Research on Manufacturing Technology of New Energy Vehicle Based on NDT

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Abstract. For the detection of laser welding defects of new energy vehicles, the traditional detection methods are inefficient and have limited accuracy. The existing visual detection methods mainly use area array cameras and image processing algorithms for detection. The image acquisition efficiency of the area array camera is low. The traditional image processing methods are vulnerable to the strong reflection on the surface of new energy vehicles, and the recognition speed and accuracy are limited. Therefore, in this paper, the linear array high-resolution camera is used for two-dimensional image acquisition, and the deep learning method is used for the recognition of weld defects. Based on the single-stage target detection network, the YOLO network is optimized according to the particularity of weld defects. The weld data set and defect data set are prepared, and the data set is used to train the optimized YOLO model. The feasibility of the method is verified by experiments, which can meet the mainstream weld length detection standards in the automotive industry.

1. Introduction
With the gradual improvement of people's living standards, cars have become the main means of household transportation. The automobile manufacturing industry has also developed vigorously. In the new era, with the deepening of people's understanding of automobiles, the continuous improvement of automobile quality requirements, and the continuous saturation of the automobile market, the fierce competition of automobile manufacturers is increasing. The requirements of automobile quality control are gradually improved and become the focus of automobile manufacturers [1]. New energy vehicle assembly is a very important link in the automobile manufacturing industry. The quality of new energy vehicle assembly has a great impact on the quality of automobile manufacturing. At the same time, the assembly of new energy vehicles is closely related to the appearance of automobiles, so the assembly quality control of new energy vehicles has become an important concern of the automobile industry [2].

The weld quality inspection methods in the manufacturing of new energy vehicles are mainly visual inspection and destructive inspection. Visual inspection is the simplest and most important means of manual inspection. It requires the staff responsible for the assembly of new energy vehicles to observe the welds when they are in the state of online assembly and welding. Destructive inspection will cut and destroy the test parts and then observe and test them, which will undoubtedly greatly increase the cost of testing. A new detection method is
needed to meet the online measurement requirements of the automotive industry, which achieves high precision, high efficiency, and easy cost control, and realizes the rapid measurement of laser welding defects of new energy vehicles [3]. This paper uses the deep learning method to identify weld defects. The neural network optimized based on YOLO is used for deep learning of the collected images to improve the recognition effect of small targets such as weld defects. Establish weld data set and weld defect data set. This method can automatically and quickly identify the laser welding seam of new energy vehicles, detect the laser welding defects, judge the proportion of the weld defect area in the weld, and realize the judgment of the laser welding quality of new energy vehicles. The accuracy of weld defect identification is higher and the error of length detection meets the requirement of the automobile industry. It avoids the omission and low efficiency of manual visual inspection, and at the same time realizes the rapid nondestructive inspection, avoiding the tedious inspection process of other inspection methods. Experimental results show that the proposed method based on line-array image deep learning can meet the requirements of the quality detection of laser welding of the car bodies.

2. Weld defect Detection based on optimized YOLO network

2.1. YOLO Test principle

YOLO is a single-stage detection algorithm for end-to-end detection. The biggest advantage of this algorithm is its fast speed, which greatly improves the speed of deep learning detection. Although the convolutional neural network has realized a more efficient sliding window technology. The amount of calculation for sliding windows of different sizes is still huge [4]. YOLO specifically realizes the sliding window technology, which directly divides the image into small grids and generates feature maps of the same size through convolution. Each element in the feature map corresponds to a small square of the original image, and the target of the center point in the small square is predicted by using the corresponding element [5].

After extracting the feature information of the image by using the convolution layer, YOLO uses the full connection layer to map the feature information in the sample space to obtain the predicted value. The network structure refers to the GoogleNet model, which contains 24 convolution layers and 2 fully connected layers, as shown in Figure 1.

![Figure 1 YOLO network structure](image)

In the convolution layer, the convolution kernel $5 \times 5$ is mainly used to reduce the number of channels, which is followed by the convolution kernel $2 \times 2$ [6].

