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ORIGINAL ARTICLE

A welding quality detection method for arc welding robot based on 3D reconstruction with SFS algorithm

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Abstract In the modern manufacturing industry, the welding quality is one of the key factors which affect the structural strength and the comprehensive quality of the products. It is an important part to establish the standard of welding quality detection and evaluation in the process of production management. At present, the detection technologies of welding quality are mainly performed based on the 2D image features. However, due to the influence of environmental factors and illumination conditions, the welding quality detection results based on grey images are not robust. In this paper, a novel welding detection system is established based on the 3D reconstruct technology for the arc welding robot. The shape from shading (SFS) algorithm is used to reconstruct the 3D shapes of the welding seam and the curvature information is extracted as the feature vector of the welds. Furthermore, the SVM classification method is adopted to perform the evaluation task of welding quality. The experimental results show that the system can quickly and efficiently fulfill the detection task of welding quality, especially with good robustness for environmental influence cases. Meanwhile, the method proposed in this paper can well solve the weakness issues of conventional welding quality detection technologies.

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1 Introduction

Welding technology is an indispensable process in modern manufacturing industry. It plays an important role in the industrial productions. With the substantial increase of automatic industrial production lines and the rapid development of robot technologies, the welding robots are more and more applied into the complex, narrow, and dangerous working environment to replace human work, such as automobile production lines, ship manufacturing, electrolytic metallurgy, nuclear power [1]. At the same time, these industries have strict limits of the welding quality. Compared with human welding, the welding robots cannot only ensure the welding quality but also could improve the welding efficiency. Meanwhile, they also could improve the technical level of industrial productions and realize the automated production of the enterprises. Therefore, welding robots are the typical representative of intelligent manufacturing technology.

At present, more and more attention has been paid to the detection and control of welding quality in the industrial productions. The welding quality not only affects the appearance of the products but also may affect the structural strength and bring some hidden dangers to the production safety. Therefore, the link of welding quality detection is crucial to the enterprises. At present, the common detection methods of welding quality can be divided into two categories: contacting measurement and non-contact measurement. The common contacting measurement equipment is three coordinate measurement machine(CMM). But the measurement speed of CMM is too low and it may cause some danger to the the appearance of the products. During the study of non-contact measurement, industrial CT is a mature method for quality detection. Industrial CT usually uses radiation rays (X-rays) to capture the complete and accurate 3D information of objects to realize the fast and accurate 3D detection. However, the cost of the industrial CT is too high for the small and medium enterprises. And the volume of the industrial CT is relatively larger, so it is not suitable for the automatic industrial production lines. With the development of optical measurement, optical measurement has been widely used in non-destructive measurement of product appearance. Mery et al. [2] used the method based on image grey histogram to detect the welding quality, and she also put forward an evaluation method of the weld appearance. Based on the analysis and processing of the grey images of the welds, Wang et al. [3] proposed the detection method of welding quality based on mathematical morphology to achieve the detection and location of welding defects.

With the development of pattern recognition and machine learning, some methods based on machine learning are applied into the detection of welding quality. In order to realize the detection of the welding quality, Zhang et al. [4] used neural network to realize the recognition of weld defects. Compared to the traditional image processing methods, the recognition method could well solve the problems of fuzzy boundary and it could improve the recognition accuracy rate. Besides, Li et al. [5] used the defect identification algorithm based on the recursive least squares parameter estimation to detect the welding quality and this method could effectively realize the online detection of welding defects. Meanwhile, the algorithm had certain fault tolerance and robustness. Wang et al. [6–8] explored the relationship between weld pool defect and image features. Through the collection and processing of weld pool image of MAG, the relationship between singular eigenvalue and welding defects was explored to realize the welding defect detection. During the detection researches of welding quality, most of the research works are done based on the 2D grey image to achieve the detection of welding quality. Due to the factors of the angle, the light transformation and so on, the recognition effect based on 2D image will be greatly affected and the detection methods of welding quality are not robust. Therefore, this paper combines the 3D information of welds and machine learning to realize the automatic detection of the welding quality.

At present, the researches about 3D reconstruction have been a hot research topic in the field of computer vision, and they have been widely applied into virtual reality, reverse engineering, robot navigation, industrial measurement, and so on. The common methods of 3D reconstruction include stereo vision [9, 10], structured light vision [11], time of flight (TOF) [12], shape from shading (SFS) [13], and so on. By acquiring two or more 2D images from different angles, stereo vision is used to obtain the 3D coordinates based on the triangulation principle. However, stereo vision has the disadvantages of large computation and poor match efficiency. It is difficult to be applied into the industrial environment with single structure and simple texture. The 3D vision methods based on structured light project some certain patterns onto the object surface of by the optical projector. And the 3D models of the different objects can be reconstructed from the processing of distorted images with the light patterns. The common structured light methods are coded structured light and line structured light [14–16]. The measurement equipment of the coded structured light is too large due to the large volume of projector device, so it is difficult to be applied into industrial production. Meanwhile, the line structured light belongs to the local vision sensor which cannot get much information about the welds and the scanning rate of the line structured light is too slow. The measurement accuracy of TOF has low measurement accuracy. At the same time, the noise will increase with the increase of the measurement distance. According to the certain reflection model, the methods based on SFS algorithm establish the constraint relationship between the shape of the object and the brightness of the image to recover 3D shape of the object. In recent years, many scholars have studied this method to recover the 3D shape of the object, and applied it to pattern recognition, industrial detection and so on. Meanwhile, this method only needs one image to recover 3D information of the object and this method has high efficiency. Therefore, in this paper, the 3D shapes of welds are reconstructed by the method of SFS algorithm.

