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Technical Paper

Weld appearance prediction with BP neural network improved by genetic algorithm during disk laser welding

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ABSTRACT

The appearance of welds is the external manifestation of welding quality. The morphology of molten pools is significantly associated with the weld appearance, but the approach to measure the morphology of molten pools during laser welding remains an outstanding challenge up to now. In this study, the shadows of molten pools were formed to describe the morphology of molten pools. Principal components analysis (PCA) is applied to analyze the characteristics of the molten pools' shadow in order to reduce their redundancy. Then BP neural network improved by genetic algorithm (GABP) is established to model the relation between welding appearance and the characteristics of the molten-pool-shadows. The effectiveness of the established model is analyzed through two different welding speed experiments, and the results verify its prediction performance. The work provides an effective way to predict the weld appearance and assess the welding quality in real-time.

1. Introduction

Laser welding is the most solicited technique for industrial application for its advantages in narrowly focusing laser radiation to a small area and high intensity heat source, which are instrumental in deep penetration and high-speed welding [1–3]. The inherent flexibility of the laser welding is due to its ability to operate in both the conduction mode for shallow penetration welding and the keyhole mode in deep penetration welding [4,5]. However, without a thorough physical understanding of the associated molten pools phenomena, the potential of laser welding cannot be fully excavated.

The morphology of the molten pools is the final outward manifestation of the compositive force of the metal vapor pressure, the surface tension, the gravity and the pressure of the shielding gas during laser welding, and it plays an important role in determining the weld appearance. An impressive amount of researches have been carried out to explain the behaviors of the molten pools. Yamada et al. [6] used X-ray images of inside materials with intense synchrotron radiation to observe the keyhole and defects of the molten pools during laser welding, and the relation between the shape of molten pools and welding quality was studied, but the X-ray photograph system is expensive and harmful on operators' health. Some researchers employed numerical simulation methods to study the mechanism of the molten pools during laser welding [7–9]; these methods are highly depending on the accuracy of the numerical simulation models. Zhang et al. [10] presented the dynamic behaviors of spatter formation, and clarified the spatter formation mechanisms in the high-power fiber laser welding of a thick plate at low welding speed with high-speed imaging system, but the phenomena and mechanisms of high speed laser welding were not studied. Recently, Zhang and Gao [11] applied an auxiliary diode laser illuminant to get the visual information of the molten pools morphology, and studied the relation between these visual information and the welding quality with fitting method.

Artificial neural networks have been used in a wide range of membrane process applications and are particularly suited to problems which involve the manipulation of multiple parameters and non-linear interpolation [12,13]. BP neural network is a typical artificial neural network, which can implement any complex nonlinear mapping functions proved by mathematical theories, and approximate arbitrary nonlinear functions with satisfactory accuracy. Compared with other forecast methods, BP neural network is advantageous in terms of high tolerance of data errors. Suganthi et al. [14] applied back propagation (BP)-based artificial neural network (ANN) models for the prediction of multiple quality responses in micro-EDM operations. Zhang et al. [15] developed an ANN model combining learning vector quantization and BP algorithm

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to map the complex relationship between process conditions and quality indexes of low-pressure die-cast. Oktem [16] constructed an ANN based on BP learning algorithm for the surface roughness prediction. According to the learning algorithm of BP model, the accuracy of the BP model is highly depending on the initial weights and thresholds of the neural network. Therefore, the BP model should be improved in order to get the global optimized parameters, not the local optimized parameter, of the neural network.

This paper continues our previous study [11], in which a high speed visual sensing system with a specific wavelength auxiliary diode laser light was designed to illuminate molten pools and casted its shadow. The high-speed camera (frame rate: 5000 frame/s) helps us to capture the detailed visual morphology information of a molten pool. The area of a casting shadow (abbreviated as A), maximal distance between points in the casting shadow and the keyhole position (abbreviated as D), maximal width of the casting shadow (abbreviated as W) and tilt of the casting shadow (abbreviated as T) were defined as the characteristics to describe the morphology of a molten pool. In this study, the PCA algorithm was applied to reduce the redundancy of the characteristics data of the morphology information of the molten pool. A BP neural network improved by genetic algorithm is studied to characterize the nonlinear relation between these characteristics of molten-pool-morphology and welding appearance which was represented by the weld height and weld width. The established model is verified by two different welding experiments, and the results show the effectiveness and robustness of the established prediction model of the weld appearance.

