Online Monitoring of Variable Polarity TIG Welding Penetration State Based on Fusion of Welding Characteristic Parameters and SVM

Liang Liu, Huabin Chen and Shanben Chen

Abstract In variable polarity TIG (VPTIG) welding of aluminum alloy, effective recognition of welding penetration states is a hot research topic. It is also one of the key factors for the quality of weld and the joint represent. We established an intelligent sensor system for VPTIG welding to obtain the welding current, misalignment and interval, the clear weld pool images and wire feed speed online. With an effective image processing algorithm, weld pool width is measured accurately online. To investigate the complicated relationships between the welding parameter and different welding condition, an improved Support Vector Machines (SVM) classification model based on artificial fish swarm algorithm is built. The work shows that the proposed Support Vector Machine model classifies aluminum alloy welding states effectively.

Keywords VPTIG · Weld width recognition · SVM · Weld joint penetration

1 Introduction

With the progress of science and technology, welding in the national economy plays an increasingly important role, weld process according to fusion state can be divided into three categories: not penetration, full penetration and over penetration [1]. From the Angle of welding process, full penetration is one of the most important prerequisite to form solid and reliable welding joint. The beginning of the aluminum alloy welding process or welding arc energy is small and will turn up lack of penetration. At this time, Positive molten weld width is smaller, on the back of board, it is completely not fusion penetration, and the weld residual high is small. Full penetration state appears in welding process of middle or welding arc energy is large, the surface shows uniform weld width, the welding plate surface shape is

L. Liu · H. Chen (✉) · S. Chen
Intelligentized Robotic Welding Technology Laboratory,
Shanghai Jiao Tong University, Shanghai 200240, China
e-mail: hbchen@sjtu.edu.cn

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well, the back of the welding plate is penetration completely, it has certain proper weld width, the welding plate shape also is very smooth. over penetration state usually occurs in the situation that welding current is too large or weld gap is too large. At this state, characterized by positive fusion width is too large [2], and the heat affected zone is too wide. During the welding process, the weld joint penetration could be identified online by the welding characteristic parameter.

At present, for the state of the aluminum alloy welding molten pool classification have been studied at home and abroad. In order to obtain Welding characteristic parameters during the VPTIG process, intelligent sensor system has been employed. Lv using the arc sound signal recognizes alloy welding penetration status in the process of aluminum [3, 4], in order to study the further characteristic of arc sound signal, she put forward a new way of time-frequency-time domain feature extraction of penetration, including the auditory attention AC-ROI extraction preprocessing method and the maximum modulus threshold denoising method, they could effectively remove the noise and extract the most related information. Fan et al. [5] got molten pool image from right in front of the molten pool, oblique rear and bottom three directions at the same time. Bi et al. [8] developed an online monitoring system based on the MAG welding process, it can acquire arc sound signal and predicted the penetration status. They determine the relationship between the joint penetration and welding parameters. Despite the above achievements, in the sensing of VPTIG joint penetration, more welding parameters like misalignment and interval should be added to verify the joint penetration during the welding process.

In order to achieve an accurate recognition model of the weld penetration, and traditional linear models can hardly describe the dynamic state of the welding process, hence the non-liner models are applied to correlate the welding parameters with the penetration. Currently, some non-liner models are widely applied in industrial automation and manufacturing intelligence. Chen and Chen [6], Chen et al. [7] proposed the fuzzy adjusting D-S evidence fusion method to fuse the basic probability assignments of different sensors, his fusion results showed that the reignition rates were much higher with more sensors and the general recognition rate was related to the recognition rates of single sensor. Bi et al. [8] put forward an online monitoring method based on the MAG welding process, the PCA dimension to obtain vector BP and RBF neural network monitoring model is set up, its aim is to implement online assessment for the MAG fusion state. Wang et al. [9] used the BP-network to design the Pattern classifier. It is found that through samples training and optimizing, a classification of 88–100% has been made for detection of the four distinct penetration states, that the “excessive penetration”, “full penetration”, “unstable penetration”, and “partial penetration”. In additional, according the research of Zhang et al. [10], an alternative to the conventional weld penetration sensing methods in pulsed gas tungsten arc welding is proposed for implementation at manufacturing sites. In this paper, a novel hybrid approach based on the combination of Support Vector Machines (SVM) and artificial fish swarm algorithm (AFSA) is proposed.

2 The Experimental Setup

To get the clear information in the process of aluminum alloy welding online, such as pool image information, welding current, wire feed speed, the test plate gap and the misalignment. we design the welding experiment system. As illustrated in Fig. 1, experiment system mainly includes: YASKAVA HP20D Robot, DX100 Robot controller, laser auxiliary illuminant, welding power source, wire feeder, high speed CMOS camera, DC power supply (110 v), servo robot sensor, and the clamping device.

2.1 *Welding Power Source and Welding Robot*

The welding power source is Miller's Dynasty 700 Variable Polarity TIG power source, its wire feeder is Jet line 9600. The welding robot used in the system is YASKAWA's HP20D robot. It has six degrees of freedom and could easily meet the welding tasks.