According to the detection task of different welding quality, the automatic classification algorithm is designed in this paper based on SFS algorithm and support vector machine (SVM) algorithm. Firstly, the SFS algorithm is used to realize 3D reconstruction of the weld appearance. Secondly, the curvature information of 3D shape of weld is extracted as the feature vector. Finally, the SVM classification strategy is selected to realize the automatic detection of welding quality and achieve a better classification effect. The main contributions of this paper are described as follows: (1) According to the shortcomings of the traditional detection methods of welding quality based on 2D image, the 3D information of welds is adopt in this paper. (2) Through the defects analysis of the traditional methods of 3D reconstruction, the weld is reconstructed by the method of SFS algorithm, and this method is simple and efficient for industrial applications. (3) The SVM classification strategy is used to do the classification task and the automatic classification task of welding quality can be well realized.

This rest of this paper is organized as follows: Section 2 introduces the method of 3D reconstruction based on SFS algorithm, Section 3 introduces the method of feature

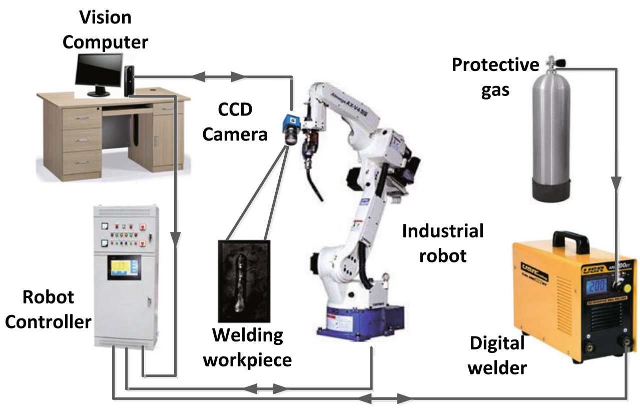


Fig. 1 The structure of welding robot system

extraction of the welds with different welding quality, Section 4 introduces the classification methods based on SVM algorithm, Section 5 is about the analysis of the experimental results, and finally, the conclusion and prospect of this paper is described in Section 6.

2 System configuration

In order to complete the automatic detection task of the welding quality, this paper sets up the welding experimental platform based on the industrial robot, and the structure of the welding system is shown in the Fig. 1. It includes industrial manipulator, industrial robot controller, digital welder, welding protective gas, the visual system, and welding workpiece.

For the robot vision system, the CCD camera is installed at the end of the industrial manipulator, so the monocular vision system is set up. Here, the industrial manipulator uses the Motoman UP6 industrial manipulator to do the welding task. The high-performance CCD industrial camera with a total pixel number of 1280*1024 HV-1351UM-M is adopted and the collected images are transmitted to the visual computer through USB ports of visual computer.

At present, the intelligent welding robot technology has been greatly improved. It can realize the autonomous planning of robot path and optimize the welding process. However, due to the interference of environmental factors, the welding quality will be greatly affected and it will affect the appearance, structural strength, comprehensive quality and so on. Therefore, the detection of welding quality is very necessary. To achieve the detection task of welding quality, the following process as shown in the Fig. 2 must to be done:

(1) Image pre-processing. An effective filter is selected to remove the noise signal for the 3D reconstruction of welds.
(2) 3D reconstruction. The speed and efficiency of algorithm is the core of the welding system. In order to accelerate the 3D reconstruction, the SFS algorithm is adopt.
(3) Feature extraction. Through the analysis of traditional images features, the curvature information of 3D welds is selected to construct the feature vector of different welds.
(4) Classification of welding quality. Aimed at the small sample welds, the SVM classification method is adopt in this paper to achieve the detection task of welding quality.

3 3D reconstruction of weld shape

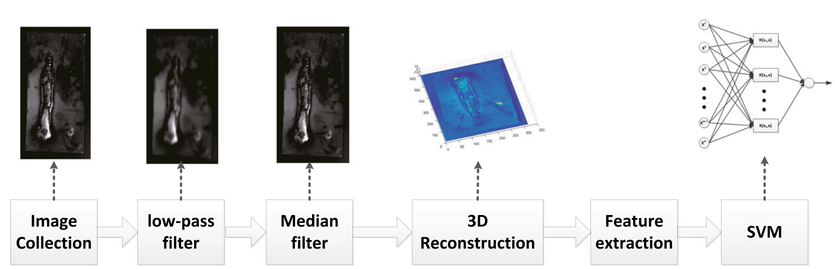
3.1 Image preprocessing

During the process of the SFS algorithm, the efficiency and accuracy of 3D reconstruction have a great relationship with the image quality. In the process of image generation and image transmission, the images will be disturbed by the noise of different degrees. At the same time, the light reflection and the mirror reflection will bring some certain interference information to the 3D reconstruction. These factors will affect the quality of the 3D reconstruction, and affect the results of feature extraction. Therefore, it is necessary to preprocess the weld images.

The object of 3D reconstruction algorithm is gray images, so the color image must be converted to a grayscale image. The conversion from the RGB image to grayscale image can be achieved by equation as follows.

$$I_{gray}(u,v) = [0.3\ 0.59\ 0.11]\begin{bmatrix} I_{clor\,R}(u,v) \\ I_{clor\,G}(u,v) \\ I_{clor\,B}(u,v) \end{bmatrix} \tag{1}$$

Fig. 2 The system flow chart



where I_{gray} is the calculated grey image, (u, v) is the pixel coordinate, $\{I_{clorR}, I_{clorG}, I_{clorB}\}$ are the red, green, and blue components of color images respectively. The camera in this paper is a color CCD camera, so the color image captured must be converted the grayscale image for the 3D reconstruction of welds. If the monotone camera is used, this step could skip.

