Discrimination of molten pool penetration based on genetic algorithm optimization of BP neural network

Boxue Chang¹, Jingyue Huang²

¹Guilin University Of Aerospace Technology, Guilin, 541004, China
²Guilin University Of Electronic Technology, Guilin, 541004, China

Abstract: The metal spatter and light intensity of CO₂ welding in the vicinity of the melt pool during the short transition of the melt droplet seriously affect the realtime and reliability of weld feature extraction. The mapping relationship between welding pool characteristic parameters and melting depth is established by using BP neural network optimized by genetic algorithm. The results show that the training results and test results of the optimized BP neural network model of genetic algorithm have little error and meet the requirements of precision. The model can well reflect the relationship between the melting depth and the characteristic parameters of the melting pool.

1. Introduction

The degree of weld penetration is closely related to the welding quality. The size parameters such as weld width and penetration are important factors that affect the welding quality. The welding pool has the most direct influence on the welding size parameters. Therefore, the key to ensure welding quality is to control the characteristic quantity of the molten pool during welding process, and establishing the relationship between welding process parameters and the characteristic quantity of the molten pool is the premise to realize the prediction and control of welding results [1].

In recent years, the error reverse propagation neural network (BP-ANN) based on gradient descent has been used by some scholars in China for the prediction and analysis of welding pools. However, the neural network based on gradient descent converges slowly and has a strong dependence on initial weights and thresholds, and is prone to fall into local optimal solutions. Genetic algorithm is a parallel global search algorithm with natural selection and genetic law, which shows a good macroscopic search ability. Combining the BP-ANN with the genetic algorithm, the global optimization of the initial connection weights and thresholds of the BP-ANN using the genetic algorithm can well solve the dependence of the BP-ANN on the initial connection weights and thresholds, and avoid local optimization[2].

In this paper, genetic algorithm and BP neural network are combined, first the near infrared CCD camera is used to obtain the image of the melting pool, then the image of the melting pool is preprocessed, its edges are detected, and its features are extracted. Then, based on the results of feature extraction, an error reverse propagation neural network is established, and before network training, genetic algorithm is used to optimize the initial connection weight and threshold of the network, and a genetic neural network prediction model between the deep melt pool and the width of the melt pool, welding current, and welding voltage is established. It will provide some reference for the welding melting depth discrimination.
2. Test device

The test devices used include control systems, image processing systems, visual sensing systems, welding guns, walking mechanisms, and welding worktables, as shown in Figure 1. The image acquisition is accomplished through the visual sensing system. After the welding is completed, the image of the melting pool is matched with the melting depth of the melting pool.

![Fig. 1 Diagram of experimental device](image)

The test uses the NBC-350 inverter CO₂ gas protection welding machine. The gas protection gas is pure CO₂ gas, the gas flow rate is 10L/min, the wire diameter is 1.2 mm, the wire length is 10mm, the base metal is a low-carbon steel plate, and the welding gun is vertical with the base material. The welding speed is 550mm/min, the industrial CCD camera model is MV1-D1312I, the camera is fixed next to the welding gun, the camera has a window of 544 × 544, and the sampling frequency is 485 frames per second. The test uses the Ketianjian high-speed collection system for data collection [3].

3. Image preprocessing and feature extraction in melt pool

3.1 Image preprocessing

Most of the background in the original image of the melt pool is not related to the part of the melt pool to be processed, so the part to be processed is intercepted from the original melt pool image, as shown in Figure 2a. The use of median filtering removes the interference and influence of noise generated by CCD cameras during shooting, random noise of signal transmission inclusions, and strong arc light generated by arc welding during welding, and effectively suppresses noise. While reducing the interference of Arc light on the boundary of the melting pool, it can clearly reflect the outline of the melting pool [4][5]. Finally, the edge detection of the Canny operator and the morphological method are used to divide the image of the melt pool, so that the melt pool and other parts are clearly distinguished, and it is easier to extract the relevant feature information from the melt pool image, as shown in Figure 2b.

![Fig.2a Melt pond interception map](image)

![Fig.2b Melt pool edge map](image)
3.2 Feature extraction
In order to describe the geometry of the front of the melt pool, the characteristic parameters are extracted from the pre-processed melt pool image and expressed in digital form. To establish the relationship between the geometry parameters of the front of the melt pool and the depth of fusion, the geometric parameters of the front of the melt pool must be defined. Figure 3 is the definition of the front parameters of the melt pool. The geometry parameters of the molten pool shape mainly include: the maximum width $W$ of the molten pool, the semi-length $L$ of the molten pool, and the posterior area of the molten pool $S$. The maximum width of the pool is defined as the distance of the boundary points of the two pools perpendicular to the maximum distance in the welding direction.

Fig. 3 Definition of melt pond shape and geometric parameters

4. Research on Optimization of BP Neural Network Infusion Deep Recognition Model by Genetic Algorithm

4.1 BP neural network
BP-ANN is a multi-layer feedback network using a reverse propagation learning algorithm. Its structure is shown in Figure 4. A neuron is represented by a node. The network consists of an input layer, an implicit layer, and an output layer node. The hidden layer can be one layer. It can also be multi-layered, with each node connected by weights and thresholds [6]. The forward calculation of each neuron is calculated by multiplying the input vector and the weight, and then subtracting the mission value from the threshold, and the difference is converted by the transfer function. Get output.