2.2 *The Module of High Speed CMOS Intelligent Camera*

The Program of high-speed CMOS intelligent camera welding experiment system can complete storage and acquire card camera parameters at the same time. Exposure time, number of sampling frames, image size and other parameters can be

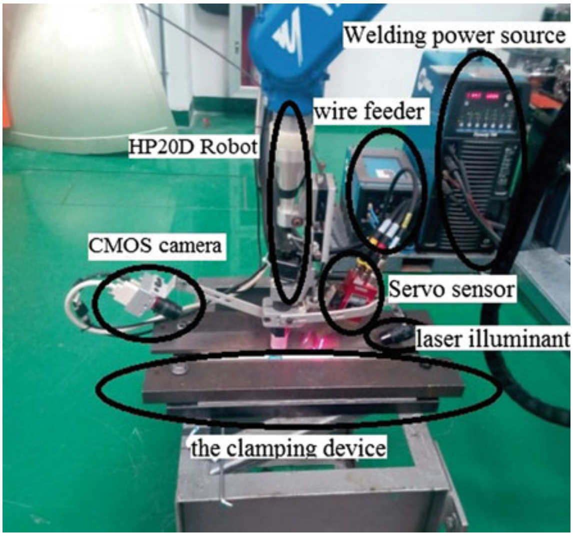


Fig. 1 Aluminum alloy plasma arc welding experiment system

set separately. Laser is adopted in system as auxiliary illuminant of inhibition of arc, the laser pulse peak power can reach 75 W, the peak time is 100 ns. Through UNO microcontroller development board, we get camera shutter and laser light source synchronized, we can also trigger the camera with TTL.

2.3 Auxiliary Light Source Module and Filter Module

The innovation place of this test system is it can effectively inhibit the arc light; hence we could collect the molten pool images clearly. Auxiliary light source is a pulsed laser, and its peak power can reach 75 W, its spectrum characteristic is shown in Fig. 2. As we can see, its central wavelength is 900 nm, and its half the bandwidth is 5 nm. To cooperate with the auxiliary light source module, at the same time, considering the arc interference suppression time. The test system adopts filter module and filter uses a narrow bandwidth of the filter, it allows the center wavelength of 900 nm, and half the bandwidth is 5 nm.

2.4 Data Acquisition Module and Isolation Module

Test system uses Advantech's ADAM6024 to acquire welding current and wire feed speed. To acquire the data that we need, we should develop the software of the ADAM6024, the main functions that we have used are ReadAI, ReadDio and WriteReg function. Read AI function is mainly to read the misalignment, the interval of the welding plate, wire feed speed and welding current. The ReadDio is

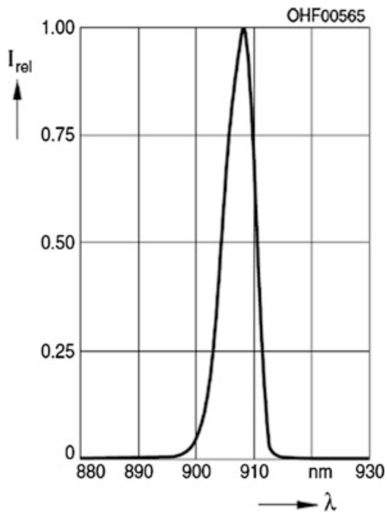


Fig. 2 The features of pulsed laser spectrum

mainly to read the signal of the beginning of arc start, WriteReg is mainly to control the values of wire feed speed and welding current, the aim of this function is to control the weld forming.

When the variable polarity TIG welding start arc, it will produce the high frequency, the high frequency may have the influence on the data acquisition module and make the data not accuracy, so we add the Isolation module. The Isolation module provides 8 road digital quantity input: 6 road completely independent channels and 2 road isolation channels. All channels with 5000 VRMS isolation protection function, the aim is to avoid the influence of ground loop and prevent input line surge caused by the damage.

3 Result and Discussion

3.1 Obtain Molten Pool Images

To get the pool image information in the process of aluminum alloy welding, welding current, wire feed speed, the test plate gap and the misalignment of amount of information, we design the welding experiment system. Experiment system mainly includes: laser auxiliary illuminant, controller, high speed CMOS camera, lens, filter, laser lens, DC power supply (110 V) and the clamping device. The system is shown in Fig. 1.

As shown in Fig. 3, they are the welding molten pool images, In the experiments, we increase the value of the welding current gradually with 1 A/s from beginning of 300 A, and we increase wire feed speed with 0.5 cm/min from beginning of 80 cm/min. With the increase of welding current, the arc force will increase, so that the welding state will transit from lack of penetration to over penetration state. The welding process parameters are shown in Table 1.