The main process of YOLO target detection is to import the image. Scale it to the required size, divide the image into cells and boundary boxes composed of cells. Each cell is responsible for predicting the target with the center point in the cell and predicting a category C. Each cell predicts B boundary
boxes [7]. Each sub-region is directly sent into the convolutional network to directly output the prediction results of the boundary box. The predicted value tensor of the boundary box is shown in Figure 2.

![Figure 2 Predictive value tensor](image)

The prediction results of the boundary box include the coordinates of the boundary box \((x,y)\), the length \(h\) and width \(w\) of the boundary box, and the confidence of the boundary box. So the magnitude of the tensor predicted by the bounding box is \(s \times s (5B + C)\). The confidence degree of the boundary box contains two parts: one is the possibility \(\text{pr}(\text{object})\) of the target; the other is the accuracy of the boundary box. The accuracy of the boundary box can be expressed by the cross comparison between the prediction box and the actual box, which is expressed as: \(\text{Iou}_{\text{truth}}\) [8]. If \(p_{(\text{class}, \text{object})} \times \text{Iou}_{\text{truth}}\) is used to represent the probability that the target in the boundary box belongs to a certain category, then the category confidence degree of each boundary box is \(p_{(\text{class}, \text{object})} \times \text{Iou}_{\text{truth}}\), and the boundary box can be selected by setting the confidence threshold according to this confidence degree.

YOLO filters the bounding box through the non-maximum suppression algorithm: that is, after finding the bounding box with the highest confidence, if the intersection and union ratio between it and some other bounding boxes is too large which means the coincidence degree of the two bounding boxes are too high, the bounding box will be eliminated [9].

### 2.2. Optimization of YOLO model for weld inspection

At present, YOLO network mainly extracts semantic information from high-level feature maps. Since there is little target location information in high-level feature maps, if low-level feature map information is ignored, the location information will be inaccurate. The accuracy of small target detection can be improved by keeping the features of the small target in the low-level feature map and fusing multi-scale features for detection. Taking the feature map size of 416*416 as an example, the multi-scale feature layer fusion is shown in Figure 3:

![Figure 3 Diagram of multi-scale fusion](image)
Two prediction scales were established by fusing 52×52 and 26×26 feature layers. The specific fusion method is to change the number of channels of the high-level feature image through 1×1 convolution kernel to make it equal to the number of channels of the low-level feature image. After up-sampling, local feature fusion between the feature images of different scales is carried out. Finally, the aliasing effect is eliminated through the convolution kernel. The final output is that the characteristic diagram is a tensor with a depth of 75.

3. Laser welding training for new energy vehicles

Sigmoid is the most classic activation function:

\[ S(x) = \frac{1}{1 + e^{-x}} \]  

(1)

Its value range is [0,1], and the shape of the function is S-shaped. Its derivatives are easy to calculate and are non-zero. But it has the following problems. When the neuron is trained with the back propagation algorithm, the gradient disappears, and the output of the neuron is close to 1 or 0. Thus, it cannot continue training in the deep network. The output of the function is not symmetric about the origin center. The calculation of the Sigmoid function on the index is a very time-consuming, resulting in very slow convergence speed of training. Therefore, the Leaky-ReLU function is used as the training activation function during training:

\[ f(x) = \begin{cases} 
  x & x > 0 \\
  ax & x \leq 0 
\end{cases} \]  

(2)

It not only achieves high training efficiency without saturation problems at the time \( x > 0 \), which means it can train directly without pre-training and avoid the situation that the input falls into the hard saturation zone during training, leading to the failure to update the neuron parameters.

4. Inspection and validation experiment of laser welding defects on the car body

4.1. Training experiment scheme

The training platform was set up on the computer, which adopted Linux version Ubuntu16.04 and GPU 12GBGTXTitanX. The acquisition method described in the previous section is used to collect images of objects under test by the industrial camera and make labels. A total of 600 images are obtained from the training data set. Input the pre-training weights into the model and adjust the parameters for data set training. Parameter setting: the number of training categories is 3; the number of pictures in each iteration is 32; the number of iterations is 50200; the initial learning rate is 0.001; the momentum is 0.9, and the threshold is 0.75.

