Weld identification technology of pressure steel pipe for wall-climbing robot operation

Junjie Zhu[1], Jun Hu[1], Lianwei Liu[1],Yanzheng Zhao
1. Three Gorges Power Plant, China Yangtze Power Co., LTD., Yichang 443000, China
2. Shanghai Jiao Tong University, Shanghai 200240, China

Abstract: With the continuous development of hydropower industry in China, the test and maintenance task of hydropower generator set is increasingly heavy. As a key component of the generator set, the water inlet pressure steel pipe, because of its large diameter and long distance characteristics, makes the past by manual detection and maintenance of the operation mode has a long period, high labor intensity and other problems. With the progress of robot technology, mobile robots are considered to solve the above problems instead of manual work. In the inspection and maintenance of pressure steel pipe, there are many tasks around welding seams. In order to improve the quality and efficiency of robot operation, it is necessary to realize high-precision welding seam identification. This paper takes the welding seam identification of pressure steel pipe as the research content, adopts the semantic segmentation method based on improved DeepLabv3+, takes the two-track wall-climbing mobile robot as the test platform, and takes the actual pressure steel pipe as the test object to carry out the algorithm instantiation test and analysis. Field tests show that the pressure steel pipe weld identification technology can identify the weld efficiently and accurately, which is helpful to improve the working efficiency and accuracy of the wall-climbing robot.

Key words: hydropower pressure steel pipe, wall-climbing robot, weld identification

As one of the core components of hydropower unit, the inlet pressure steel pipe has the characteristics of large diameter, long stroke and high drop, which leads to the problems of long time limit, low efficiency, high labor intensity and high danger factor in the past manual inspection and maintenance tasks. With the continuous progress of robot technology, it is considered to replace the manual completion of pressure steel pipe inspection and maintenance by cooperating with the work function module by climbing the wall mobile robot. Because it is necessary to carry different functional units to move on the inner wall of the pressure steel pipe, the movement mode of the wall-climbing robot is mostly wheeled or tracked. The adsorption method of the wall-climbing robot is different according to the adsorption material, and the common types are permanent magnet and negative pressure. Because the material of the pressure steel pipe is a magnetic conductive material, the permanent magnet adsorption method is generally selected. In the work tasks, there are a lot of processes that take the weld as the work target or positioning basis, which require the wall-climbing mobile robot to extend the weld movement or maintain the required position and posture relationship with the weld. This requires the wall-climbing robot itself to have high-precision welding seam recognition ability.

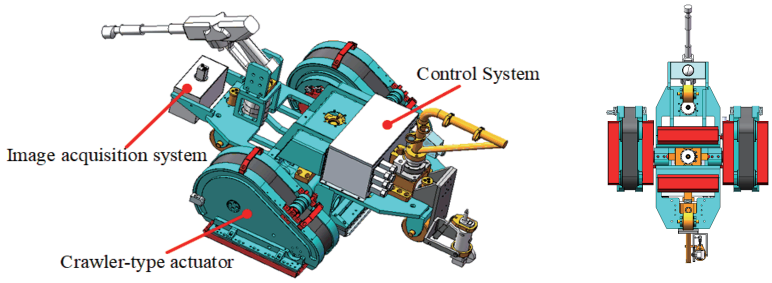
Machine vision and image processing technology are often used in research fields related to welds. Researchers use vision sensors to extract the required weld feature information through a series of image processing to realize the identification and tracking of the weld. Zhang Yufei and Zhang Yishun used the watershed algorithm to extract the weld foreground information, the morphology method to close the internal area of the weld, and the Canny edge detection operator and Hough Transform to extract the weld edge and calculate the center line. Yu Jiajie et al. collected images by laser structured light camera, suppressed noise by Gaussian filter, obtained optimal segmentation threshold by OTSU algorithm, and obtained weld area by binarization processing. Li et al. proposed a weld tracking algorithm, which uses cumulative gray frequency to separate the weld and dynamically ADAPTS to the initial position and size of the search window. At the same time, a sequential gravity method (SGM) is designed to extract the smooth weld centerline to reduce the influence of joints and noise on the location of feature points.

