Online porosity defect detection based on convolutional neural network for Al alloy laser welding

Deyuan Ma¹, LeShi Shu*, Qi Zhou¹, Shenjie Cao¹ and Ping Jiang¹

¹ The State Key Laboratory of Digital Manufacturing Equipment and Technology, School of Mechanical Science and Engineering, Huazhong University of Science and Technology, Wuhan, Hubei, 430074, China

*Corresponding author’s e-mail: leshishu@hust.edu.cn

Abstract. Porosity is one of the most serious defects in Al alloy laser welding. The online detection of the porosity can identify the weak position of weld seam and take remedial measures accordingly. In this paper, a convolutional neural network (CNN) model where the input is the signal spectrum graphs extracted by wavelet packet decomposition (WPD) is constructed to identify the porosity during Al alloy laser welding in real-time. The porosity monitoring platform is set up to obtain the keyhole opening area signal and the keyhole depth signal in the welding process. The sliding window scanning algorithm is used to scan the signals and the weld seam, and the time-frequency spectrum graphs are obtained by WPD processing on the signals in each sliding window. Through analysis, when there is porosity in a small weld seam section of the current sliding window, the signal spectrum graphs are messy at this moment, while when there is no porosity, the signal spectrum graphs are clean and the frequency bands are concentrated in low-frequency part. The CNN model is constructed to classify the signal spectrum graphs under different porosity status, thereby it can identify the porosity in the weld seam.

1. Introduction

Al alloy has been widely used in aerospace, automobile manufacturing and other fields because of its light weight, high strength, and good corrosion resistance. Laser welding is an ideal welding method for connecting Al alloy due to its small thermal deformation and large weld depth-width ratio. However, porosity defects often appear in Al alloy laser welding process, which adversely affect the mechanical properties of the weld seam [1].

For porosity defects, the current studies mostly use X-ray and other radioactive detection methods or post-welding destructive test methods to detect them. Huang et al [2] used X-ray to detect and diagnose porosity in 5A06 Al alloy TIG welding based on the machine learning method. Yu et al [3] realized the identification and online monitoring of hydrogen porosity in Al-Mg alloy GTAW process based on the arc spectrum information. Harooni et al [4] detected the porosity in zero-gap lap laser welding of AZ31B Mg alloy through the destructive experiment after welding. Gaja et al [5-6] detected internal porosity and cracks by observing abrupt changes in acoustic emission signals. With the help of X-ray technology, Zhang et al [7] used data processing methods to diagnose different degrees of hydrogen porosity.

However, the use of radioactive rays is expensive and susceptible to environmental interference, and the post-welding destructive experiments will render the workpiece unusable. With consideration of these issues, a porosity detection method based on WPD processing and CNN modeling is proposed in our research. The WPD spectrum graphs of each small segment of keyhole geometrical morphological characteristic signals are identified and classified by CNN, and the porosity generated during Al alloy
laser welding can be detected online.

2. Experiment setup

The experiment system is shown in Figure 1 (a). In this experiment, a fiber laser IPG YLS-30000 with a maximum power of 30 kW is used, and the wavelength of laser beam is 1070 nm. The workpiece is 7075 aluminum alloy plate (200 mm × 100 mm × 8 mm) with the mass fraction is 0.4% Si, 0.2% Ti, 5.1-6.1% Zn, 0.18-0.28% Cr, 2.1-2.9% Mg, 0.3% Mn, 1.2-2.0% Cu, 0.5% Fe, and the rest is Al. The surface of the workpiece is polished to remove the oxide film before welding and cleaned with acetone. The laser welding process parameters used in this experiment are shown in Table 1. Laser deflection angle refers to the angle between laser beam and workpiece surface, the negative value represents that the laser beam inclines to the welding direction. The shielding gas was Ar with a flow rate of 20L/min.

The keyhole opening images in the welding process are acquired by using the paraxial high-speed camera, and the keyhole opening area is extracted by image processing. The keyhole depth signal is acquired by coherent light imaging technology, as shown in Figure 1 (b).

![Figure 1. (a) The experimental system. (b) Schematic representations of using coherent light imaging technology to measured keyhole depth.](image)

| Laser Power | Welding Speed | Defocusing amount | Laser deflection angle |
|-------------|---------------|-------------------|------------------------|
| 6000 W      | 4 m/min       | 0 mm              | -10°                   |

3. Proposed method

3.1. Data acquisition and processing

The keyhole opening images are acquired by the high-speed camera in the welding process. Image processing is performed on the keyhole opening images, and the processing procedures are shown in Figure 2. The number of pixels in the region of keyhole is calculated as keyhole opening area. A total of 6000 images are obtained and batch processed during the whole welding process, and the keyhole area signal is extracted. The keyhole depth signal is collected synchronously by the coherent light imaging module, and the number of data points obtained is also 6000. The final acquired keyhole geometrical morphological characteristic signals is shown in Figure 3. It can be seen that the keyhole opening area changes irregularly, while the keyhole depth changes periodically during the welding process.
Figure 2. The processing procedures of the keyhole opening image.