However, gray image cannot eliminate the noise information. In order to better remove the image noise. In this paper, the selection of a suitable image filter is very important. The valuable information of 2D images is mainly concentrated in the low frequency part, while the image noise often belongs to the high-frequency signal. In order to remove the noise information of the images and preserve the important information of the 2D images, this paper uses Gauss low-pass filter algorithm to filter weld images.

However, there will inevitably be some relatively large noise signal, Gauss low-pass filter algorithm cannot completely remove the noise signal. Median filter is a common nonlinear signal processing algorithm, it can be a good way to eliminate the larger noise information, and maintain the details of the grey image. At the same time, the median filter can also prevent the edge blur of the gray image and preserve image details. Therefore, in this paper, combined with the gray operation, low-pass filter and median filter, the image pre-processing of the weld image is done.

3.2 3D reconstruction of weld

In the industrial production and application, the efficiency of 3D reconstruction is very important. During the SFS algorithm, it requires only one grey image and it could recover the 3D shape of the object to be measured. The efficiency is relatively high and it can meet the needs of real-time 3D reconstruction. So this algorithm is very suitable for 3D reconstruction of the welds. The model of SFS algorithm can be described in the Fig. 3.

At present, the SFS algorithms usually use the ideal surface model to simplify the problem to be solved. Under the assumptions of ideal conditions, the brightness model of Lambertian surface can be expressed as follows:

$$E = I\rho * cos\beta = I\rho * \frac{(pp_0 + qq_0 + 1)}{\sqrt{p_0^2 + q_0^2 + 1}\sqrt{p^2 + q^2 + 1}} \quad (2)$$

where I is the intensity of incident light source, ρ is the reflection coefficient, β represents the angle between the direction vector of the surface and the direction of the incident light. $S = (p, q, 1)$ represents the direction vector of object surface. $n_0 = (p_0, q_o, 1)$ represents the direction of the incident light source. The SFS algorithms could solve the problem from the intensity of the grey images to recover the direction of the object's surface, and the height information of the object surface could be solved through the integration operation of the direction vector of the object surface.

At present, during much researches of SFS algorithm, the common SFS algorithms could be divided into four categories, minimization methods, evolution methods, local analysis methods, and linearization methods [13, 17]. The 3D reconstruction based on SFS algorithm is an ill posed problem and the Eq. 2 exists multiple solutions. Therefore, it is necessary to add some constraints to the 3D reconstruction based on SFS algorithm [18]. The common constraints of the illumination model are described as follows:

(1) Brightness constraint:

$$\iint (E - R)^2 d_x d_y \quad (3)$$

where E is the Luminance information obtained from the initial image, R is estimated luminance information.

(2) Smoothness constraint:

$$\iint \left(p_x^2 + p_y^2 + q_x^2 + q_y^2\right) d_x d_y \quad (4)$$

where p and q are respectively the gradient of X and Y directions.

(3) Integrability constraint:

$$\iint (p_x - q_y)^2 d_x d_y \quad (5)$$

(4) Brightness gradient constraint:

$$\iint ((R_x - E_x)^2 + (R_y - E_y)^2) d_x d_y \quad (6)$$

In this paper, the 3D reconstruction of the welds is completed by the linearization method proposed by Tasi [13]. This algorithm is simple and efficient and it is adopted for 3D reconstruction of welds. In order to solve the height

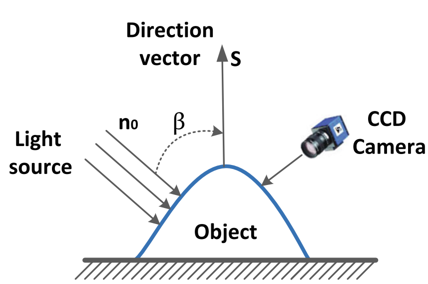


Fig. 3 The SFS algorithm model

information of the object surface, the discretization operation of the reflection function is performed. The discretization model of the reflection function can be expressed as follows:

$$p = \frac{\partial z}{\partial x} = z_{i,j} - z_{i,j-1} \tag{7}$$

$$q = \frac{\partial z}{\partial y} = z_{i,j} - z_{i-1,j} \tag{8}$$

$$f(z_{i,j}) = E - R(z_{i,j} - z_{i,j-1}, z_{i,j} - z_{i-1,j}) \tag{9}$$

where p and q are respectively the gradient of X direction and Y direction, i and j represent the row index and column index of the image, and f represents the reflection function. At the same time, the reflection function can be expressed as Taylor series expansion. The expression of the reflection function can be expressed as follows:

$$f(z_{i,j}) \approx f({z_{i,j}}^{n-1}) + (z_{i,j} - {z_{i,j}}^{n-1})\frac{\partial f}{z_{i,j}}({z_{i,j}}^{n-1}) \tag{10}$$

where n is the number of iteration.

Here, the height values of the object surface through n-iterations exterior could be expressed as follows:

$$z_{i,j} = {z_{i,j}}^{n} \tag{11}$$

Based on the above derived results, the form of the reflection function can be expressed as follows:

$$\frac{\partial \mathrm{f}}{z_{i,j}}\left({z_{i,j}}^{n-1}\right) = -\left(\frac{(pp_0 + qq_0 + 1)}{\sqrt{{p_0}^2 + {q_0}^2 + 1}\sqrt{p^2 + q^2 + 1}} - \frac{(p+q)\left(pp^0 + qq^0 + 1\right)}{\sqrt{(p^2 + q^2 + 1)^3}\sqrt{{p_0}^2 + {q_0}^2 + 1}}\right) \tag{12}$$

Combined with these constraints of the illumination model, the final height information of the object surface can be solved by iteration process in the case of a given initial value. The SFS algorithm can well meet the needs of real-time detection of welding quality and it is very suitable for the industrial applications.