In recent years, researchers have gradually proposed some algorithms based on neural network to detect and locate welds. The recognition effect of traditional image processing methods will decrease significantly when the noise changes are the same. In the edge extraction stage, DONG et al. obtained the weld contour by integrating Sobel, Prewitt and Robert operators, and built a multi-class classifier to identify the weld through the support vector mechanism. Zhang Shikuan used U-Net model and YOLO-v2 model of parallel downsampling module to effectively detect and segment weld images containing a lot of noise such as smoke and splash lines. However, the quality of weld images taken in the above research is mostly ideal, and the welding seam is difficult to be identified and detected stably and accurately due to the interference caused by corrosion and sediment viscosity inside the pressure steel pipe of hydropower station.

Therefore, in view of the complex environment and poor light conditions, this paper realizes robust and accurate weld identification function based on the semantic segmentation model with DeepLabV3+ as the frame and MobileNetv2 as the main stem network, and calculates the weld position and Angle according to the recognition results.

1. Overall design of wall-climbing robot

The overall scheme of the wall-climbing robot structure is shown in Figure 1. The two-track mobile robot system is mainly composed of mobile unit, universal electric control cabinet and function module. The mobile unit is the carrier for the robot to realize the wall movement and operation, which is mainly composed of the frame, two groups of motion execution units (servo motor direct drive track motion mechanism) and non-contact permanent magnet adsorption module. The motion execution unit is connected with the moving unit body through the crankshaft, which can adapt to the wall surface with different curvature radius. The motion execution unit does not contain a steering mechanism, and the steering is achieved through the differential speed of the track. The adsorption module is composed of two groups of body adsorption devices and four groups of track adsorption devices. The adsorption module is respectively installed in the lower part of the moving module and the lower part of the car body. The magnet and the wall are in a non-contact state and have a certain height air gap. When the robot climbs the wall, the adsorption module does not contact with the inner wall of the pressure steel pipe. The self-weight of the wall-climbing robot is 140kg. The auxiliary function module can be regarded as a load relative to the wall climbing machine per person, and the total weight is not more than 200kg under the premise of meeting the needs of the operation.



(1) Wall climbing robot platform **(2) Step by step magnetic sucker**

Figure 1 Overall scheme of wall-climbing robot

The adsorption module is composed of 2 groups of vehicle body adsorption devices and 4 groups of track adsorption devices. The adsorption module is respectively installed in the lower part of the moving module and the lower part of the car body. The magnet and the wall are in a non-contact state and have a certain height air gap. When the robot climbs the wall, the adsorption module does not contact with the inner wall of the pressure steel pipe.

2. Welding seam identification principle

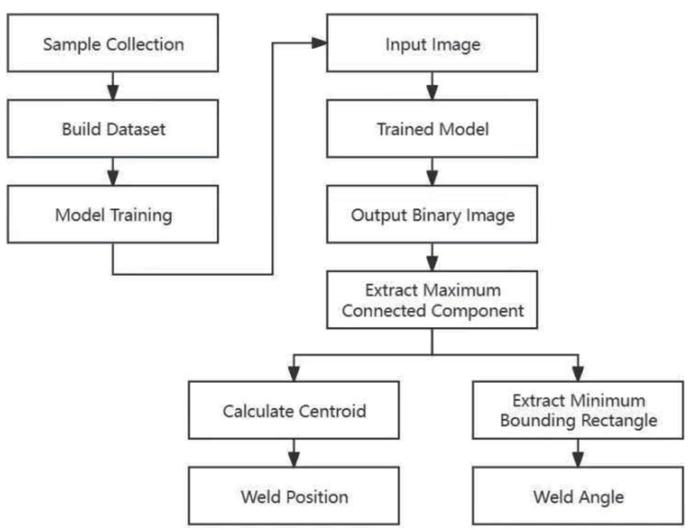


Figure 2 Weld identification process

The weld identification process is shown in Figure 2. The Hikang robot industrial camera equipped with the robot collects pictures of multi-channel welds and selects 300 images from each weld to construct a data set, in which the sample number ratio of learning set and test set is 9:1. Labelme is used to manually label the weld position as the true value. By means of rotation, addition and subtraction exposure, the data of the marked sample set was enhanced, and the sample size was expanded to 1500. The learning set is input into the semantic segmentation model for learning, and the weight parameters in the model are iteratively optimized. By extracting the maximum connected contour of the recognition result, the noise part identified by mistake is excluded, and the weld is obtained. According to the extracted contour, the position of the centroid and the minimum external rectangle are calculated to obtain the position and Angle of the weld in the image. Since the focus of this paper is on the robot's recognition ability of the weld, the subsequent calculation of the position and Angle of the weld will not be introduced too much, only the purpose of the recognition results of the weld will be shown.