2. Experimental setup

The molten pools, spatters and plasma can be photographed and observed by special vision systems during the high power laser welding [10]. By analyzing the spectrum of the molten pools and plasma, it is believed that the radiation of a molten pool mainly covered the near infrared band, while the plasma radiation gathered at the ultraviolet band. In order to get the clear images of the molten pools' shape, these interferences should be eliminated. In our experiment, a diode laser light illuminant (wavelength: 980 nm, 25 W) was equipped at the side of laser beam to illuminate the molten pool, and a narrow-band filter with spectral band of 960–990 nm was installed in front of the camera lens. The diode laser illuminant was fixed at an angle of 45° with the workbench plane, so the shadows of the molten pools would be casted on the workpiece. The characteristics of the molten pools' shadow are defined and analyzed to get the information of the molten pool morphology during laser welding. The type of the camera is NAC high-speed CMOS camera (frame rate: 5000 frame/s, resolution: 512 × 500 pixels), and the laser welding source is high-power disk laser TruDisk-10003 (power: 10 kW). The camera and laser-welding beam are fixed on a Motorman 6-axis robot, which was employed to find the exact welding position in welding process. The diameter of the laser beam is 480 μm. During the laser welding, the robot which carried the camera and laser beam kept immobilization, and the workpiece was moved back toward the welding direction by the workbench. The structure of the experimental setup is shown in Fig. 1.

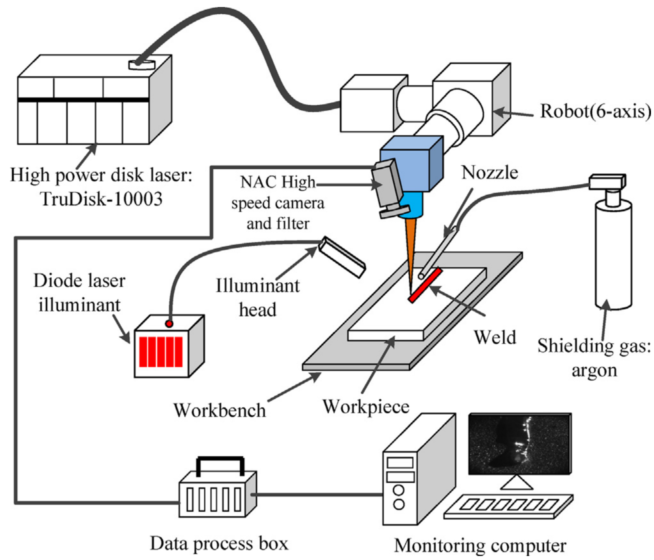

Fig. 1. The structure of experimental setup.

3. Using principal components analysis (PCA) to analyze the characteristic data

From the experimental setup, the frame rate of the camera used to capture the molten pool shadow was 5000 frames/s; so large quantities of images were recorded during laser welding. With each recorded image, four characteristics of molten pools' shadow were extracted [11]. PCA is able to reduce the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation in the data set. It is achieved by transforming the original data to a new set of variables, the principal components (PCs), which are uncorrelated, and which are ordered so that the first few PCs retain most of the variation in all of the original variables [17,18].

PCA is highly useful in analyzing data which contains relationships between the existed variables. It is proved successfully in many applications such as reducing dimensionality, data compression, and fault detection.

In PCA algorithm, the input vector X is defined as $X=(x_1, x_2, \ldots, x_n)^T$, which consists of the four characteristics. The four characteristics are of different orders of magnitude, so normalizations of each characteristic are required before applying PCA algorithm. The mean value of all input vectors X is denoted by $\mu_X = E\{X\}$, and the correlation coefficient matrix R is calculated by Eq. (1).

$$R_X = E\{(X-\mu_X)(X-\mu_X)^T\}, \quad R_X = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nn} \end{pmatrix} \tag{1}$$

The components of R_X, denoted by r_{ij}, represent the covariance between the components x_i and x_j, if x_i and x_j of the data are uncorrelated, and the covariance matrix is symmetric. In general, once the covariance matrix was calculated, the eigenvectors could be found from the covariance matrix easily. The next step is to order them by their eigenvalues from largest to smallest. The sequence shows the components in order of the significance of the dimensions. Therefore the diagonal elements-eigenvectors of R_X are $(\lambda_1,e_1), (\lambda_2,e_2), \ldots, (\lambda_p,e_n)$, where $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n$.

Thus the principal components are calculated by Eq. (2).

$$Y_i = e_i' X = \sum_{k=1}^{p} e_{ik} X_k \tag{2}$$

where $\mathrm{Var}(Y_i) = e_i' \sum e_i = \lambda_i, \quad i = 1, 2, \ldots, n;$ $\quad \mathrm{Cov}(Y_i, Y_k) = e_i' \sum e_k = 0, \quad i \neq k.$

The first principal component which is a linear combination of $x_1, x_2, \ldots, x_n$, has the maximum variance, i.e., the $\mathrm{Var}(Y_1)$ is