4 Detection of welding quality

4.1 Feature extraction

Faced with the variability of object, the background environment, illumination, and so on, an accurate and stable feature of weld is the key part of detection of welding quality. The feature representation of the 2D image can be divided into edge feature, geometric feature, and so on. The edge feature is simple and stable. However, the edge feature is not suitable for the complex objects. The geometry features have the advantages of translation invariance, rotation invariance, and transformation invariance, which have been widely applied into image classification. The common geometric features include image singular value, Hu matrix, Zernike matrix, and so on. However, due to factors of the environmental change, occlusion problems and other factors, the recognition effect based on 2D features will be greatly affected. So this paper uses the features of 3D object to realize the detection of the welding quality.

At present, the curvature information is the common features of the 3D shape. And the curvature information includes the maximum curvature, minimum curvature, total curvature, Gauss curvature, mean curvature, and so on [19]. Curvature information is the most basic features of object surface. The curvature information of the object surface has the advantage of attitude invariance and does not change with the object motion. Compared with the traditional 2D image features, the curvature information of the object surface has the following advantages:

1. Compared with the 2D image features, curvature information can provide more abundant information.
2. The curvature information can provide high accuracy about the shape characteristics of the object to be measured, which can better describe the appearance of the weld.
3. The curvature information has the advantages of posture invariance and good robustness.

Therefore,the curvature information of the weld is used as the features of different welds in this paper.

Hessian matrix is a high order differential equation, which is a common method in the image feature extraction. It is widely applied into object detection and shape analysis. At the same time, Hessian matrix also is widely applied in medical image segmentation, 3D reconstruction, and so on. For 2D images, the Hessian matrix can be constructed by two order partial derivatives. The form of the Hessian matrix can be expressed as follows:

$$H = \begin{bmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial x \partial y} \\ \frac{\partial f}{\partial y \partial x} & \frac{\partial f}{\partial y^2} \end{bmatrix} \tag{13}$$

where f represents the 2D grey image, x and y represent the row index and column index of grey image and H represents the Hessian matrix. The eigenvalues of the Hessian matrix are respectively equal to the maximum curvature Q_1 and minimum curvature Q_2. The total curvature, Gauss curvature and mean curvature can be constructed through the maximum and minimum curvature. The specific expressions can be described as follows:

(1) Gauss curvature:

$$K = Q_1 * Q_2 \tag{14}$$

(2) Total curvature:

$$H = \frac{1}{2}(Q_1 + Q_2) \tag{15}$$

(3) Mean curvature:

$$C = \sqrt{\frac{Q_1^2 + Q_2^2}{2}} \tag{16}$$

Various welding quality have different 3D appearances and different appearances determine different curvature information. Therefore, the curvature information can be used to distinguish the different welding quality. By solving the above curvature information, curvature information of welds can be used to construct the feature vectors as the input of recognition algorithm of welding quality.

In the actual experiment, the curvature information of the different object surfaces is very different, so it is difficult to apply the curvature information directly to the actual recognition and classification tasks. Here, this paper uses the idea of normalization to eliminate the difference of different objects.

$$M_i = \frac{M_i - M_{min}}{M_{max} - M_{min}} \tag{17}$$

where M_i represents curvature information which needs to be normalized, M_{max} and M_{min} represent the maximum and minimum values of curvature information.

4.2 Detection method based on SVM

An efficient and stable identification algorithm for the detection of welding quality is also the key part of the whole process. During the evaluation of the welding quality, it is necessary to establish a suitable evaluation algorithm.

At present, the common classification methods include similarity classification method [20], K-nearest nei-ghbors (KNN), artificial neural network (ANN) [21], SVM [22]. The SVM classification method is based on the VC theory of statistical learning and the principle of structural risk minimization, and it has shown excellent performance in solving small sample, nonlinear problems, and high dimensional spaces. Therefore, the SVM classification algorithm is selected in this paper to complete the automatic detection of welding quality. The SVM classification algorithm can find the optimal hyperplane $w^T\phi(x) + b = 0$ to maximize the difference between different classes, and the optimal classification problem can be expressed as a constraint problem. The form of the objective function can be expressed as follows:

$$\begin{cases} \min \phi(w) = \frac{1}{2}\|w\|^2 \\ s.t.\ y_i\left(w^T x_i + b\right) - 1 \geq 0 \end{cases} \tag{18}$$

In the practical application and research, due to the complexity of the classification samples, the samples often show the linearly non-separable characteristics. In order to better achieve the classification task of different samples, the slack variable ξ_i is introduced to the objective function. The new form of the Eq. 18 can be expressed as follows:

$$\begin{cases} \min \phi(w) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m}\xi_i \\ s.t.\ y_i\left(w^T x_i + b\right) \geq 1 - \xi_i \\ \quad \xi_i \geq 0, (i = 1, 2, \cdots, m) \end{cases} \tag{19}$$

where C is the specified constant which is called the penalty factor. Adding penalty terms to the objective function is a more common method of optimization. It controls the degree of penalty for misclassification samples. In order to construct the linear discriminant function, SVM classification method changes the input vector space into a high dimensional space by a nonlinear transformation. Through the increase the dimension of the input vector space, SVM classification method could obtain the optimal classification plane in this new space and achieve the linear separable task. The function form of nonlinear transformation could be expressed as follows:

$$f(x) = w^T\phi(x) + b \tag{20}$$

where $\phi(x)$ is the mapping function and it could transform the input vector space into a high dimensional space. So the objective Eq. 19 can be updated as follows:

$$\begin{cases} \min \phi(w)\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m}\xi_i \\ s.t.\ y_i\left(w^T \phi(x_i) + b\right) \geq 1 - \xi_i \\ \quad \xi_i \geq 0, (i = 1, 2, \cdots, m) \end{cases} \tag{21}$$

