Research on image segmentation of inner cylinder wall with annular weld based on deep learning

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Abstract. Based on the characteristics of autonomous learning with deep learning and high recognition rate, an image segmentation study based on Faster R-CNN for the inner wall annular weld is proposed. The method extracts pixels containing annular weld feature information by using an RPN network to improve target detection speed. Then, the convolutional layer output detection model is shared by the RPN network and the Fast R-CNN network to realize accurate detection of the annular weld in the video image. The research results show that the proposed method can accurately detect the circumferential weld bead and segment the image under the condition of poor video image quality, and has the advantages of strong anti-interference ability and accurate identification.

1. Introduction
With the continuous improvement of the modern manufacturing level, the welding technology has also been continuously improved, and it has become an indispensable part of the manufacturing field and has been widely used. Due to the various environmental and human factors in the process of pipe welding, the quality of the welding will inevitably lead to various defects, resulting in the existence of safety hazards. If the pipeline has minor defects during welding, it may cause a major accident, which not only causes huge waste of funds, damages the environment, but also causes casualties, resulting in incalculable losses. In order to ensure the quality and safety of the welded workpiece and prevent accidents, it is very important to detect the weld quality [1-3] of the pipe.

At present, the automatic detection technology of weld image segmentation mainly relies on traditional image processing, manual feature presentation and pattern recognition. Luo Chaoqun et al. [4] proposed a weld zone enhancement algorithm based on the improved piecewise linear threshold method. Firstly, the weld image is smoothed and suppressed in the airspace by guided filtering, and then the improved piecewise linear threshold method is adopted in the frequency domain. Enhance the weld area. Liu Nongcong [5] and others compared the grayscale image and color image processing algorithms, and adopted the image weld based feature recognition method, and proposed an improved weld image vector median filtering algorithm and an improved enhancement algorithm based on normalization. The image contrast is effectively improved to achieve accurate positioning of the weld center line, and how to quickly find the weld area and accurately extract the weld seam under the complicated background of the oil and gas pipeline. Huo Ping [6] performs threshold segmentation on the filtered weld image to remove image noise, and then uses edge morphology to perform edge detection. The center line of the light stripe is extracted by averaging the upper and lower boundaries of the detected edge.
In recent years, the weld image feature changes and noise caused by the complex welding process in the industrial field put forward higher requirements for the weld image segmentation algorithm. With the rapid development of computer vision technology, especially deep learning has achieved great success \cite{7-8} in image recognition and classification, prompting people to try to apply it to industrial inspection. At present, there are few applications for weld seam image detection based on deep learning. In this paper, the inner wall of the cylinder with annular weld is taken as the research object, which is mainly for the precise segmentation of the welds of small robots under the complicated pipeline. A research on the image of annular weld seam based on Faster R-CNN \cite{9} is proposed. Each frame image in the weld video is used as a training set. R-CNN introduces the convolutional neural network to extract the depth features, and then a classifier determines whether the search area contains the target and its confidence, and obtains more accurate detection results.

2. Faster R-CNN

The convolutional neural network consists of an input layer, a convolutional layer, a down-sampling layer, a fully connected layer, and an output layer. CNN-based object detection technology evolved from Region-CNN to Fast R-CNN to Faster R-CNN. Although Region-CNN has achieved good results, the selection of candidate regions affects the speed of detection, making it take too long to limit the scope of application. Fast R-CNN is first convoluted and then cropped, which causes different candidate area frames to repeatedly calculate the convolution of the overlapping part of the image. Moreover, the candidate regions in Fast R-CNN are obtained through selective search. The calculation speed and effect are very common, and the speed of real-time monitoring cannot be achieved. Therefore, the researchers proposed the Faster R-CNN algorithm. This method can quickly generate candidate regions using the RPN network, and implements the Regional Suggestion Network (RPN) and Fast R-CNN network sharing parameters in training.

The Faster R-CNN consists of two phases, the first phase RPN (Region Proposal Network) region of interest extraction phase, and the second phase of the Fast R-CNN target detection phase.

The RPN network is a series of small windows that are different in size and aspect ratio by sliding a series of small features in a shared feature map. RPN replaces selective search (SS) and improves the speed of target detection. The phase of target detection uses the Fast R-CNN method. Faster R-CNN greatly improves the efficiency of network operation by unifying candidate frame selection, feature extraction, scale normalization of interest regions, target classification and target regression into a whole deep learning framework. In this paper, the annular weld seam detection segmentation inside the pipe is also based on the Faster R-CNN algorithm \cite{10}.

3. Research on Segmentation Extraction of Inner Wall of Cylindrical Welded Joints Based on Deep Learning

3.1 Data set preparation

Convolutional neural networks are a process of supervised learning that requires a large number of training samples. At the same time, the weld image is the basis of the ring weld inspection. Because the weld non-destructive test has a very strong professionalism, which causes the weld image to be accurate and difficult to mark, there is no large open weld image data set \cite{11-12}. Weld inspection methods based on machine learning or deep learning require the support of a large number of weld images, and the lack of data sets hinders research in this area.

In this paper, the video collected by the camera carried by the small robot is used for image collection, and the model is manually labeled. Selecting representative pictures in a large number of captured images for training enables the network model to extract different features and has better generalization ability. The research in this paper is aimed at the ring weld. When the small robot walks inside the pipe, the weld seam in the video is taken. There is a change in the scale. From far to near, the size of the ring weld is from small to large. Using the video captured by the camera, 1000 weld images were collected, and the data was expanded to 2000 sheets by flipping and transforming the
image without affecting the original weld features. The collected partial image data set is shown in Figure 1.