4.2. Experiment data

The line array camera measurement system and the target detection network based on YOLO optimization are used for weld quality detection, and the detection process is shown in Figure 4:
4.3. Data calculation and evaluation

The detection method proposed in this paper is evaluated according to the following three criteria: weld recognition rate, weld defect-recognition rate, and detection length error. Three workpieces with 13 welds were measured by the proposed method. The number of welds and defects can be obtained by the number of boundary boxes in the initial drawing and the number of orange boundary boxes in the trimmed drawing. The distance from the left edge of the left green boundary box to the right edge of the right green boundary box is taken as the length of the weld, and the length of the orange boundary box is taken as the length of the defect. Determine the total number of pixels between the edges of a bounding box, which is calculated by the actual length of each pixel.

The number of welds and defects is obtained by visual measurement of these workpieces, and the length of welds and the total length of defects is obtained by manual measurement with a ruler, which is taken as the actual length. During the measurement, the distance between the midpoints of the edge is taken as the length of the weld. The distance between the midpoints of the defect edge is taken as the length of the weld defect. The precision of the scale is 0.02mm. The measurement results are shown in Table 1. The unit of length in the data is mm.

| Number | Check weld length | Actual weld length | Total length of detected defects | Total actual defect length | Weld length detection error |
|--------|-------------------|--------------------|----------------------------------|---------------------------|-----------------------------|
| 1      | 53.42             | 53.78              | 6.83                             | 6.80                      | 0.25                        |
| 2      | 53.74             | 53.54              | 12.40                            | 12.28                     | 0.20                        |
| 3      | 53.96             | 53.78              | 22.46                            | 22.42                     | 0.18                        |
| 4      | 53.33             | 53.08              | 10.67                            | 10.56                     | 0.25                        |
| 5      | 52.72             | 52.46              | 38.66                            | 40.12                     | 0.26                        |
| 6      | 53.74             | 53.30              | 6.40                             | 6.36                      | 0.44                        |
| 7      | 53.47             | 53.22              | 7.54                             | 7.48                      | 0.25                        |
| 8      | 54.03             | 40.46              | 41.52                            | 12.55                     | 0.22                        |
| 9      | 52.68             | 52.54              | 16.18                            | 15.88                     | 0.14                        |
| 10     | 53.45             | 53.18              | 6.53                             | 6.34                      | 0.27                        |
| 11     | 54.91             | 54.78              | 5.48                             | 5.49                      | 0.13                        |
It can be seen from Table 1 that all 13 welds were identified successfully. There were 44 defects in all the 13 welds, among which 42 were detected and 2 were not. The detection errors of weld length are all within 0.5mm, which meets the requirements of ±1mm standard for weld length detection in the mainstream in automobile industry. The detection of the total length of weld defects is accurate. The error mainly comes from the failure to identify the defects in the weld. The total length error of weld defects correctly identified is within 0.2mm. It is concluded that with the help of the line array scanning image acquisition system, this method can accurately identify the weld and has a high recognition rate for weld defects, which can meet the requirements of weld detection for the total length of defects and has a high detection accuracy for the length.

5. Conclusion
In this paper, the k-means clustering method was used to advance the accuracy of small target detection. Laser weld data set was made for the training of a deep learning model so as to realize the recognition of weld in workpiece image and the recognition of weld defect in the cutout weld image. Finally, the deep learning model is trained, and various operations in the training are carried out. Experiments verify the feasibility of the proposed method, and it is concluded that the proposed method meets the requirements of online detection of weld defects.
In this paper, the weld defect detection target is small. Because the single-stage target detection network adopts the direct regression method, the detection effect of the small target is limited, and only the feature map of a high level is extracted. However, the low-level feature map contains rich location information, which is complementary to the information of the high-level feature map.

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