3.2 Camera Calibration

The molten pool images are gotten by the camera, so the geometric feature sizes of the images are different from the real molten pool, and There is a mapping relationship between them. In the welding system of this paper, visual sensor fixed on the welding gun, the position between the visual sensor and the welding gun doesn't change. For convenience of calibration and analysis, the experiment selected a calibration method which is 5 mm * 5 mm checkerboard as shown in Fig. 4. Only the molten pool's width is needed, so the horizontal direction is calibrated. The two points A_i (i = 1–2) have the coordinates (X_i, Y_i) and the distance of adjacent two points along the X direction is 5 mm. The calibration coefficients k_x can be determined as Eq. (1). Hence, based on the extracted molten pool edge and the calibrated correlation, the real width of the molten pool is calculated.

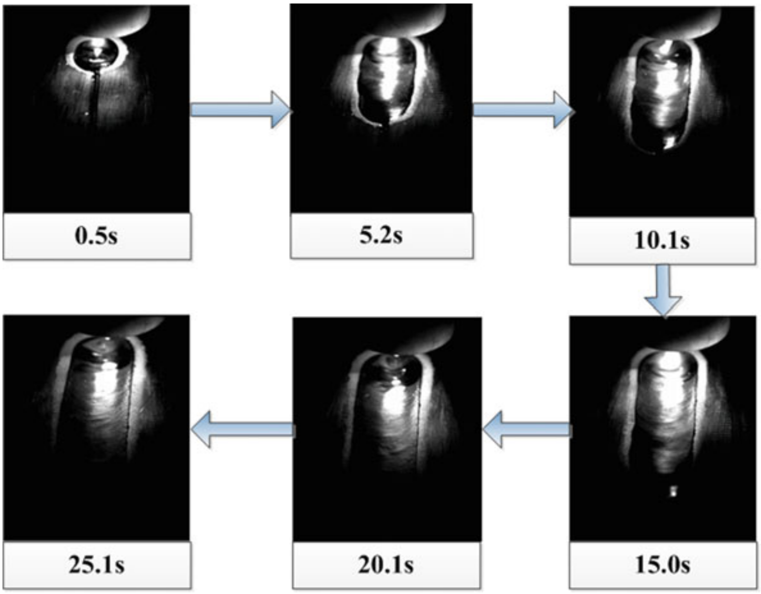
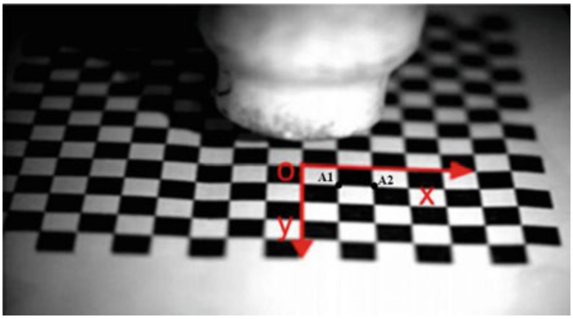


Fig. 3 Molten pool images under different welding current condition

Table 1 Welding process parameters

Welding parameters	Value
Current (A)	300–420
Dimensions of the workpiece (mm)	300 * 50 * 8
Travel Speed (mm/min)	180
Wire-feed Rate (cm/min)	80–140
Gas flow rate (L/min)	12

Fig. 4 Camera calibration of image processing



$$k_x = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}/5 = 0.04841 \quad (1)$$

3.3 To Extract Molten Pool Status Parameters

The proposed system aims to accommodate measurement of different properties of weld pool. This section presents a case study to measure the width of bead to demonstrate this system.

The following two assumptions are made to obtain good results using this procedure.

1. The edge of the molten pool can be found in images.
2. The desired boundary movement from one frame to another is smooth. This assumption is valid for most cases because the change in the bead width will hardly be abrupt.

The steps to measure the molten pool width can be described as follows.

- Getting the interest area from the images that we call the ROI area. To know where to start tracking the edges of the bead, the region of interest allowing to reduce the amount of calculations to process the image and find the edges.
- Image enhancement: The mean shift filter is applied to reduce noise, increase the chance to find the edge, and improve the reliability of measurement. The mean shift filter is an iterative filter, Two-dimensional median filtering's output is $g(x, y) = \text{med}\{f(x - k, y - l), (k, l) \in W\}$, among them, $f(x, y)$, $g(x, y)$ are the original image and processed image respectively. W is the two-dimensional templates, in this paper, we choose W as 3 * 3 area.
- Thresholding: Otsu's thresholding method is employed in this paper to remove weak edges and preserve the strong ones. It uses the thought of clustering, the number of gray level images is divided into two parts, so the grey value of the difference between the two parts is the largest, and each part of the gray scale difference is minimum.
- Edge detection: The Canny edge detector is used to find reliable edges in an image.
- Line selection: After obtaining a range of possible lines from the Hough Transform, a decision has to be made.
- Calculate the width in the unit of "mm" by applying the extrinsic parameters.

Based on the results of molten pool image feature extraction and calibration, for variable polarity TIG weld pool image that we get, we do the Median filtering, the automatic threshold segmentation and we can extract the weld width of weld pool with the progressive scan. The image processing process as shown in Fig. 5.