The nonlinear mapping transformation of SVM is realized by the inner product function. The different inner product function will lead to different types of SVM algorithms, so the specific SVM model can be expressed as shown in the Fig. 4. In the Fig. 4, X^i represents the Input feature vector, $K(x_i, x)$ represents the inner product function of nonlinear mapping and it could realize the mapping of input vector space to a high dimensional space. At present, there are four kinds of common inner product functions: linear kernel function, polynomial kernel function, radial basis kernel function, and S function. As a common kernel function, the radial basis kernel function is adopted in this paper. It can better solve the classification task of linearly non-separable samples. The form of the radial basis kernel function can be expressed as follows:

$$k(x_i, x_j) = \exp\left(-g\left\|x_i - x_j\right\|^2\right) \tag{22}$$

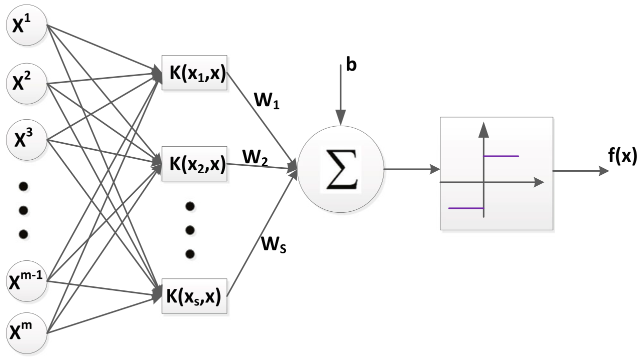


Fig. 4 The SVM system model

Based on the radial basis function, the SVM model can be constructed by selecting the appropriate penalty factor and parameters of the kernel function. In this paper, the idea of cross validation is used to solve the parameters of C and g by grid search strategy [23]. The method uses coarse search to determine the better parameter values of SVM model. Finally, based on the results of coarse search, the optimal values are determined by the fine search. Combined with the weld images, the search results of the parameter of SVM model are shown in the Fig. 5. The red number in the Fig. 5 indicates the accuracy of cross validation. In the search process of SVM parameter optimization, the final accuracy of cross validation is 95.1%.

5 Experiment

In order to better verify the performance of detection method of the welding quality, this paper designs a series of welding experiments. The experimental system is shown in the Fig. 6.

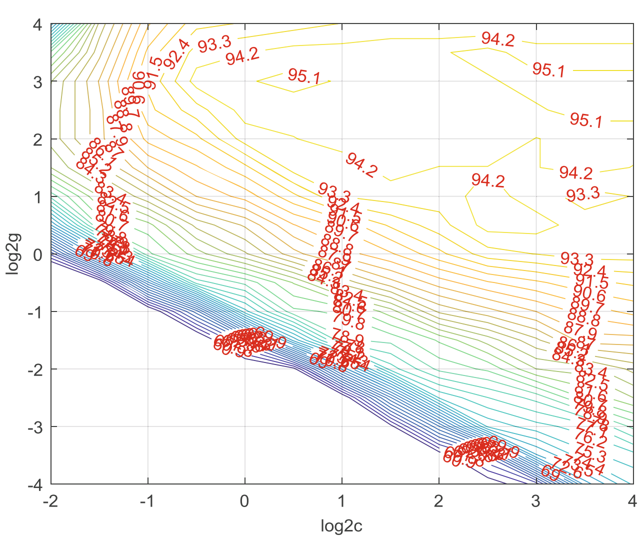


Fig. 5 The search results based on cross validation

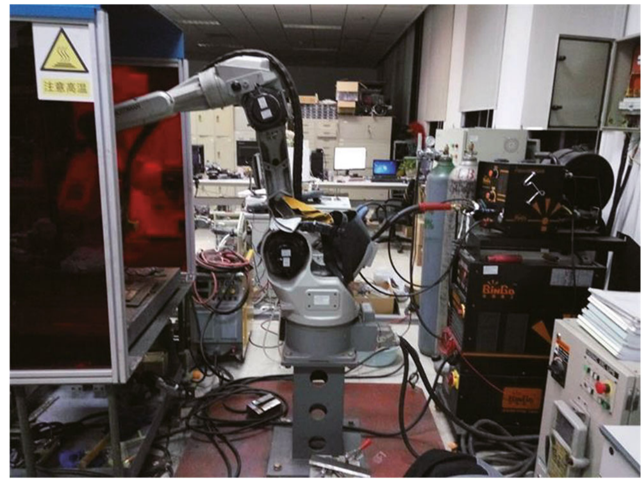


Fig. 6 The experimental system

5.1 3D reconstruction of weld shape

In order to verify the performance of 3D reconstruction of welds, much weld experiments are done. The inadequate penetration and incomplete fusion are common welding defect which seriously affect the structural strength and the comprehensive quality of the product. So we adjust the welding current, welding voltage, welding speed, and other welding parameters to form these welding quality and apply them to the performance verification of detection algorithm. Here, this paper selects three welding workpieces with different welding quality . The specific pictures of the welding workpieces are shown in the Fig. 7.

According to the above experimental results, the welding quality of these welds in the Fig. 7a is regular and the welding quality is better. The partial area of the weld in the Fig. 7b is not good and it belongs to inadequate penetration. The weld in the Fig. 7c is the worst. The weld is not completely formed and the appearance of weld is not neat. It belongs to incomplete fusion. The welding workpiece without weld in the Fig. 7d is set to be the contrast experiment. At the same time, this paper uses the SFS algorithm to reconstruct the above four sets of welding workpiece. The experimental results of the 3D reconstruction are shown in the Fig. 8.

According to the above 3D experimental results, the 3D reconstruction based on SFS algorithm can quickly and efficiently recover the 3D shape of welds. It could better solve the 3D reconstruction of different welds with simple and single texture. However, the 3D reconstruction based on SFS algorithm also has some shortcomings, for example, the results of 3D reconstruction are not very ideal. But the characteristics of each type of welding quality can be obtained and meet the requirements of the classification task of welding quality by the experiment verification.