DeepLabv3+ is a deep learning model for semantic image segmentation. Its main feature is that it uses a technology called "Atrous Convolution" to increase the sensitivity field. Traditional convolution operations only consider pixels in the neighborhood. In contrast, Atrous convolution expands the valid range of the kernel without increasing the number of parameters. This method allows the network to better understand the entire image, thus improving the segmentation accuracy.

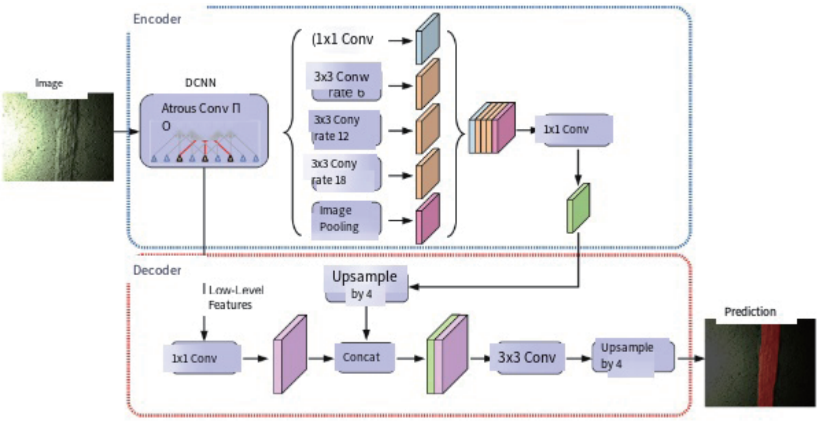


Figure 3 DeeplabV3+ model

The algorithm model of DeepLabv3+ is shown in Figure 3, which adopts the classic encoder (downsampling) -decoder (upsampling) structure design method. The blue box in the upper part of the figure is the encoder, in which the Dynamic Convolution Neural Network (DCNN) part is the backbone network of semantic segmentation, and the backbone network adopted is Xception. Xception has a certain number of parameters and computational overhead, which may be more suitable in the scenario where more powerful feature representation capability is required. Considering the operating platform and recognition efficiency, the backbone network is replaced by MobileNetv2, which is more suitable for resource-constrained environments such as mobile devices and embedded systems.