According the above work, the welding pool width has been acquired real-time during the welding process. The wire-feed rate and the welding current could be

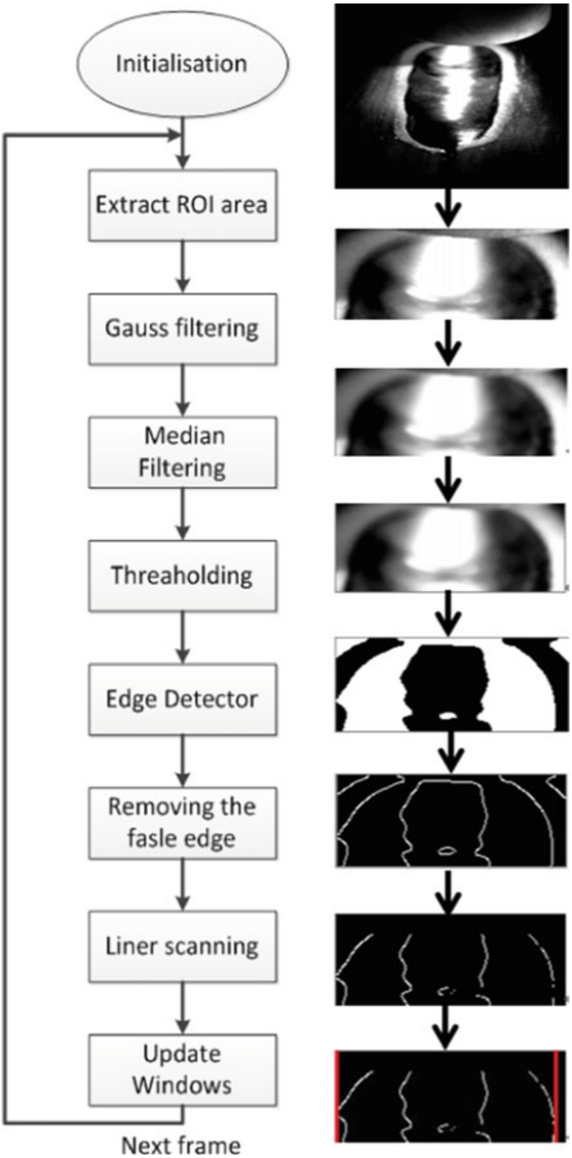


Fig. 5 Weld pool width of image processing

acquired by the Data acquisition Modules real-time during the welding process, the misalignment and interval are gotten from the Servo robot sensor real-time during the welding process, and the data will be transported to the Industrial personal computer by the Ethernet cable. The Fig. 6 shows the curves of the wire-feed rate, welding current, the misalignment and interval during the welding process. The Fig. 7 is the welding picture of Workpiece Morphology.

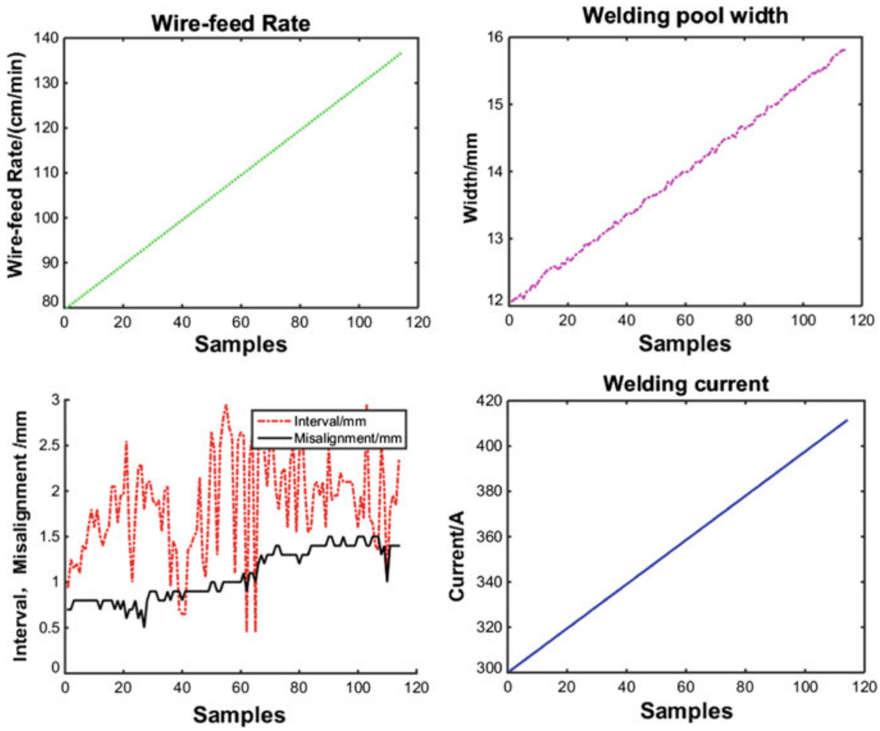
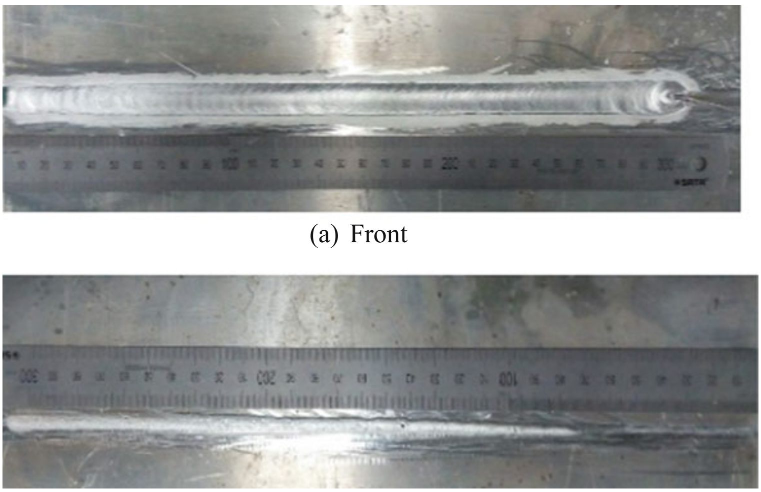