Fig. 4 BP neural network

In the course of network training, the error reverse propagation algorithm based on gradient descent is used to study. The output value and expected value error are calculated in the past, and the weight value and threshold value are adjusted in reverse, so that the desired input and output nonlinear mapping relationship is realized or approximated repeatedly. However, the slow convergence speed of
BP algorithm can easily lead to excessive network learning time, especially when solving complex problems, it often requires repeated training and trial and error. In addition, there is no basis for the selection of initial weights and thresholds of neural networks [7]. Once the inappropriate initial weights and thresholds are randomly generated, the network training converges slowly or even does not converge. Therefore, BP-ANN has obvious limitations.

4.2 Genetic optimization of BP-ANN

Genetic algorithm is a computational model that simulates the biological evolution process of natural selection and genetic mechanism in Darwin's biological evolution. It searches for global optimal solutions by simulating the survival principles of the fittest and random information exchange of chromosomes within the population during the evolution of species. Good global optimization ability.

In order to overcome the disadvantages of the slow convergence of BP-ANN and the dependence on the initial connection weights and thresholds, this paper introduces the genetic algorithm into the selection of the initial connection weights and thresholds of BP-ANN, and constructs a BP-ANN based on genetic algorithm. The training of the network is divided into two steps. First, the genetic algorithm is used to globally optimize the initial weight and threshold of the network, and the optimal individual is assigned to BP-ANN. Then BP-ANN continues to refine the weight and threshold. Finally, the optimal network connection weight value and threshold value are obtained, and a higher precision BP-ANN model is established.

In the optimization, the genetic algorithm relies on the fitness function to evaluate the merits of the individual. The higher the individual's adaptability function value, the closer to the optimal solution. Therefore, choosing a suitable adaptability function often becomes the key to realizing the genetic algorithm.

In the optimization process, network weights and thresholds are encoded into individuals [8]. Genetic algorithms select, cross, and mutate individuals according to the individual adaptation function values. Through these genetic operations, the evolutionary process of species is simulated, evolving from generation to generation, and approaching the optimal solution. When the individual with the largest adaptive function value is obtained, the genetic algorithm ends, the best individual obtained is assigned to BP-ANN, network training is conducted, and a high-precision BP-ANN model is finally obtained. The genetic optimization process of BP-ANN is shown in Figure 5.

![Figure 5: Flow chart of genetic neural network](image)

4.3 Establishment of predictive model

The first 20 of the 30 data groups based on the test system test are taken as the training set of BP-ANN. In order to achieve data comparability, the sample data is normalized before network training, and all sample data is converted into [0, 1]. The normalization function is

\[ x_i^* = \frac{x_i - x_{imin}}{x_{imax} - x_{imin}} \]

In the formula: \( x_{imax}, x_{imin} \) is the maximum and minimum value of the sample data \( x_i \); \( x_i^* \) is
the normalized value.

4.4 Simulation and verification of the model

Using a three-layer BP-ANN model, the input layer has 3 neurons, the input welding current, the welding voltage, and the width of the melting pool, and the output layer has 1 neuron, which outputs the melting depth of the welding pool. The number of implicit layer nerve elements can be obtained by the trial value method. After network training, if the network test error is large, the number of implicit layer nodes can be modified. The entire BP-ANN structure is $3 \times 10 \times 1$, and the transfer function between the layers of the network is a log function. The optimization algorithm uses an adaptive learning rate BP algorithm with momentum factor. Before BP-ANN training, the initial connection weight and threshold of the network were optimized by genetic algorithm. In the genetic algorithm, the fitness function takes the norm of the error matrix between the predicted value and the expected value, IE

$$f = \left\{ \sum_{i=1}^{3} [y(x) - y(x)']^2 \right\}^{1/2}$$

In the equation: $y(x)$ is the true value, and $y(x)'$ is the predicted value. The initial population size is taken as 50, the maximum genetic algebra is taken as 100, the cross probability is taken as 0.7, the probability of variation is taken as 0.01, and the gap is taken as 0.95. The optimized individual is obtained. The optimized individual is assigned to BP-ANN for training and learning of the BP algorithm. The maximum number of network training is set at 1000, the training target is 0.01, and the learning rate is 0.1. After the network training is over, the construction of the welding deep fusion prediction model is completed.

Based on Matlab platform, the model of welding deep melt model is established. Fig. 6 is an iterative diagram of the fitness function graph and BP-ANN during training. It can be seen that after the population is inherited to 15 generations, the square sum of errors is already very small. The initial weights and thresholds obtained by the genetic algorithm are assigned to the BP neural network, and the BP neural network is trained. When iterated to the sixth generation, the learning performance is $7.5642 \times 10^{-3}$ to achieve the training goal.

![Fig.6 Genetic neural network training results](image)

The simulation results of 9 training samples of the established genetic neural network are shown in Figure 7. It can be seen that the simulation value of the neural network model and the experimental value have less error, and the relative error is less than 3.21 %, which is within a reasonable range.
5. Conclusion

(1) A method for determining the deep fusion of CO$_2$ welding pool with complex morphology by optimizing BP neural network by genetic algorithm is proposed.

(2) A genetic neural network prediction model was established between the fusion depth and the welding voltage, the welding current and the width of the welding pool and the melting depth of the CO$_2$ welding pool. The nonlinear relationship between the melting depth and the characteristic parameters of the melting pool was determined.

(3) The relative error of the model prediction accuracy is less than 4.6%, which has reached a high accuracy, which proves the correctness and reliability of the model. It has certain theoretical and practical significance for the deep fusion analysis and prediction of CO$_2$ welding pools.

Acknowledgements

This research was financially supported by the Opening Project of Guangxi Colleges and Universities Key Laboratory of robot & welding (JQR2018ZR01).

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