Applications of Molten Pool Visual Sensing and Machine Learning in Welding Quality Monitoring

Meiling Sun¹,², Mingxuan Yang¹,², Binrui Wang¹,², Lijuan Qian¹,² and Yuxiang Hong¹,²*

¹College of Mechanical and Electrical Engineering, China Jiliang University, Hangzhou 310018, China
²Key Laboratory of Intelligent Manufacturing Quality Big Data Tracing and Analysis of Zhejiang Province, China Jiliang University, Hangzhou 310018, China
Email: hongyuxiang@cjlu.edu.cn

Abstract. On-line monitoring of welding quality is very important to the realization of intelligent welding technology and has become a research hotspot in the field of welding technology. This article reviews the research results and latest research progress of welding quality on-line monitoring based on molten pool visual sensing in recent years. First, it introduces the characterization of welding quality by the two-dimensional geometric features and three-dimensional topographic features of the molten pool in detail, and then analyzes the application of machine learning and feature engineering in the online prediction of welding status; we discuss the deep neural network and welding quality at the end. The work done in this paper reviews the progress of online monitoring technology for welding quality and provides a basis for the follow-up work.

Keywords: Weld pool vision sensing; Welding quality; Intelligent machine learning; Deep neural network; Online inspection.

1. Introduction

With the development of modern science and technology, the industrial level has also improved. Welding has become an important processing technology. The interdisciplinarity of welding technology, optoelectronic technology and control science provides the foundation for welding automation. Welding components are also widely used in various fields such as aerospace [1], bridge construction [2], automobile manufacturing [3], and industrial production [4]. Real-time tracking of welds is a prerequisite for realizing welding production automation and guaranteeing welding quality [5]. In the traditional welding seam surface inspection technology, the subjective judgment of the inspector will have a great impact on the accuracy of the inspection results, which is difficult to meet the requirements of modern production. The subjective judgment of the tester will have a great impact on the accuracy of the test results, and it is difficult to meet the needs of modern production. With the research and development of technology, the online welding quality inspection technology based on molten pool vision and machine learning has become more and more widely used in various fields, and the research that combines deep neural networks with welding quality monitoring has also become a trend.
2. Visual Characterization of Welding Quality by Dynamic Molten Pool

2.1. The Two-dimensional Geometric Features of the Molten Pool and the Welding State Stability

According to previous studies, geometric characteristic parameters such as the length and width of the molten pool, the penetration depth, and the area of the molten pool can effectively reflect the stability of the welding process.

Researchers from various countries have made a lot of attempts to measure the geometric parameters of the molten pool. Zhang et al. [6] used point-like laser delivery technology to model the obtained data and established a three-dimensional angle-based real-time variable molten pool model. Based on this model, the molten pool can be accurately calculated. Hong et al. [7] have studied the relationship between the dynamic changes of the molten pool characteristic parameters and the edge weld lack of penetration. The experimental results show that the lack of penetration will seriously affect the sudden change of the center of mass of the weld pool along the weld length. Liu et al. [8] used image processing to extract the welding process characteristics, and then used the support vector machine model to train the test data. The experimental results show that the model can accurately determine the three types of weld state, weld width and weld depth and improve the stability of the welding process. Wu et al. [9] proposed a new vision sensor system for measuring the width, length, area and other characteristic parameters of the keyhole. From the analysis of the dynamic experimental data (as shown in figure 1), the width of the back beam and the keyhole were obtained. And then the use of extreme machine learning methods to predict the width of the weld, providing accurate feedback information.

![Figure 1. Measured data in dynamic welding experiments. (a) Measured data for keyhole characteristic and backside bead width. (b) Inputted welding parameters.](image)

During the laser welding process, the laser beam interacts with the welding material. When the temperature rises to a certain level, the molten metal begins to evaporate at the position of the laser beam, and a small hole is created in the center of the molten pool. Most of the laser beam is trapped in the small hole. Other reflects back laser light head. At the same time, the small hole generates a large amount of laser-induced plume and plasma. As the welding progresses, the keyhole continues to deepen. When the surface tension of the welding metal and the pressure of the molten pool are balanced with the evaporating momentum in the keyhole, the keyhole is in a dynamic equilibrium state, and this state will continue throughout the welding process. As shown in figure 2.