Fig. 6 The curves of welding processing



(a) Front

(b) Back

Fig. 7 Welding pictures of workpiece morphology

3.4 The Dynamic Model of the Welding Process

According the above work, the welding current, misalignment, interval, weld pool width and wire feed speed are gotten. There is a link between these welding process Characteristic parameters and the situation of the penetration state. The general relationships between the characters parameters and welding parameters can be obtained however with some irregularities, these irregularities and complexity is an inherent nonlinear characteristic of the welding process. As a nonlinear modeling method, an AFSA-SVM will play an important role in correlating the welding process characteristic parameters and the situation of the penetration state despite some uncertainty and complexity.

Based on practical experience and welding process model analysis, the thermal inertia effect in aluminum alloy VPTIG process, namely there appear to be a link between the welding parameters and the situation of the penetration state. So, the inputs are determined as welding current, misalignment, interval, Weld pool width and wire feed speed, the output is the situation of the penetration state.

3.5 The Model of the Aluminum Alloy Molten Pool Status Classification

In this paper, we determine welding penetration state by using Support Vector Machine (SVM) modeling, The SVM classification method is used to predict the actual welding state. The Support Vector Machine (SVM) method was applied to multi-source sensor information fusion state forecast, in the process of welding pool width, wire feed speed, welding current, misalignment gap and the misalignment, these five amounts are as input variables of Support Vector Machine (SVM), output variables are three kinds of typical penetration state. On the concrete implementation, we use Libsvm toolbox to fusion state prediction of it, so we need to design k sample (k − 1)/2. The toolkit's main function is training function svmpredict and forecast function svmtrain, and the prediction function can get classification accurately.

Vapnik put forward a new method of machine learning according to statistical learning theory, that called SVM, it based on the theory of structural risk minimization principle, through proper subset selection function and the subset of discriminant function, That minimize the risk of learning machine and ensure the little error of the classifier is obtained by limited training samples, the independent test set the test error still very smalle [13], the SVM has the strict theoretical and mathematical foundation, there is no local minimum value, small sample learning make it has strong generalization ability, it doesn't rely too much on the quality and quantity of the sample.

The basic idea of SVM is to change the data space to the corresponding high-dimensional space by non-linear change, and then to obtain the optimal linear classification surface in the new space. The two or more samples are separated correctly and the classification interval is the largest, for a given linear classification data can be used with hyperplane:

$$w \cdot x + b = 0 \tag{2}$$

where w is the weight vector and b is the classification threshold, and it is required that the classification line correctly classify all the samples.

$$y_i(w \cdot x_i + b) - 1 \geq 0, \quad i = 1, 2..., n \tag{3}$$

The hyperplane that satisfies the above condition and makes the classification interval the largest is the optimal classification surface. After finishing, the optimal class surface problem can be expressed as the following constraint optimization problem, that is, under the constraint of Eq. (2).

$$\phi(w) = \frac{1}{2} \parallel w \parallel = \frac{1}{2}(w \cdot w) \tag{4}$$

Finally, we can get the optimal classification function is:

$$f(x) = \mathrm{sgn}((w \cdot x) + b) = \mathrm{sgn}(\sum_{i=1}^{N} a_i y_i (x_i \cdot x) + b) \tag{5}$$

where: a_i is the Lagrangian factor solved by the quadratic programming problem, and N is the number of support vectors. For linear indivisible cases, the penalty function can be added by adding a penalty function to the objective function by introducing the relaxation variable in the constraint condition. The generalized optimal class surface problem can be further evolved to obtain the minimum of the following functions:

$$\phi(w, \xi) = \frac{1}{2}(w \cdot w) + C\sum_{i=1}^{N} \xi_i \tag{6}$$

where C is a constant, it actually controls the effect of the degree of punishment on the wrong sample and achieves a compromise between the proportion of the misclassified sample and the complexity of the algorithm. If a problem is not linear in its defined space can be divided into the kernel function$K$ (X_i, X), the problem can be converted to a new space, the corresponding discriminant function is

$$f(x) = \mathrm{sgn}(\sum_{i=1}^{N} a_i y_i (x_i, x) + b) \tag{7}$$

Radial basis kernel function is currently the most widely used kernel function, using this kernel function, its form is as follows:

$$K(x_i, x_j) = \exp(-g\|x_i - x_j\|^2), \quad g > 0 \tag{8}$$

In this paper, the parameter g is an important parameter in the kernel function and affects the complexity of the SVM classification algorithm. To sum up, the penalty parameter c and the kernel function parameter g are the key parameters that affect the SVM classifier performance. g as a search for optimization variables.