![Figure 1. Partial image data set](image)

3.2 Faster R-CNN algorithm image segmentation detection

The flow algorithm of the annular weld seam image segmentation based on Faster R-CNN is proposed as follows. First, the original image is input into VGG16\(^{[13]}\) to extract the deep feature map. In this experiment, the image was sorted into two categories: image frames with welds and image frames without welds. There were 1000 images in each category, 80% of which were used as training sets and 20% as test sets. In order to speed up the convergence of the model, a pre-trained strategy is used to fine tune the parameters. The training parameters of all the training processes are as follows: the training frequency is 10000 times, the weight attenuation coefficient is 0.0005, the learning rate of the determined weight parameter is 10\(^{-12}\), and the weight is updated by the random gradient descent method. Second, after obtaining the deep special investigation through VGG16, the regional suggestion and the regional score are obtained through the RPN network. Third, the deep feature map and the region score are extracted and input into the pooling layer of the region of interest, and the features suggested by the corresponding region are extracted, and the classification score of the region and the candidate frame after the regression are output.

(1) Convolution layer. The convolution operation puts the input data into multiple filters. The layer that implements object feature extraction is called the convolution layer. In the VGG16 network, there are 13 convolutional layers. After convolution calculation, 13 different feature maps are obtained. Because the RPN network shares the convolutional layer with the Fast R-CNN network, 13 feature maps are used for the extraction of candidate regions. The time and accuracy of R-CNN's overall training has been further improved. The activation function used in convolution calculations is the modified linear unit (ReLU) activation function.

\[
 f(x) = \max(0, \sum_i w_i \alpha_i)
\]  

Where \( \alpha \) is the output of the previous layer; \( w \) is the connection weight.

(2) ROI poolings. The R-CNN selective algorithm is used to extract the possibility region from the original image and transform it into object feature information according to the mapping relationship. Then the summary information is collected and the size of the input is reduced. The essence is to use the generality of the local variable characteristics to perform the dimensionality reduction operation. There are many ways to achieve dimensionality reduction. This paper uses maximum pooling.
\[ P_{\text{max}} = \max_{i,j} M^k_{i,j} \]  

Where \( P_{\text{max}} \) is the maximum pool; M is the feature map; k is the number of convolution kernels.

(3) RPN. The convolutional feature map after the convolutional layer is used as an input to the regional suggestion network, and a plurality of rectangular candidate regions are used as outputs. In order to obtain the selected area, sliding window processing is required, and the convolutional feature map has a plurality of windows. Each window proposes k target candidate regions, and the connection between the window and the target candidate region is represented by an anchor, and each anchor has a different length and proportion. Enter each window into fully connected layer 1, which is entered into a 256-dimensional low-dimensional vector. The feature vector is input to the fully connected layer 2, which is divided into two sub-network layers: a cls layer and a reg layer. The border sorting layer is used to output the probability that there is a pipe weld for each target candidate frame, and each window has a total of 2k outputs. The candidate box represents the position with \((x, y, w, h)\), the coordinates are represented by \((x, y)\), and \((w, h)\) represent the width and height, respectively. The border regression layer outputs the amount of translational scaling of the anchor. For each window, there is a total of 4k coordinated output, as shown in Figure 2.

![Figure 2. RPN network](image)

4. Experimental results and analysis

In this paper, the pipe weld of the inner wall of the cylinder is the focus of image segmentation. After the data is expanded to 2000 sheets by flipping, panning, etc., the image is sorted into two categories: image frames with welds and image frames without welds, and 1000 images for each category. 80% of them are used as training sets and 20% are used as test sets. Read the acquired weld image and enter it into the Faster R-CNN network. In order to better reflect the better segmentation effect of the weld extraction using the Faster R-CNN network, this experiment uses the traditional method of extracting the center of the light bar (the gray center of gravity method \([14]\)) for the weld segmentation and the segmentation effect. comparing. The comparison results of different weld seam segmentation methods are shown in Fig. 4: Fig. 4(a)-(b) are weld seam original images. Figures 4(c)-(d) are weld seam results extracted by the gray center of gravity method. Figures 4(e)-(f) show the segmentation results of the Faster R-CNN network.

The segmentation results show that both segmentation methods can better extract the contour of the weld. Faster R-CNN has the ability of deep learning, which combines the multi-level features of weld image. It can accurately acquire the characteristics of the whole weld by continuously training the characteristic information of the ring weld. Compared with the traditional method, the extraction of Faster R-CNN Higher effect and extraction accuracy.
It can be seen from Table 1 that the accurate identification rate of the inner wall weld of the pipeline based on Faster R-CNN is over 90%, and the error rate is lower than the conventional method. However, the weld seam recognition rate cannot be further improved. The reason may be that the inner wall weld of the pipe is not easy to detect, and the recognition effect is not good. However, when the weld is relatively obvious, it is easy to identify and is not easily misjudged.

5. Conclusions
In view of the fact that today’s pipeline welding is easily interfered by environmental factors and human factors, combined with deep learning technology, deep neural network is applied to the welding process. In this paper, the Faster R-CNN convolutional neural network is used to detect the cylindrical annular weld seam, and 80% of the data is used for training. The other 20% of the data is used as a test set to identify whether the accuracy of the pipe weld is more than 90%. However, this method still has many shortcomings. First of all, the accuracy needs to be further improved. When the
pipe weld is not obvious, the recognition effect is not good and it is easy to be misjudged. Secondly, the speed of neural network training should be increased to meet the higher requirements for real-time processing of welds when small robots walk in the inner wall of pipes.

ACKNOWLEDGEMENTS
This work is supported by National Natural Science Foundation of China under grant NO.61863037.

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