Through the parameter analysis of the balanced state of the weld pool keyhole, the stability of the welding state can be judged. Based on this direction, You et al. [10] established the data driving model and combined it with the feedforward neural network prediction model and the support vector machine classification model, to ensure the accurate estimation of the welding state and the effective identification of welding defects. At the same time, You et al. [11] use the RGB components to segment the UV/V images of plumes and splashes. According to the mechanism of metal plume generation, the laser-induced metal plume is connected to the small hole (laser focus position). By
calibrating two cameras and calculating the number of pixels covered by the metal vapor and small holes, the size of the metal vapor and small holes can be determined. Wang et al. [12] proposed a new classification method for the dynamic characteristics of metal plumes. Based on the accuracy and correlation coefficients, they selected the plume area, plume centroid horizontal coordinates, and the number of splash points from the extracted features. This model helps predict the welding quality during the welding process and improves the stability of the welding state.

![Figure 2. Schematic diagram of the keyhole.](image)

2.2. Three-dimensional Morphology of Molten Pool and Welding Penetration State

It is known that the penetration state of the weldment has a great influence on its welding quality. According to previous studies, the geometric information of the surface of the three-dimensional molten pool can be used as the basis for judging the penetration state. Researchers have done a lot of research on this. In GTAW welding, Chen et al. [13] used the characteristics of different penetration states to propose a back-propagation artificial neural network (BPANN) prediction model for the recognition of penetration states, which can accurately and timely adjust the welding current. Chen et al. [14] linked the height of the molten pool surface to the counter electrode image (REI) of the molten pool surface, and used a robust image processing algorithm to determine the location of the REI. Then by assuming a spherical surface of the bath, the bath surface is established to calculate DERI reflection model, the geometry of the bath and the arc length based on height index. The experimental results show that the method is used for welding process monitoring. Zhang et al. [15] adopted an innovative method when observing the evolution of the penetration state and the changes in the surface morphology of the molten pool during GTAW welding. The laser dot matrix sensor was used to observe the oscillation of the molten pool in three dimensions, and three corresponding oscillation modes under the penetration state were found.

Li at al. [16] extracted the oscillation frequency of the molten pool and the fluctuation amplitude of the center of mass based on the robust algorithm of the reflected laser image centroid. This will facilitate real-time monitoring and control of the penetration state. Zhang et al. [17] aimed at the defect detection of aluminum alloy GTAW welding, based on the study of the generation mechanism of arc sound, using Fisher distance and principal component analysis two feature selection methods to screen the frequency components related to welding quality defects, and established an SVM-GSCV model to identify partial penetration, normal penetration and over penetration states. The final result verifies that the method has high accuracy and robustness. Zhang et al. [18] used a Biprism Stereo vision system to detect and stereo match the surface features of the molten pool, and obtained triangular meshes and point clouds in three states of partial penetration, full penetration and over penetration of the molten pool. And the effectiveness of this method has been further proved in experiments.

3. Online Prediction of Welding Status Based on Feature Engineering and Machine Learning

The vision inspection of the molten pool in the welding process has the advantages of not directly contacting the weld, strong reliability, and large amount of information available. It can directly take
in the image of the molten pool area to reflect the dynamic behavior of the molten metal during the welding process. Gao et al. [19] proposed a multi-sensor fusion system based on support vector machine technology, and transformed the characteristic signals obtained from the sensors into time domain and frequency domain as the characteristic vector of SVM classification. Experimental results show that the integrated sensor can effectively detect welding quality defects. Wang and others On the basis of the passive vision method, three types of visual detection and acquisition experiments of near-infrared light, metal characteristic spectrum and visible light are designed. According to the positive correlation between x and the image quality of the molten pool, the best molten pool is obtained by comparing the band of near-infrared light. The image window [20], and then processed by a 1064nm narrow-band filter, can effectively suppress arc interference [21]. Liang et al. [22] adopted infrared penetration filter based on the spectral distribution of GMAW arc light in the range of 200～1100nm for low carbon steel at a current of 100A and used the characteristics of high radiation energy of near-infrared light melting pool and low arc radiation energy. The light sheet effectively solves the problem of the image sharpness drop of the molten pool caused by the insufficient photosensitive intensity of the camera. This technology has important guiding significance for the feature extraction of molten pool information and the intelligent control of the welding process.

4. Welding Defect Diagnosis Based on Deep Learning

Deep learning has developed rapidly in recent years. Using deep learning models to predict welding quality has become a hot issue in the welding field. Researchers at home and abroad have done a lot of research on different deep learning models. Zhang et al. [23] used a multi-vision sensor system to capture the high-power disc laser welding process, and used the wavelet packet decomposition method to decompose the captured signal, and then extracted it through a series of processing. The characteristics of spatter and keyhole in the molten pool in the laser welding process, and based on this optimization by genetic algorithm, a deep confidence network is established to detect the real-time welding status of welding, with high accuracy and robustness. As shown in figure 3.