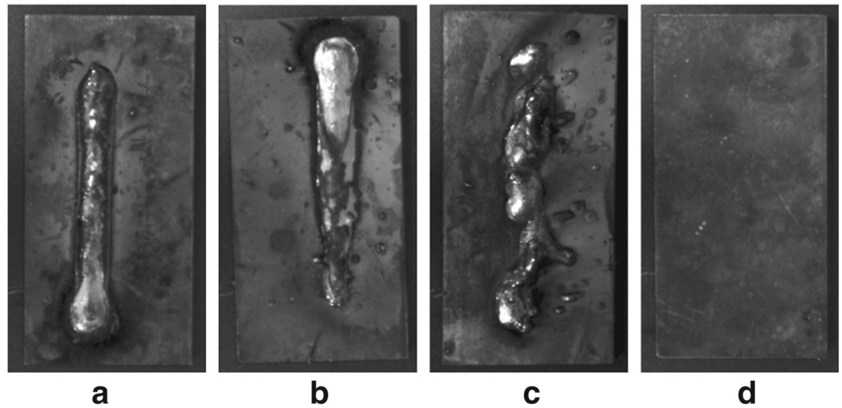


Fig. 7 2D gray images of different welds. **a** Integrity weld. **b** Inadequate penetration. **c** Incomplete fusion. **d** Workpiece

5.2 Feature extraction of weld

Feature extraction of weld is the precondition of the detection methods of welding quality. Based on the results of 3D reconstruction, the curvature information is calculated as the feature vector of the 3D shape of the weld, and it is used as the input of the classification method of the welding quality.

Here, the total curvature information is selected as an example and we calculate the total curvature information of the four kinds of welding workpieces in the Fig. 8. The special results of the total curvature information are shown in the Fig. 9.

Through the above experimental results, it can be seen that the calculated results of the total curvature of the welds

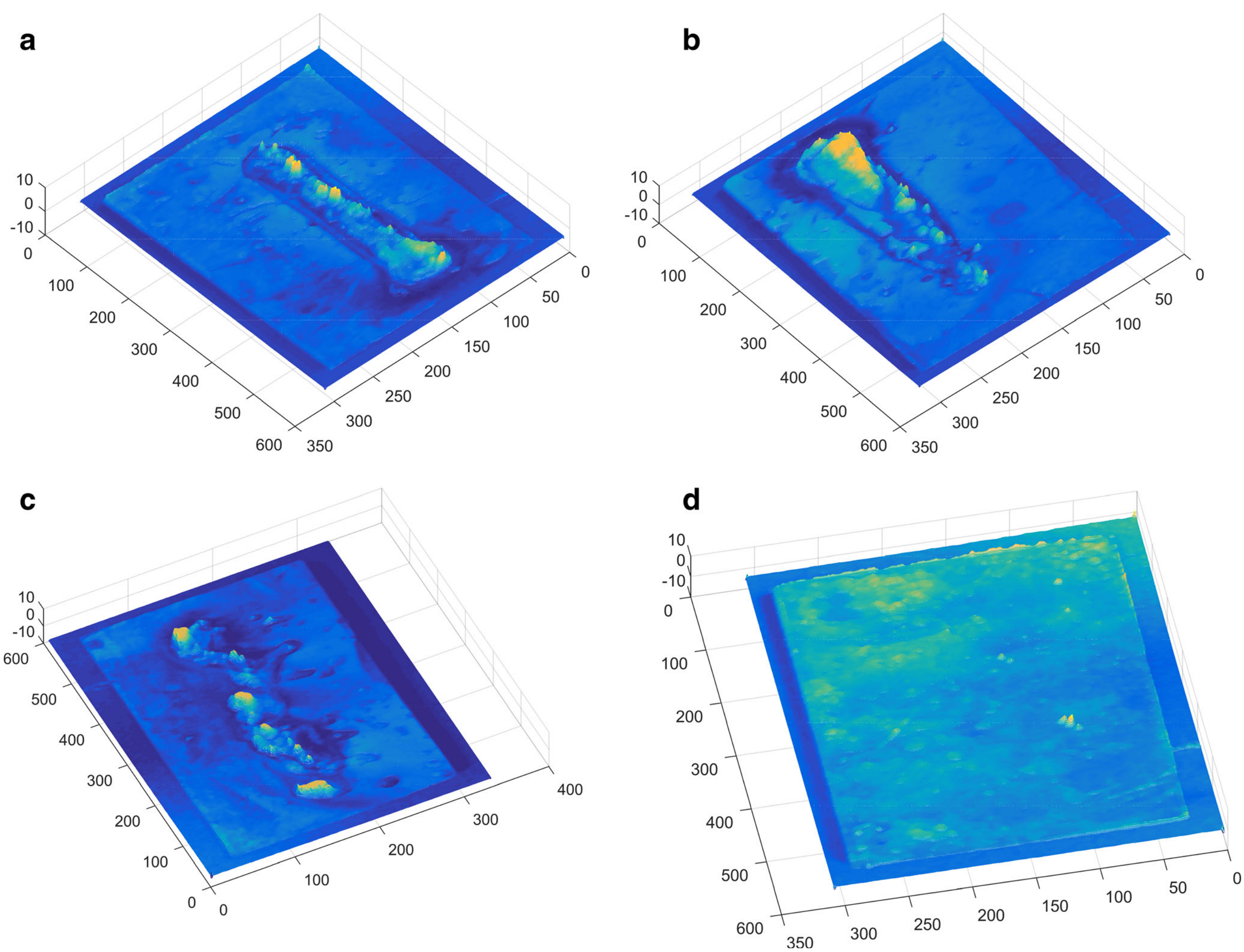


Fig. 8 The 3D Reconstruction of different welds. **a** Integrity weld. **b** Inadequate penetration. **c** Incomplete fusion. **d** Workpiece