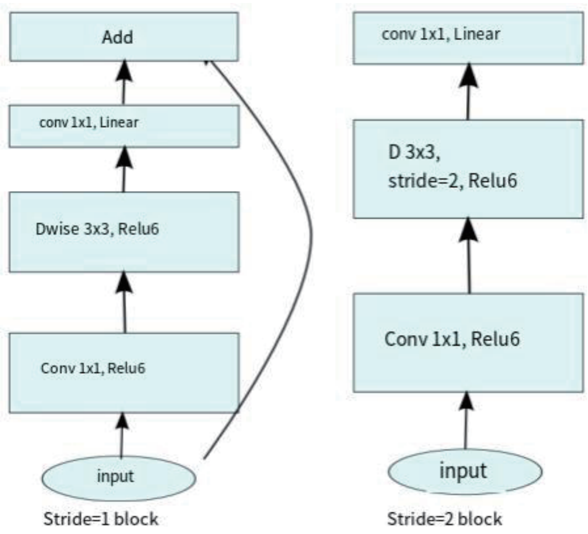


Figure 4 Architecture of blocks in MobileNetv2

MobileNetv2 is a lightweight convolutional neural network, which is composed of two types of blocks, which are divided into two types according to Stride. The structure is shown in Figure 4, aiming to realize efficient image recognition and semantic segmentation in the case of limited computational resources. It employs a range of lightweight design strategies, including depth-separable convolution, linear bottleneck, and reciprocal residual structures, to improve performance while maintaining low model complexity. Feature extraction is divided into two parts: high-level semantic extraction and low-level semantic extraction. Firstly, 1x1 convolution check channel is used for upper association, which plays a similar role to full join. Next, feature extraction is carried out by using three hollow convolution kernels. Hollow convolution can increase the receptive field without increasing the number of parameters, which helps to capture broader context information. Finally, the size of the feature maps is reduced by pooling operation, and the extracted feature maps are combined by concatenate operation. Then 1x1 convolution is used to change the number of channels to obtain high-level semantic information. For the bottom feature map output by the backbone network, 1x1 convolution is carried out to perform channel transformation, and then the above combined and channel transformed high-level feature information is up-sampled 4 times, so that its size is the same as that of the low-level feature map, and then combined again through concatenate operation. The combined result is finally 4x upsampled again to restore it to the input size to get the result.

3. Model training and experimental verification

The model in this paper runs on the Nvidia Jetson Xavier NX development board, and the system is Ubuntu18.04. In this paper, the semantic segmentation model is output to ONNX type and converted to engine type, which is deployed by TensorRT.

3.1 Model Training

In the process of training the model, it is necessary to define a loss function to quantify the difference between the output value and the true value of the semantic segmentation model. The model updates the weight parameters by backpropagation, so as to reduce the difference between the output value and the true value, which makes the model prediction more accurate, so as to achieve the purpose of learning. The binary cross entropy is used in the loss function in this paper, which can effectively avoid the gradient dissipation in the optimization process. The optimizer uses the adaptive moment estimation algorithm Adam (Adaptive Moment Estimation), which designs independent adaptive learning rates for the parameters in the model by calculating the first-order and second-order moment estimates of the gradients. The learning rate is an important hyperparameter in deep learning training, which controls the step size of the model during each parameter update. A large learning rate may lead to instability or even divergence in the optimization process, while a small learning rate may lead to slow convergence. In this paper, cosine annealing algorithm is adopted to dynamically update the learning rate of the optimizer.

The decline process of the loss function in the training process of the semantic segmentation model in this paper is shown in Figure 5. After 100 rounds of training in total, the value of the loss function decreases rapidly within 20 rounds, and the training has converged at about 80 rounds.

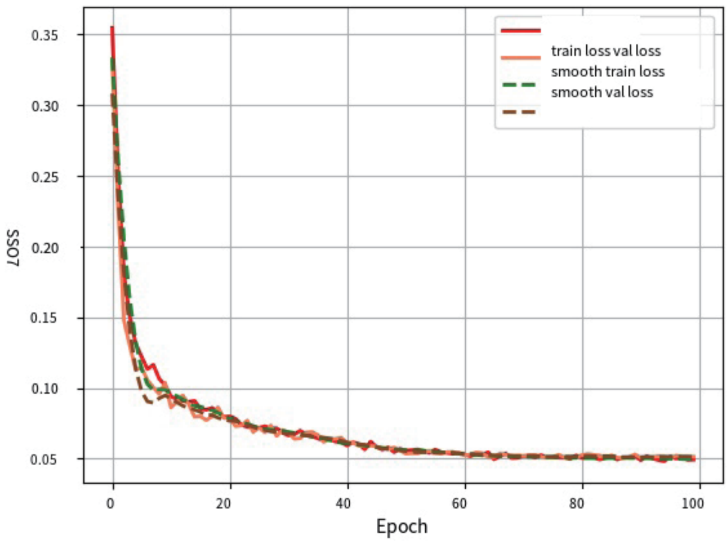


FIG. 5 Loss function curve of model training

During the training process, the images of the verification set will not be learned by the segmentation model. The images in the verification set are output and visualized, as shown in Figure 6, which intuitively shows that the model can identify most welds from the collected images after training.