![Figure 3. The structure of DBN](image)

Feng et al. [24] proposed the concept of deep welding. That is, the application of deep learning technology to change the monitoring and penetration detection technology of the GTAW welding process. As shown in figure 4. In this new framework, they use a generative adversarial network to denoise images, and then use classic convolutional neural networks for image selection, and propose two integration methods combining multiple neural networks to improve the data acquired in different devices Model performance. Yang et al. [25] proposed an automatic detection and recognition method for welded joints based on the Deep Convolutional Neural Network (DCNN) model for the quality defects of welded joints. In this method, two DCNN network models are proposed, which are used for data enhancement and target detection respectively. This model avoids
the manual features of traditional machine learning methods, and also meets the speed and accuracy required by modern industrial environments. Since unknown disturbances in the welding process will adversely affect the uniformity of penetration, it is necessary to introduce penetration feedback control in welding, but the feedback control lags due to influencing factors such as mirror reflection, heat radiation and arc. In order to solve this problem, Peng et al. [26] proposed a visual acquisition method of weld pool width after GTAW welding to achieve closed-loop control of weld penetration. In specific experiments, the researchers changed the geometry of the weldment to interfere, and finally the molten pool could still maintain a stable penetration state.

![Figure 4. Framework overview of DeepWelding.](image)

![Figure 5. Architecture of Resnet.](image)

At the same time, small key hole TIG welding has great advantages in energy density, welding effect and penetration ability. In order to improve the welding quality and automation level of small key hole TIG welding, Xia et al. [27] developed an advanced convolutional neural network (the architecture of Resnet is shown in figure 5) to identify different welding states, and introduced a metric learning strategy for center loss to optimize the training process. It laid a solid foundation for the development of the small key hole TIG welding online inspection system. Zza et al. [28] proposed a coaxial visual laser welding penetration status diagnosis system and used the optimal network. The lattice structure and hyperparameters have optimized the convolutional neural network. And tested on the efficient computing platform TX2. The experimental results show that the accuracy and recall of this method are higher than other methods.

In the actual welding process, the recognition of weld penetration has always been a long-standing problem due to the space limitation of the sensor on the back of the weld. Jiao et al. [29] designed an end-to-end convolutional neural network on this point, which automatically defines...
and extracts features. A transfer learning method based on a residual neural network is proposed to improve the accuracy and speed of training. And verified its effectiveness through experiments.

5. Conclusion
The intelligent machine learning method of welding process molten pool visual feature extraction technology will become an important development direction of welding process monitoring technology in the future, and it will also be more in line with the needs of my country's economic development and national conditions. At present, the online inspection of welding quality has been actively researched and developed at home and abroad, but due to the complexity and variability of the welding process, this technology still needs further research. Although there are many deep learning algorithms, how to realize information sharing and fusion judgment among multiple neural networks while reducing the complexity of the algorithm has not yet been solved well. This will also become an important research direction.

Acknowledgement
This project was supported by National Natural Science Foundation of China (51605251), Zhejiang Province College Student Science and Technology Innovation Program Foundation (Xinniao Program Foundation for the Talents) (2020R409017), Key Program of Students Scientific Research Foundation of China Jiliang University (2020X23045), Opening Fund of Experiment Program of China Jiliang University (XL2020009).