The steps of using Support Vector Machine model is: Firstly, Obtaining the Support Vector Machine training data, and then selecting the kernel function of Support Vector Machine adopts and relevant parameters, selection of kernel function is the radial basis function (RBF) kernel function parameter g and penalty parameter c will be get from optimization algorithm, after using the training data to training of Support Vector Machine, support vector is obtained to determine the structure of Support Vector Machine model, and then that can be used to determine the Support Vector Machine model to forecast the unknown data.

3.6 The Optimization of SVM Parameters

Kernel functions and penalty factor are important impact factors that related to the Support Vector Machine (SVM) classification accuracy, in order to get a higher state of aluminum alloy welding molten pool classification accuracy [14], so the artificial fish algorithm [15] is bring up. The algorithm is mainly using the fish's foraging behavior, cluster and collision, it starts from the structure the underlying behavior of a single fish, From the fish in the local optimization of each individual to the global optimal value emerged in the group. Artificial fish algorithm has a good ability to overcome the local extremum, it can obtain the global extremum, and the function value of target function is only used in the algorithm. without special information such as gradient value of the objective function, the search space has certain self-adaptive ability. Figure 8 is the process that artificial fish algorithm optimizes the SVM parameters.

Artificial fish algorithm is mainly using the three basic behaviors of fish: foraging behavior, cluster and collision, using top-down optimization model from the underlying behavior of the individual, the fish of each individual in the local optimization, the aim is to achieve the global optimal value purpose of stand out in the group. Foraging behavior: Setting the artificial fish current state and choosing another state perception scope in its random. If the state of the objective function is greater than the current state, then getting close to the state of the new choice, otherwise, selecting the new state, and judging whether meet the conditions, if the select number reaches a certain number, it still does not meet the conditions, moving a step randomly.