Figure 3. Keyhole geometrical morphological characteristic signals and the WPD results of sliding window scan.

WPD is an advanced time-frequency analysis method, which can obtain the signal spectrum graphs containing both time domain information and frequency domain information. In addition, WPD can decompose the high-frequency part and low-frequency part of the signal simultaneously [8], so as to evaluate the stability of signal fluctuation. In order to quantify the degree of keyhole fluctuation at each moment in the welding process, the sliding window scanning algorithm is used to scan the keyhole geometrical morphological characteristic signals, and the 4-layer WPD processing is performed on the data in each window to get the time-frequency spectrum graphs, as shown in Figure 3. It is worth noting that if the size of the sliding window is too large, the resulting spectrum graphs will be too few to train a reliable CNN model, and meanwhile, the risk of averaging different porosity status before and after the sliding window will be increased. However, if the size of the sliding window is too small, it may lead to the failure of the window to completely cover some large porosity. After many experiments and tests, the size and step-length of the sliding window are finally set to 20. It means that the sliding window contains 20 data, and each time slides forward 20 data. The keyhole opening area signal and the keyhole depth signal are scanned into 300 spectrum graphs respectively. In order to increase the amount of data and improve the prediction accuracy of the subsequent CNN model, the image flipping method is used to increase the number of the spectrum graphs, and finally 1200 spectrum graphs are obtained.
The sliding window scanning algorithm is also used to scan the longitudinal section of the weld seam. In order to make each segment signal and each segment weld seam corresponding in the time domain, the weld seam is also divided into 300 sections. As shown in Table 2, it is found through analysis that when porosity appears in a certain section of the weld seam, the time-frequency spectrum graph of the signal segment corresponding to this weld seam section are relatively messy. Deep color bands appear simultaneously in the low-frequency bands at the bottom and the high-frequency bands at the middle and upper parts of the spectrum graph, which indicates that the fluctuation of keyhole is violent, and the welding process is unstable. When there is no porosity in a certain section of the weld seam, only the low-frequency bands at the bottom of the spectrum graph appear dark, indicating that the keyhole is within the normal fluctuation frequency range. This shows that the formation of porosity is closely related to the violent unstable fluctuation of the keyhole [9-11].

Table 2. Porosity status and corresponding the signal spectrum graph.

| Porosity status | Spectrum graph of keyhole area signal | Spectrum graph of keyhole depth signal | Weld seam section |
|-----------------|--------------------------------------|---------------------------------------|-------------------|
| Porosity        | ![Graph](image1.png)                  | ![Graph](image2.png)                  | ![Graph](image3.png) |
| No porosity     | ![Graph](image4.png)                  | ![Graph](image5.png)                  | ![Graph](image6.png) |

3.2. Construction of CNN model

CNN is currently one of the most widely used deep learning algorithms [12], its powerful image processing capability can automatically extract the features of the input images and complete classification. The convolution kernel inside the CNN performs a convolution operation on each region of the image to extract the depth features of the image. The pooling operation reduces the size of the image features after the convolution operation, thereby reducing the amount of calculation. Finally, the task of image classification is completed by fully connected layers and softmax layers. In this paper, a CNN model is constructed to classify the signal spectrum graphs under different porosity status. After the model training is completed, the real-time detection of the porosity defects in Al alloy laser welding can be realized. The architecture of the CNN model is shown in Figure 4, including six convolution layers, six pooling layers, two fully connected layers and a softmax layer, and a dropout layer is added to each of the first two convolution layers to prevent overfitting. 1000 spectrum graphs from the data set are randomly selected for training, and the remaining 200 spectrum graphs for verification.

Figure 4. The architecture of CNN model.
4. Results and discussion
The variation of accuracy and error in the training process of CNN model are shown in Figure 5. The number of iterations is 1500, divided into 6 epochs, with 250 iterations in each epoch.