References
[1] Zhang Z, Zhang L and Wen G, et al. 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.
[2] Wang Y, Zang A, Mahmoodkhani Y, et al. 2021 The Effect of Bridge Geometry on Microstructure and Texture Evolution During Porthole Die Extrusion of an Al-Mg-Si-Mn-Cr Alloy Metallurgical and Materials Transactions A-Physical Metallurgy and Materials Science 52: 3503-3516.
[3] Gao X, Li Z, Wang L, et al. 2019 Detection of weld imperfection in high-power disk laser welding based on association analysis of multi-sensing features Optics and Laser Technology 115: 306-315.
[4] Sun J, Li C, Wu X, et al. 2019 An effective method of weld defect detection and classification based on machine vision IEEE Transactions on Industrial Informatics 15: 6322-6333.
[5] Xiao R, Xu Y, Hou Z, et al. 2019 An adaptive feature extraction algorithm for multiple typical seam tracking based on vision sensor in robotic arc welding Sensors and Actuators A: Physical 297: 111533.
[6] Zhang W, Liu Y and Zhang Y, et al. 2013 Real-time measurement of the weld pool surface in GTAW process Trends in Welding Research 2012: Proceedings of the 9th International Conference (ASM International) 7: 1640-1645.
[7] Hong Y, Chang B, Peng G, et al. 2018 In-process monitoring of lack of fusion in ultra-thin sheets edge welding using machine vision Sensors 18: 2411.
[8] Liu G, Gao X, You D, et al. 2016 Prediction of high power laser welding status based on PCA and SVM classification of multiple sensors Journal of Intelligent Manufacturing 30: 821-832.
[9] Wu D, Chen H, Y Huang, et al. 2018 Online monitoring and model-free adaptive control of weld penetration in VPPAW based on extreme learning machine IEEE Transactions on Industrial Informatics 99: 1-1.
[10] You D, Gao X and Katayama S 2015 A novel stability quantification for disk laser welding by using frequency correlation coefficient between multiple-optics signals IEEE/ASME Transactions on Mechatronics 20: 327-337.
[11] You D, Gao X and Katayama S. 2015 WPD-PCA-based laser welding process monitoring and defects diagnosis by using FNN and SVM IEEE Transactions on Industrial Electronics 62: 628-636.
[12] Wang T, Chen J, Gao X, Wu L, et al. 2017 Quality monitoring for laser welding based on high-speed photography and support vector machine Applied Sciences 7: 299.
[13] Lv N, Xu Y, Li S, et al. 2017 Automated control of welding penetration based on audio sensing technology Journal of Materials Processing Technology 250: 81-98.
[14] Feng Z, Chen J, et al. 2017 Monitoring weld pool surface and penetration using reversed electrode images Welding Journal 96: 367-375.
[15] Zhang K, Zhang Y, Chen J, et al. 2017 Welding pool oscillation behaviors for pulsed GTA welding based on laser dot matrix sensing IEEE Annual International Conference on Cyber Technology in Automation Control and Intelligent Systems 355-358.
[16] Li C, Shi Y, Gu Y F, et al. 2018 Monitoring weld pool oscillation using reflected laser pattern in gas tungsten arc welding Journal of Materials Processing Technology 255: 876-885.
[17] Zhang Z, Wen G, Chen S, et al. 2017 Audible Sound-based intelligent evaluation for aluminum alloy in robotic pulsed GTA: Mechanism, feature selection and defect detection IEEE Transactions on Industrial Informatics 14: 2973-2983.
[18] Liang Z, Chang H, Wang Q, et al. 2019 3D Reconstruction of weld pool surface in pulsed GMAW by passive biprism stereo vision IEEE Robotics and Automation Letters 4: 3091-3097.
[19] You D, Gao X, Katayama S 2014 Multisensor fusion system for monitoring high-power disk laser welding using support vector machine IEEE Transactions on Industrial Informatics 10: 1285-1295.
[20] Yan Z, Zhang G, Qiu M, et al. 2005 Monitoring and processing of weld pool images in pulsed gas metal arc welding Transactions of The China Welding Institution 260: 37-40.
[21] Liang Z, Zhao S, Zhang M, et al. 2014 Vision sensing of weld pool for P-GMAW by an infrared transmitting filter Hanjie Xuebao/Transactions of the China Welding Institution 35: 33-46+41.
[22] Gao F, Wang K H, Zan L L, et al. 2011 Classification of MAG weld pool image based on moment invariants and fisher China Welding: English Version 4: 51-56.
[23] Zhang Y, You D, Gao X, et al. 2019 Online monitoring of welding status based on a DBN model during laser welding Engineering (English) 5: 595-812.
[24] Feng Y, Chen Z, Wang D, et al. 2020 Deep welding: A deep learning enhanced approach to GTA welding using multisource sensing images IEEE Transactions on Industrial Informatics 16: 465-474.
[25] Yang L, Liu Y, Peng J, et al. 2019 An Automatic Detection and Identification Method of welded joints based on deep neural network IEEE Access 7: 164952-164961.
[26] Peng G, Gao Y, Tian Z, et al. 2019 Penetration control of GTA welding process for aluminum alloy using vision sensing Journal of Physics: Conference Series 1303: 012139.
[27] Xia C, Pan Z, Fei Z, et al. 2020 Vision based defects detection for Keyhole TIG welding using deep learning with visual explanation Journal of Manufacturing Processes 56: 845-855.
[28] Zza B, Bla B, Wza B, et al. 2020 Real-time penetration state monitoring using convolutional neural network for laser welding of tailor rolled blanks Journal of Manufacturing Systems 54: 348-360.
[29] Jiao W, Wang Q, Cheng Y, et al. 2020 End-to-end prediction of weld penetration: A deep learning and transfer learning based method Journal of Manufacturing Processes 63: 191-197.