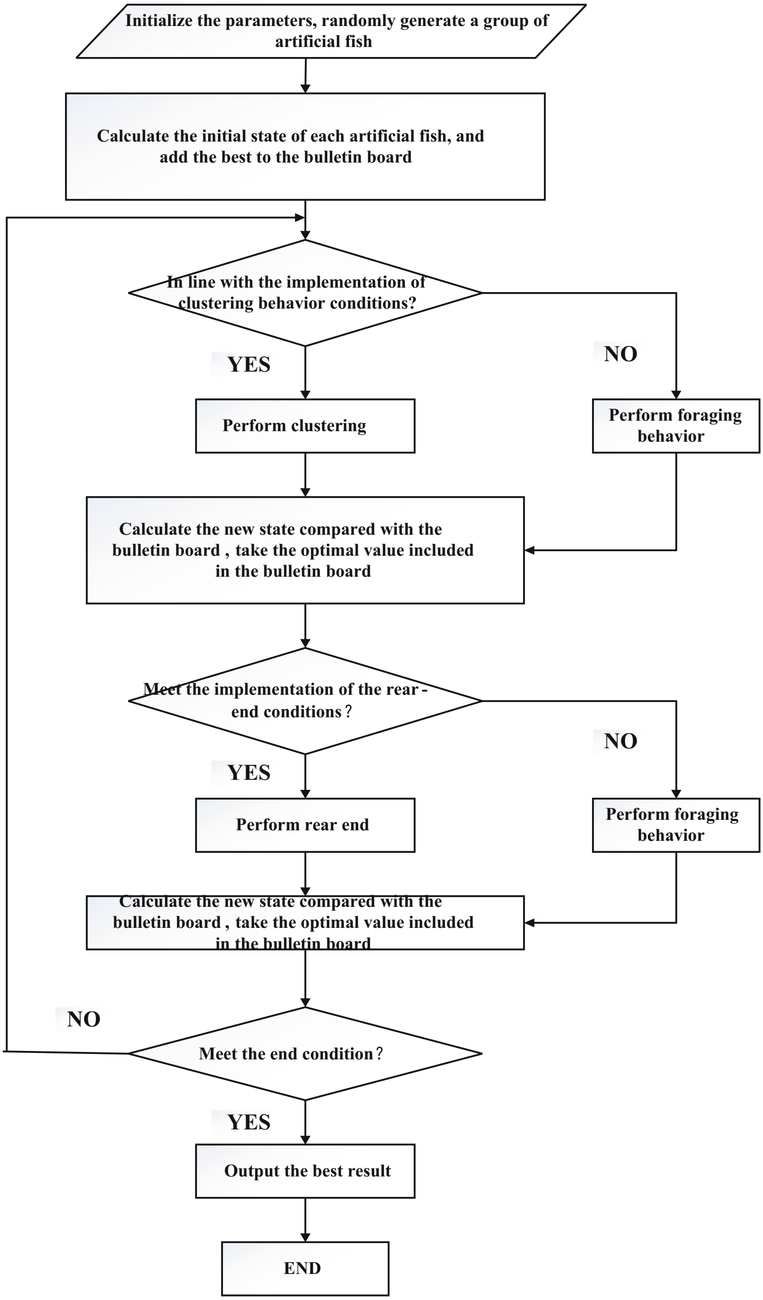


Fig. 8 The process that artificial fish algorithm optimizes the SVM parameters

- Poly group behavior: Artificial fish explores the neighbor number of partners and calculates the partners' center position. Then putting the new center of the objective function compared with the current position of the objective function. If the center position of the objective function is superior to the current position of the objective function and it is not very crowded, the current position steps to the center position, otherwise, performing the foraging behavior.
- Rear-end behavior: Artificial fish explores the optimal position of the surrounding neighbors' fish, when the objective function of optimal location value is greater than the current position of the objective function value and not very crowded, the current position step to the optimal neighbor fish, Otherwise, Executing foraging behavior.

In the Artificial fish algorithm, foraging behavior laid the foundation of algorithm convergence; Cluster behavior to enhance the stability of the algorithm convergence; Rear-end behavior to enhance the quickness and the global convergence of the algorithm; Its evaluation behavior also provides guarantee of algorithm convergence speed and stability. Among them, Cluster behavior plays a very important role, Cluster behavior would help out in local optimal solution of the artificial fish tend to the global optimal solution of the direction of the artificial fish gathered themselves together, and thus escape from the local optimal solution.

On the concrete implementation: firstly, we plug in the training and test parameters of the SVM model, optimizing parameters. We chose the best x as the parameter g of SVM, and we chose the best y as the parameter c of the SVM. The optimal coordinate mobile fish algorithm in the process of iteration is shown in Fig. 9 and artificial fish algorithm of iterative process is shown in the Fig. 10.

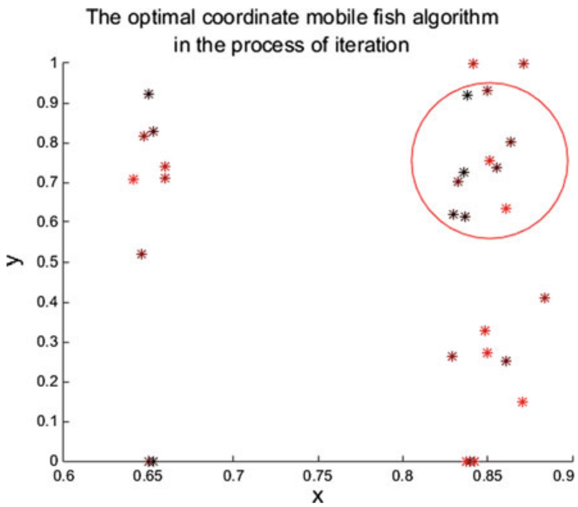


Fig. 9 The optimal coordinate mobile fish algorithm in the process of iteration

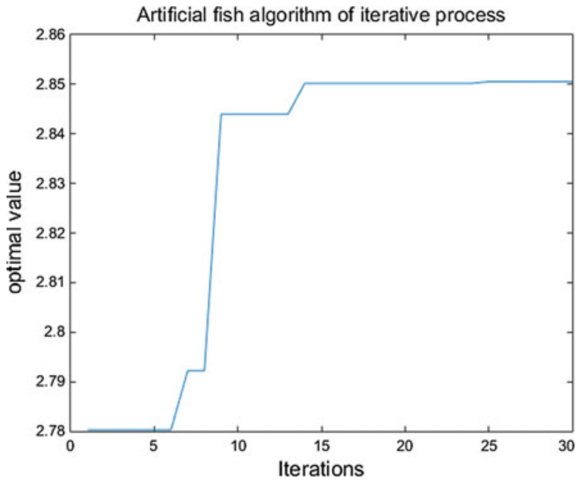


Fig. 10 Artificial fish algorithm of iterative process

3.7 Penetration Identification Based on Model

We select 1014 samples of data collection from the experiment, 300 of 1014 are as the training data, the remaining 714 are as test data. The weld pool width, wire feed speed, welding current, misalignment and interval. These five variables are the inputs to the Support Vector Machine (SVM), and the SVM outputs are three states of penetration: lack of penetration, full penetration and over penetration. The penalty factor is set to 0.85, and kernel function is set to 2.85, the penalty factor and the kernel function are very important, Different from the traditional personal experience, we have got this two factors from the Artificial fish algorithm, hence, we overcome the disadvantage of the SVM cross-validation method spends lots of time on selecting parameters, the result of the experiment is shown in the Fig. 11, the SVM classification Accuracy is 91.0364% (657/714).