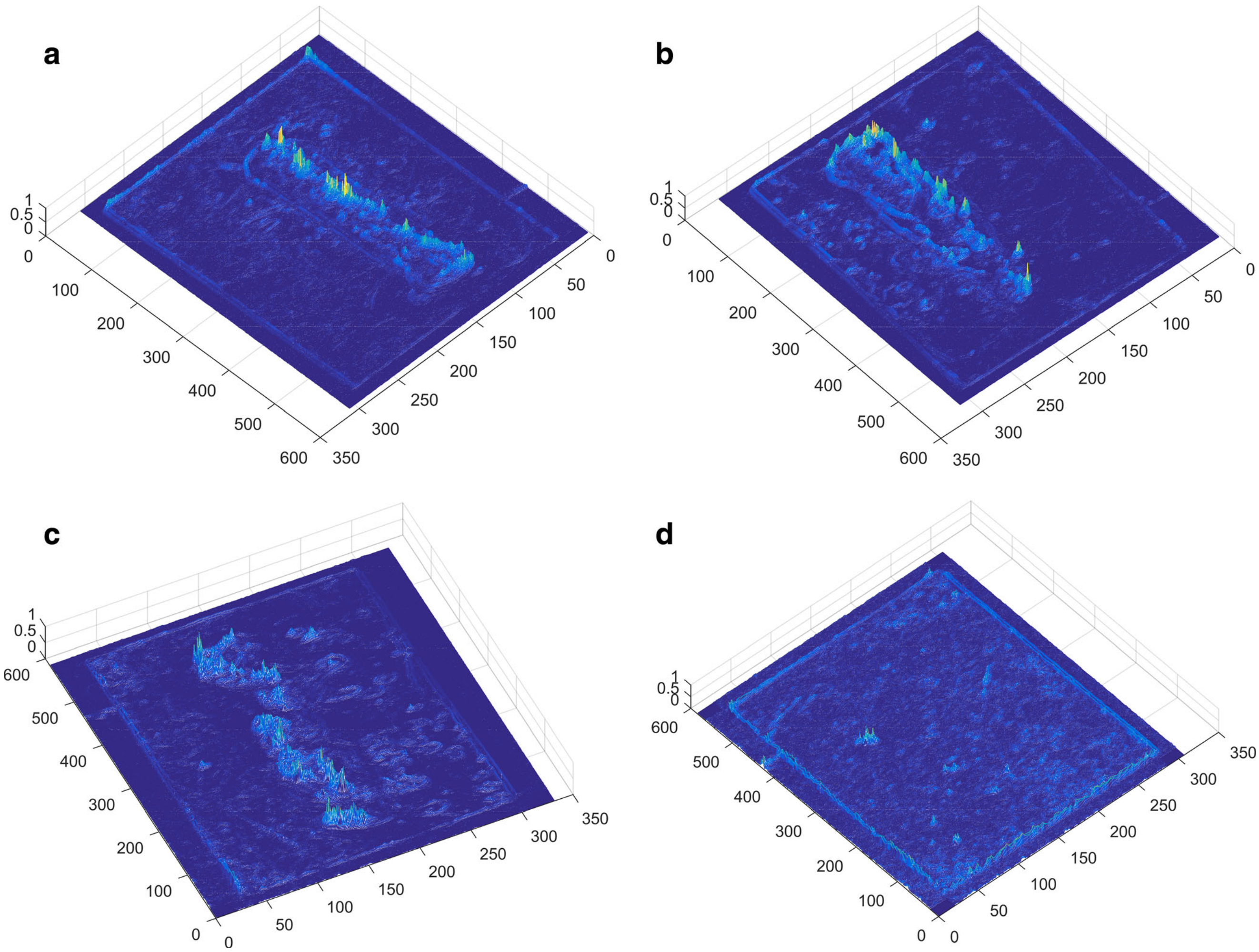


Fig. 9 The total curvature information of different welds. **a** Integrity weld. **b** Inadequate penetration. **c** Incomplete fusion. **d** Workpiece

with different appearance are different, and the calculation results of the total curvature have a great relationship with the appearance of the weld.

The weld in the Fig. 9a is regular and the curvature distribution is uniform. The curvature information in the Fig. 9b, c changed with the shape change of weld. The weld in the Fig. 9d is relatively smooth. Therefore, in this paper, the curvature information of weld is selected as the feature vector of the welds with different welding quality to achieve the detection of welding quality.

In order to better reflect the differences of feature vectors between different weld samples, the Euclidean distance is computed to measure the difference between different samples.

$$R(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{23}$$

Here, the weld in the Fig. 10a is set as a template, and this paper selects the other seven experimental samples with different welding quality. The specific pictures of experimental samples are shown in the Fig. 10. The calculated results of Euclidean distance are shown in the Table 1.

Based on the above experimental results, it can be seen that the Euclidean distance with different welding quality will vary greatly. Therefore, the curvature information of weld can be set as the feature vector to distinguish different welding quality. It could better distinguish the welding quality of inadequate penetration, incomplete fusion, and integrity.