![Figure 5. The training process of CNN model.](image)

The trained CNN model is used to predict the 200 spectrum graphs in the test set and compared with the actual porosity status. The confusion matrix of the prediction results is shown in Figure 6. It can be seen that the constructed CNN model has an average classification accuracy of 90.5% for the WPD spectrum graphs of the signals, which can meet the accuracy requirements in the actual production process. Therefore, the proposed method can realize the identification and detection of porosity defects in Al alloy laser welding process.

In order to improve the detection accuracy of porosity, it is necessary to obtain more signals under more experiments of process parameters, so as to obtain more data to train the CNN model. In the future, we will verify the accuracy, robustness and generalization ability of the proposed method based on more experimental results, and finally the sporadic porosity during Al alloy laser welding can be identified in the optimal process window with the least porosity.

![Figure 6. The confusion matrix of CNN model’s prediction results.](image)

5. Conclusions
In this paper, a porosity defect detection method based on WPD processing and CNN modeling is proposed for Al alloy laser welding. The sliding window is used to scan the keyhole geometrical morphological characteristic signals, combining with WPD to quantify the fluctuation degree of the keyhole during the welding process. Thus, the time-frequency spectrum graphs of each small segment of the signals are obtained. Through analysis, it is found that the fluctuation of the keyhole is violent when the spectrum graph is messy, and there is porosity in the weld seam of the corresponding section. The keyhole is stable when the spectrum graph is clean, and there is no porosity in the weld seam of the
corresponding section. A six-layer CNN model is constructed to classify the spectrum graphs of each segment of the signals, and the prediction accuracy reached more than 90%, indicating that the proposed method can realize the detection of porosity defects in Al alloy laser welding process.

Acknowledgement
This research has been supported by National Natural Science Foundation of China (NSFC) under Grant No. 51861165202 and No. 51721092, and the Fundamental Research Funds for the Central Universities, HUST: 2020JYCXJJ039.

References
[1] Lin R, Wang H-P, Lu F, Solomon J, Carlson BE. (2010) Numerical study of keyhole dynamics and keyhole-induced porosity formation in remote laser welding of Al alloys. International Journal of Heat and Mass Transfer, 108: 244-256.
[2] Huang Y, Wu D, Zhang Z, Chen H, Chen S. (2017) EMD-based pulsed TIG welding process porosity defect detection and defect diagnosis using GA-SVM. Journal of Materials Processing Technology, 239: 92-102.
[3] Yu H, Xu Y, Song J, Pu J, Zhao X, Yao G. (2015) On-line monitor of hydrogen porosity based on arc spectral information in Al–Mg alloy pulsed gas tungsten arc welding. Optics & Laser Technology, 70: 30-8.
[4] Harooni M, Carlson B, Kovacevic R. (2014) Detection of defects in laser welding of AZ31B magnesium alloy in zero-gap lap joint configuration by a real-time spectroscopic analysis. Optics and Lasers in Engineering, 56: 54-66.
[5] Gaja H, Liou F. (2016) Defects monitoring of laser metal deposition using acoustic emission sensor. The International Journal of Advanced Manufacturing Technology, 90(1-4): 561-74.
[6] Gaja H, Liou F. (2017) Defect classification of laser metal deposition using logistic regression and artificial neural networks for pattern recognition. The International Journal of Advanced Manufacturing Technology, 94(1-4): 315-26.
[7] Zhang Z, Zhang L, Wen G. (2019) Study of inner porosity detection for Al-Mg alloy in arc welding through on-line optical spectroscopy: Correlation and feature reduction. Journal of Manufacturing Processes, 39: 79-92.
[8] Huang Y, Li S, Li J, Chen H, Yang L, Chen S. (2019) Spectral diagnosis and defects prediction based on ELM during the GTAW of Al alloys. Measurement, 136: 405-14.
[9] Luo M, Shin YC. (2015) Estimation of keyhole geometry and prediction of welding defects during laser welding based on a vision system and a radial basis function neural network. The International Journal of Advanced Manufacturing Technology, 81(1-4): 263-76.
[10] Pang S, Chen L, Zhou J, Yin Y, Chen T. (2011) A three-dimensional sharp interface model for self-consistent keyhole and weld pool dynamics in deep penetration laser welding. Journal of Physics D: Applied Physics, 44(2): 025301.
[11] Xu J, Rong Y, Huang Y, Wang P, Wang C. (2018) Keyhole-induced porosity formation during laser welding. Journal of Materials Processing Technology, 252: 720-7.
[12] Zhang Z, Li B, Zhang W, Lu R, Wada S, Zhang Y. (2020) Real-time penetration state monitoring using convolutional neural network for laser welding of tailor rolled blanks. Journal of Manufacturing Systems, 54: 348-60.