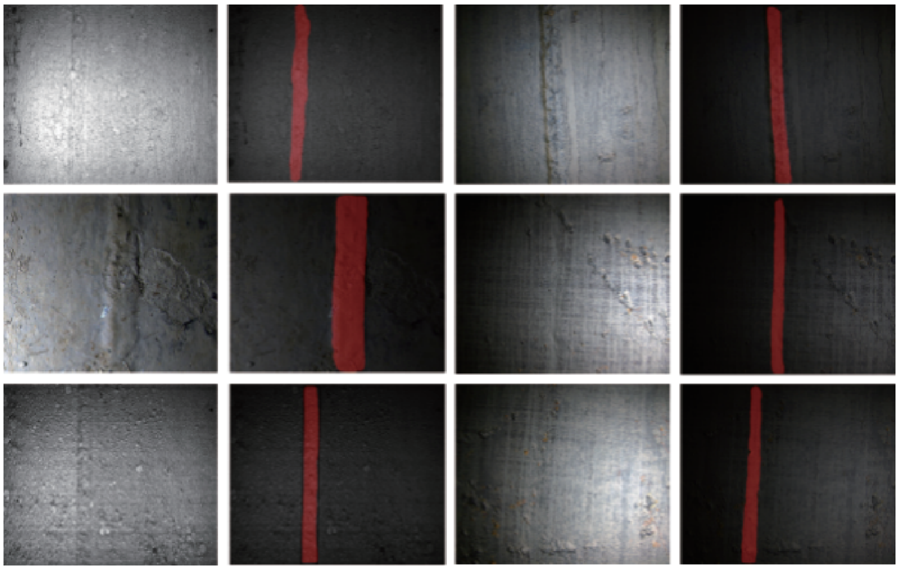


Fig.6 Verification set weld identification results

3.2 Weld identification test experiment

In this test, 5 segments of welds at different positions inside the same pressure steel pipe were selected for image acquisition and shooting, and the above trained model was used to identify welds. The recognition results are shown in FIG. 7 below.

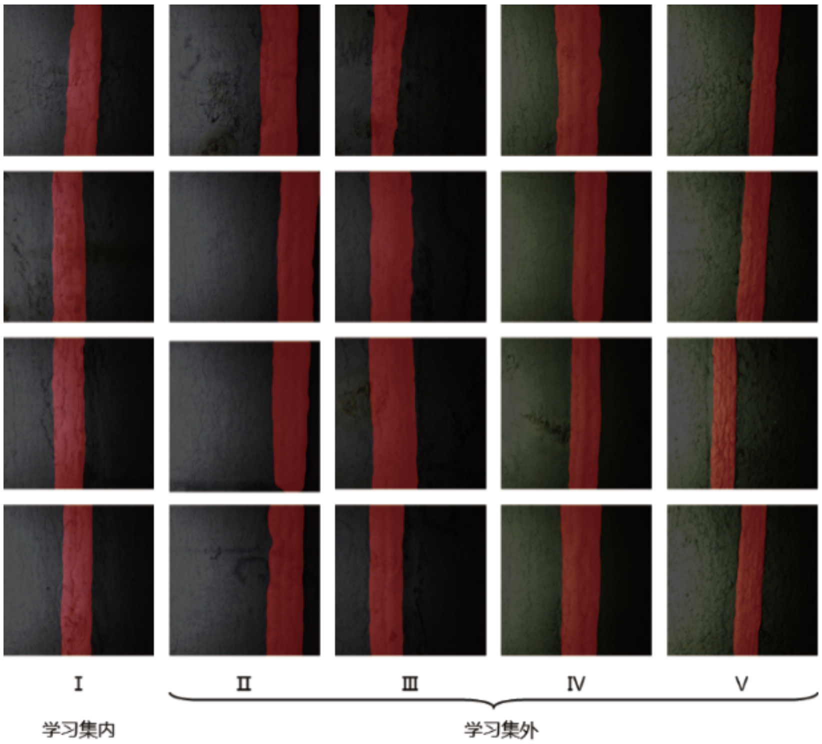


Figure 7 Test results of welding seam identification

In view of the wide variety of internal welds of pressure steel pipes, the semantic segmentation model is required to have a certain generalization ability, that is, it can maintain its good performance when processing new data, rather than can only segment the data that has been seen effectively. The welds I of this test are pictures of different positions of the welds in the learning concentration, and welds II ~ V do not appear in the learning concentration. From the recognition results of the image intuitively shows that the model has a certain generalization ability, in the face of new welds can still complete the identification task, after the paper will be a quantitative analysis of the accuracy of model recognition.