To further demonstrate the superiority of AFSA-SVM in penetration identification problem, GS-SVM are used for comparison. Figure 12 shows the classification accuracy comparison of the GS-SVM and AFSA-SVM, and it can be inferred that AFSA-SVM has higher classification accuracy compared with the GS-SVM. Figure 13 shows the time-consuming comparison of the GS-SVM and AFSA-SVM, and it can be seen that AFSA-SVM has lower time consuming compared with the GS-SVM. Table 2 shows the statistics data of the AFSA-SVM and GS-SVM. It is obviously concluded that the AFSA-SVM model is more accurate than the GS-SVM model.

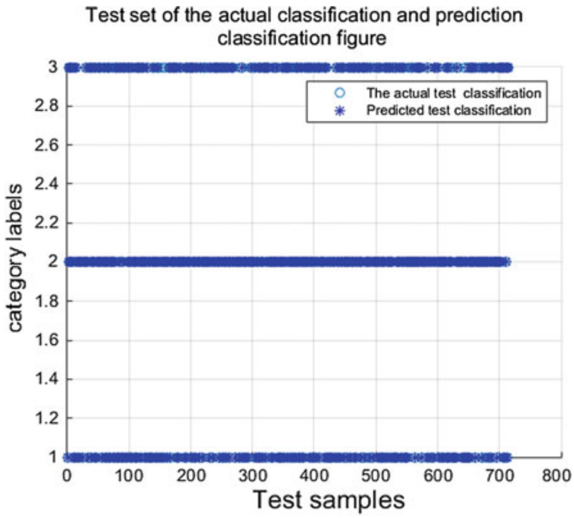


Fig. 11 The result of the SVM classification

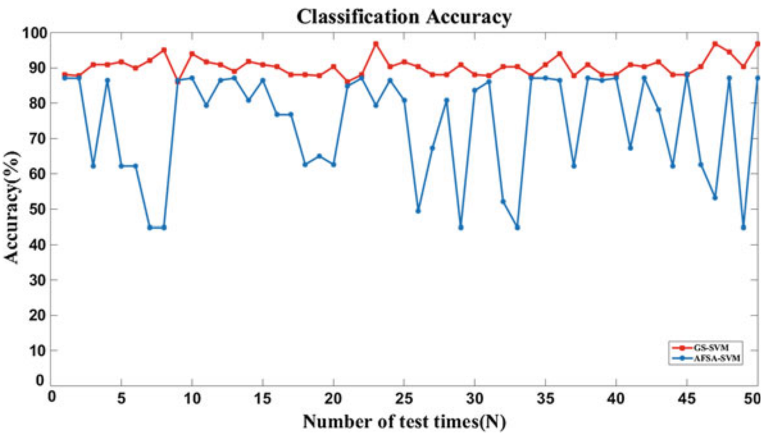


Fig. 12 The classification accuracy comparison of the GS-SVM and AFSA-SVM

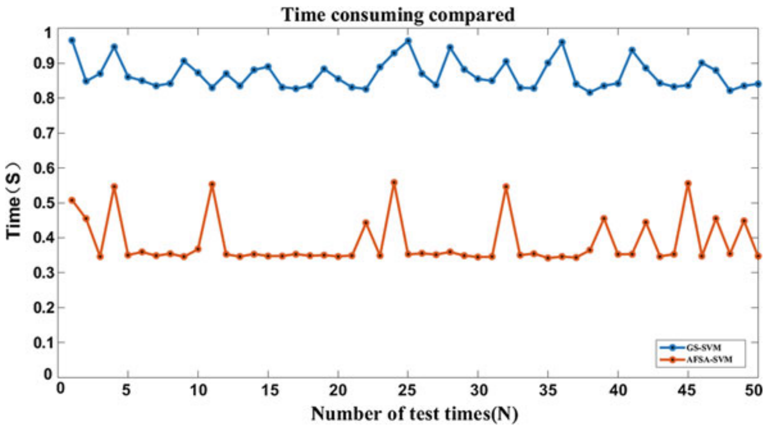


Fig. 13 The time-consuming comparison of the GS-SVM and AFSA-SVM

Table 2 Statistics data of the AFSA-SVM and GS-SVM

	AFSA-SVM	GS-SVM
Min	**80.9524**	44.8179
Max	**96.8908**	88.2352
Mean	**89.5848**	74.08123
Media	**90.14**	80.81232
Std	3.4698	**14.9766**

4 Conclusion

In the process of variable polarity TIG welding molten pool status classification for 2219 aluminum alloy, we have constructed an intelligent sensor system for TIG welding, With the one-chip microcontroller’s penalty control, we achieved the camera image and illuminated the molten pool with the auxiliary light source, so we obtained a clear image of the weld molten pool. And we developed a detection method for the weld pool width, wire feed speed, welding current, misalignment and interval. These five variables are the inputs to the Support Vector Machine (SVM), and the SVM outputs are three states of penetration: lack of penetration, full penetration and over penetration. The penalty factor and kernel function of SVM algorithm obtained by artificial fish algorithm. Experimental results show that modeling classification accuracy is 91.0364%, with promising classification effect, at the next stage of research work we will improve the SVM algorithm to achieve even higher classification accuracy.

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