yes                                      | yes                             | yes                                  | no                                 | 0.999                            |
|     |                                          | slag inclusion | yes                                      | yes                             | no                                   | no                                 | 0.992                            |
|     |                                          | crackle       | no                                       | no                              | yes                                  | yes                                | -                                |
|     |                                          | lack of fusion | no                                       | yes                             | no                                   | yes                                | -                                |
|     |                                          | incomplete penetration | no                                    | no                              | yes                                  | yes                                | -                                |
| 7   | epoch=10000, steps_per_epoch=1, learning rate=0.0001 | stoma        | yes                                      | yes                             | yes                                  | no                                 | 0.964                            |
|     |                                          | slag inclusion | yes                                      | yes                             | no                                   | no                                 | 0.644                            |
|     |                                          | crackle       | no                                       | no                              | yes                                  | yes                                | -                                |
|     |                                          | lack of fusion | no                                       | no                              | yes                                  | yes                                | -                                |
|     |                                          | incomplete penetration | no                                    | no                              | yes                                  | yes                                | -                                |
| 8   | epoch=10000, steps_per_epoch=1, learning rate=0.0001 | stoma        | no                                       | yes                             | no                                   | yes                                | -                                |
|     |                                          | slag inclusion | no                                       | yes                             | no                                   | yes                                | -                                |
|     |                                          | crackle       | no                                       | no                              | yes                                  | yes                                | -                                |
|     |                                          | lack of fusion | no                                       | no                              | yes                                  | yes                                | -                                |
|     |                                          | incomplete penetration | no                                    | no                              | yes                                  | yes                                | -                                |
| 9   | epoch=10000, steps_per_epoch=1, learning rate=0.0001 | stoma        | no                                       | yes                             | no                                   | yes                                | -                                |
By comparing the recognition results of the algorithms under different parameter configurations in Table 2, we can get that when the parameters of the Mask R-CNN algorithm are configured as epoch=667, steps_per_epoch=15, learning rate=0.001, the algorithm has the best test effect, and the specific recognition effects under this kind of parameter configuration are shown in figure 4-8 after 10000 iterations of training. The program can classify different kinds of defects correctly, locate them accurately, and have high confidence of the correct recognition. The algorithms under other parameter configurations have some shortcomings, such as wrong classification results, low location accuracy, low recognition confidence and so on.

(1) Stoma

![Figure 4](image)

**Figure 4.** The recognition results of stoma when epoch is 667, steps_per_epoch is 15 and learning rate is 0.001.

It can be seen from figure 4 that the recognition and classification results of stoma are correct, the location is accurate, and the correct recognition confidence can reach 1.000.

(2) Slag inclusion

![Figure 5](image)

**Figure 5.** The recognition results of slag inclusion when epoch is 667, steps_per_epoch is 15 and learning rate is 0.001.

It can be seen from figure 5 that the recognition and classification results of slag inclusion are correct, the location is accurate, and the correct recognition confidence can reach 0.999.

(3) Crackle
Figure 6. The recognition results of crackle when epoch is 667, steps_per_epoch is 15 and learning rate is 0.001.

It can be seen from figure 6 that the recognition and classification results of crackle are correct, the location is accurate, and the correct recognition confidence can reach 0.971. At the same time, it can also accurately identify the remaining stoma defects in the image. The classification of stoma defects is correct, the location is accurate, and the correct recognition confidence can reach 1.000.

(4) lack of fusion

Figure 7. The recognition results of lack-of-fusion when epoch is 667, steps_per_epoch is 15 and learning rate is 0.001.

It can be seen from figure 7 that the recognition and classification results of lack of fusion are correct, the location is accurate, and the correct recognition confidence can reach 0.997.

(5) incomplete penetration

Figure 8. The recognition results of incomplete penetration when epoch is 667, steps_per_epoch is 15 and learning rate is 0.001.

It can be seen from figure 8 that the recognition and classification results of incomplete penetration are correct, the location is accurate, and the correct recognition confidence can reach 0.985.

5. Conclusion

In this paper, the principle and application method of TOFD welding seam detection technology are introduced. The ultrasonic TOFD detection method is used in the construction steel structure welding seam detection. The principle and characteristics of the artificial intelligence image recognition algorithm Mask R-CNN are studied, and the automatic location and classification algorithm of welding defect in the ultrasonic TOFD scanning images based on Mask R-CNN is proposed. The algorithm with high recognition confidence is obtained. The specific conclusions are as follows:
(1) Ultrasonic TOFD method is an advanced method to determine welding quality with good reliability and high accuracy. It can be used to locate, classify and quantify the welding seam defects. Typical welding seam defects mainly include stoma, slag inclusion, lack of fusion, incomplete penetration and crackle. The characteristics of different types of typical welding seam defects are obvious, and the types of defects can be distinguished according to the characteristics. This method is widely used in the welding seam detection of building steel structure, which will improve the detection efficiency and effect in engineering practice.

(2) When using Mask R-CNN for training and testing, there are some problems such as underfitting and overfitting. This kind of problem can be avoided by ensuring enough iterations for training, increasing the number of training samples, improving the quality of dataset and pre training with COCO dataset.

(3) Appropriate adjustment of the relevant parameters in Mask R-CNN algorithm can effectively improve the recognition effect of the algorithm. In this paper, by adjusting epoch, steps_per_epoch and learning rate to form nine different parameter configurations. The algorithms under nine parameter configurations are trained for 10000 iterations to study the influence of different parameter configurations on the recognition effect of the algorithm. After 10000 iterations, the test effect is the best under the parameter configuration that epoch is 667, steps_per_epoch is 15 and learning rate is 0.001. The results show that the classification of stoma, slag inclusion, crackle, lack of fusion and incomplete penetration is correct, the location is accurate, and the correct recognition confidence is high. The correct recognition confidence of the five typical welding defects is 1.000, 0.999, 0.971, 0.997 and 0.985 respectively. After 10000 iterations of training, the algorithm with other parameter configurations has some shortcomings, such as classification error, poor location accuracy and low recognition confidence.

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