5.3 Classification of welding quality

For the detection of welding quality, a monocular vision system is installed at the end of the robot. In the movement of the manipulator, it is easy to fluctuate during the image collection. The singular value of the image has a good robustness to the image fluctuation and has good stability to the small disturbance. So it is widely applied in many applications, such as image recognition, object tracking, and

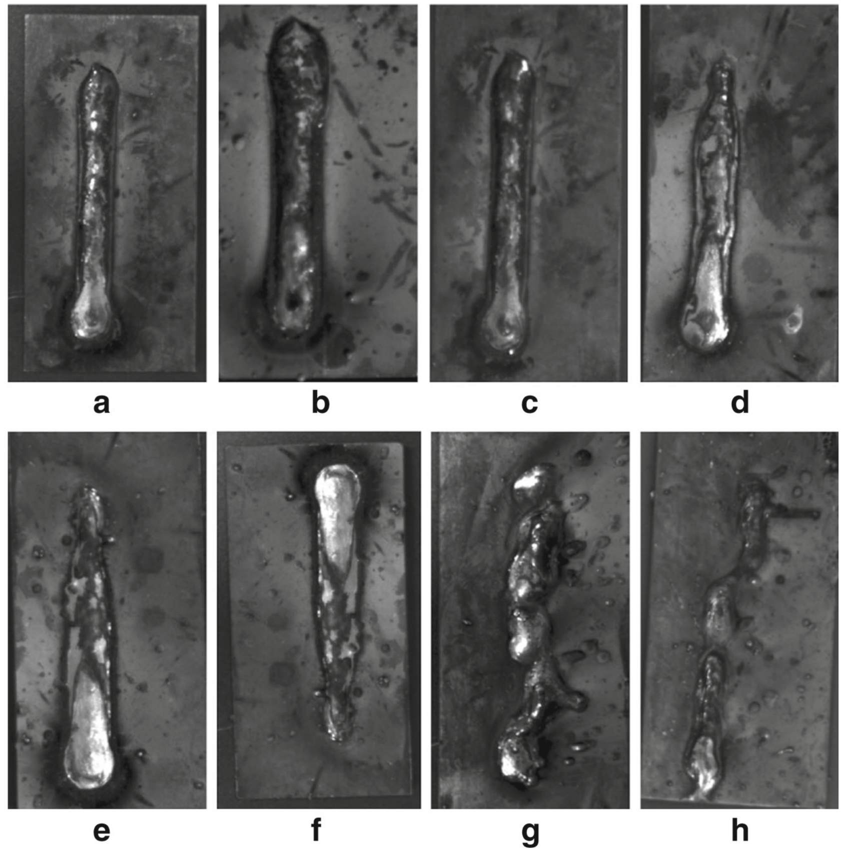


Fig. 10 2D gray images of different workpieces. **a–c** Integrity weld. **d–f** Inadequate penetration. **g–h** Incomplete fusion

so on. To better verify the performance of the proposed algorithm, in this paper, the classification method based on singular value of image is set as the contrast experiment.

In order to better reflect the robustness of the proposed method, some noise signals are added to the original image. In this paper, the noise density of salt and pepper noise is 0.02. The mean and variance of gauss noise are 0 and 0.02 respectively. The mean and variance of speckle noise are 0 and 0.03 respectively. Meanwhile, aimed at the welds with integrity weld, inadequate penetration and incomplete fusion, 60 sample images of every weld type are collected to train the SVM model. Through the process of image preprocessing, 3D reconstruction and feature extraction, the sample library of weld is constructed. Based on the algorithm of cross validation, the calculation results of SVM parameters are shown in the Table 2.

In order to verify the performance of the proposed algorithm, 300 weld images with different welding quality are collected and are set as the test samples. Combined with these test samples, the proposed method, and the classification method based on image singular value are computed. The special experimental results are shown in the Table 3.

Based on the above experimental results, the classification method based on SFS algorithm can obtain higher classification accuracy compared with the classification method based on singular value and it has better classification

Table 1 Similarity calculation based on SFS

Case	Case description	Euclidean distance	Welding quality
1	A	0.000	Integrity weld
2	B	0.170	Integrity weld
3	C	0.156	Integrity weld
4	D	0.798	Inadequate penetration
5	E	0.873	Inadequate penetration
6	F	0.846	Inadequate penetration
7	G	1.587	Incomplete fusion
8	H	1.784	Incomplete fusion

Table 2 The parameters of SVM model

Case	Case description	c	g
1	Singular value	1.4142	8
2	Proposed method	11.3137	8

Table 3 The classification results based on SVM

Case	Case description	Classification results	Accuracy rate
1	Singular value	229/300	76.33%
2	Proposed method	282/300	94.00%

performance. The classification method based on singular value of image cannot overcome the problem of image rotation, so the classification accuracy is lower. Therefore, the classification method based on SFS algorithm can well accomplish the classification task of welding quality.

6 Conclusion

Aimed at the detection task of welding quality, the automatic classification algorithm of welds with different welding quality is designed in this paper. The 3D reconstruction of welds, feature vectors computation, and the classification of welding quality are described in detail. The following conclusions are drawn:

1. According to the disadvantages of the detection methods based on 2D images features, the 3D information of weld is used to realize the detection of welding quality. The method could get rich information and the algorithm has good robustness.
2. The 3D reconstruction of the weld is realized by the monocular vision with SFS algorithm. And the method only needs one image to recover 3D shape, so the algorithm is simple and efficient.
3. Compared with 2D image feature, the curvature information of weld has many advantages, such as posture invariance, rotation invariance. And it does not change with the motion of the object.
4. The SVM method is a good solution to classification task with the small sample and nonlinear problem. So the SVM is very suitable for the detection of welding quality.

However, there are still some defects of the proposed method in this paper. Although the 3D reconstruction based on SFS algorithm can satisfy the requirement of the experiment and could deal with the 3D reconstruction of different types of welds, the effect of 3D reconstruction is not ideal. Meanwhile, the curvature feature contains limited information and it cannot be applied into the detection task of complex welds with complex structure and characteristics, such as multi-pass and circular welding. In the future, we will improve our work and select an effective and robust feature to adapt to different types of welding task.

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