3.3 Evaluation index of recognition results

The statistic commonly used to evaluate the performance of semantic segmentation models is mean Intersection over Union (mIoU), which is the ratio of intersection and union between the model's predicted results and its true value for each category, summing and then averaging the result. The formula is shown as follows:

$$mIoU = \frac{1}{N}\sum_{i=1}^{N} IoU_i \qquad \text{(Formula 1)}$$

Where IoUi is the crossover ratio of Class i labels, which is calculated by the following formula:

$$IoU = \frac{TP}{TP+TN+FN} \qquad \text{(Formula 2)}$$

The parameters in the above formula are derived from the Confusion Matrix, where TP (True Positive) represents the correctly classified Positive sample, TN (True Negative) represents the correctly classified negative sample, FP (False Positive) represents the incorrectly classified positive sample, FN (False Negative) represents the incorrectly classified negative sample.

In view of the binary classification situation in this paper, there is a large gap in the number of pixels between the background and the weld in the image, so the intersection ratio data of the weld is also presented in Table 1 below as a quantitative reference for the model performance.

Table 1 Quantified results of welding seam identification test

Weld	IoU (weld)	mIoU
I	0.88	0.92
II	0.86	0.90
III	0.76	0.83
IV	0.87	0.91
V	0.84	0.90

The intersection ratio can be understood as the degree of coincidence between the predicted value and the true value, reflecting the accuracy of weld identification. The actual requirement is that the overlap of weld identification results should be at least 65%. The quantitative data of the segmentation model in this paper shows that after learning the recognition results of four welds outside the set, the average overlap ratio of the welds reaches 0.8325, that is, the overlap degree between the recognition results and the actual location of the welds in the image reaches more than 80%.

4. Epilogue

This paper presents a pressure steel pipe weld identification technology for a wall-climbing robot with large load oriented to the working environment of pressure steel pipe. The semantic segmentation model is constructed based on DeepLabv3+ framework, and the backbone network of the original framework is replaced by Xception with MobileNetv2, which reduces the number of parameters and computational complexity on the premise of ensuring the accuracy of recognition. From the performance of the model test and the quantitative value of the evaluation index, it can be concluded that the improved DeepLabv3+ model can overcome the influence of complex environmental noise inside the pressure steel pipe and effectively identify the weld.

References

[1] Lichao Cao,Xiaoguang Liu,Xiaoming Jiang, etal. Optimization Design of Crawler Wall-climbing Robot [J]. Automation and Information Engineering, 2019, 40(2):9-13.

[2] Simin Cheng,Weiyu Chen,Peijie Cong. Research Status of Wall-Climbing Robot [J]. Mechanical and Electrical Engineering Technology.2019,48(09):6-10.

[3] Jie Wang,Zhiheng Mai,Yuenong Fei. Research status and development trend of Welding Seam Inspection Robot [J]. Transducer & Microsystems, 2020, 39(02): 1-3+10.

[4] Huanwu Cong,Fujuan Guo,Fei Lv, etal. Research on weld identification technology based on CCD image processing [J]. Electronic Measurement Technology, 2012, 35(03): 73-7.

[5] Yufei Zhang,Yishun Zhang. Research on weld image recognition Algorithm based on OpenCV [J]. Welding Technology, 2020, 49(05): 12-4.

[6] Jiajie Yu,Jianping Zhou,Ruilei Xue, etal. Weld Surface quality detection based on structured light vision and illumination model [J]. Chinese Journal of Lasers: 1-15.

[7]LI X, LI X, KHYAM M O, et al. Robust Welding Seam Tracking and Recognition. IEEE Sensors Journal [J], 2017: 5609-5617.

[8]DONG S, SUN X, XIE S, et al. Automatic defect identification technology of digital image of pipeline weld [J]. Natural Gas Industry B, 2019, 6(4): 399-403.

[9] Shikuan Zhang,Qingxiao Wu,Zhiyuan Lin. Detection and segmentation of structured light fringe in weld image [J]. Chinese Journal of Optics,2021,41(05):88-96.

[10]Chen L C, Zhu Y, Papandreou G, et al. Encoder-decoder with atrous separable convolution for semantic image segmentation[C]//Proceedings of the European conference on computer vision (ECCV). 2018: 801-818.

Author Introduction: Zhu Junjie (1973-), male, born in Wuhan, Hubei Province, is a senior engineer with a research focus on the maintenance and repair of hydroelectric generator units in hydropower stations