An efficient system based on model segmentation for weld seam grinding robot

Jimin Ge · Zhaohui Deng · Zhongyang Li · Wei Li · Tao Liu · Hua Zhang · Jiaxu Nie

Received: 7 October 2021 / Accepted: 8 July 2022 / Published online: 2 August 2022
© The Author(s), under exclusive licence to Springer-Verlag London Ltd., part of Springer Nature 2022

Abstract
Uneven surface quality often occurs when manual grinding butt welds, so robot welding seam grinding automation has become a fast-developing trend. Weld seam extraction and trajectory planning are important for automatic control of grinding process. However, the research on weld extraction is mostly focused on pre-welding. Due to the irregular shape of the weld after welding and the complex grinding process, there is seldom work that has been devoted to the weld grinding after welding. Consequently, a novel simple but efficient weld extraction algorithm is proposed in this paper, and the robot grinding path is planned. Firstly, a multi-degree of freedom bracket is designed for welding seam extraction. Secondly, the weld profile model is established, and a simple but effective weld extraction algorithm based on model segmentation is proposed to transform the calculating process of spatial point cloud into a two-dimensional point cloud calculating process. The least-square method (LSM) based on threshold comparison is used to segment the weld seam, which greatly improves the processing speed and accuracy. Then, the grinding path and grinding pose are calculated according to the extracted spatial structure of weld seam. Finally, an efficient robotic welding seam automatic grinding system based on model segmentation is built. Experiments’ results showed that the proposed method could make the irregular weld seam contour well-extract after welding and the built grinding system is efficient and reliable. The grinding efficiency is increased by 50%.

Keywords
Robot · Weld seam extraction · Model segmentation · Automatic grinding system

1 Introduction

Welding technology plays an irreplaceable role in shipbuilding, automobile, rail transport, aerospace, and other fields [1, 2]. However, welding stress will be generated in the welding zone after welding, which greatly reduces the connection strength between the workpiece. The welding stress can be reduced and the fatigue strength of the workpiece can be improved by grinding the weld seam [3, 4]. Therefore, it is of greatly important practical value and significance to grind the weld after welding. At present, the grinding process for weld seam is usually done by workers who endure the dust and noise constantly. With the development of industrial technology, robot grinding has been widely used in aerospace, energy, and other high-tech industries with its open and complex kinematic chain [5, 6].

Nowadays, CAD offline programming and manual teaching are the two main working modes of robots [7, 8]. However, the manual teaching cannot adapt to the changing environment, which may lose efficacy when grinding the large and weak-stiffness welding workpieces, especially the large structural parts such as pump truck bodies and high-speed rail bodies. Therefore, in order to meet the requirements of automatic welding seam grinding of structural parts in engineering machinery, aerospace, and other manufacturing fields, it is necessary to develop an intelligent grinding robot that can well adapt to environmental changes.

Weld identification and trajectory planning are the core of intelligent grinding robots, and robot sensor is the key part to realize weld identification and trajectory planning.
At present, various sensors are used in robots, such as vision sensors [9, 10], laser sensors [11], force sensors [12, 13], and acoustic emission sensors [14]. Among them, visual sensors are widely utilized because of their advantages of high accuracy and non-contact [15]. Passive vision technology uses cameras to capture the welding seam under natural light to detect the weld seam characteristics and the position deviation. Numerous published studies have applied passive vision technology for weld tracking in welding process [16–20]. Xu [19] designed a set of special vision sensor system for weld tracking and proposed a new improved Canny edge detection algorithm and achieved good results. However, the weld images collected in this process are often disturbed by dust, which affects the accuracy of image processing.

Structured light vision is a representative of active vision, including coded structured light [21] and laser structured light [22]. Coded structure light is mainly used for 3D reconstruction and machining path planning of workpiece. Yang [22] proposed a 3D seam extraction system based on coded structured light to plan robot welding tasks. However, due to the high environmental requirements of this method, welding efficiency is difficult to guarantee. Laser structured light is usually used to extract and track the weld contour in the form of a laser emitter and monocular camera. There are a variety of shapes of the laser stripe, including linear [23], multi-linear [24], cross [25], and triangle [26]. Shao [24] designed three lasers with different wavelengths for the welding process to measure the seam width, seam center, and the normal vector of the weld surface. The result of experiment revealed that the proposed method could meet the precision demand of space narrow butt joint. Zhang [25] proposed a weld line localization approach for mobile platform based on cross-structured light for robot welding process, and this approach could effectively reduce the influence of illumination and noise. However, the laser structured is a local-type sensor and cannot perceive the global range. Some scholars use three-dimensional coordinate scanner and binocular camera to obtain the global contour. The above methods have a series of problems, such as complex algorithms, a large amount of data processing, and high cost. It is still a difficult problem to accurately extract the weld parameters from the three-dimensional weld seam profile [27]. At present, due to the complexity of the grinding process and the irregular shape of the weld, the measurement-processing system for welding seam grinding is still immature.

In view of the problems in the above research, this work takes the unequal thickness steel plate as the research object, and investigates the robot automatic weld grinding system, including weld feature extraction method and grinding path planning technology. (1) A robotic welding seam automatic grinding system is built. (2) A simple but effective weld extraction algorithm based on model segmentation is proposed to transform the processing process of spatial point cloud into a two-dimensional point cloud processing process, then a data buffer area is created to reconstruct the weld seam morphology. (3) The mathematical model of the weld surface is established, and the rotation angle of the robot end posture is calculated through the obtained normal vector coordinates. The experimental results show that the system is reliable, the processing efficiency is increased by 50%, and the average roughness value of the weld surface after grinding can reach 0.382 μm. The research results are of great significance for engineering applications.

The rest of this paper is organized as follows. Section 2 describes the design and construction of the system. Section 3 describes the weld extraction process in detail. Section 4 describes the planning process of weld grinding path and pose and the realization process of system data interaction. Section 5 describes experiment results.

2 System configuration

2.1 Construction of system platform

In this paper, a weld seam grinding robot system platform is set up to ensure the feasibility of the method (see Fig. 1). It mainly includes three parts, which are KUKA Robot Control (KRC) system, grinding system, and laser visual system. The KRC system includes a teaching pendant, manipulator, and controller. The grinding system includes the motor, frequency converter, and grinding wheel. The visual system includes a laser vision sensor, industrial PC, and a multi-degree of freedom bracket.

The LJ-G500 laser vision sensor developed by the Keyence company is adopted (see Table 1), which can obtain 3D data combined with the robot. And it has many advantages, such as rapid projection, high precision, and high stability. At the same time, it is also easy for installation because of small size.

2.2 Design of multi-degree of freedom bracket

To satisfy the processing requirement, a multi-degree of freedom is designed to install a laser vision sensor and a grinding wheel, which can ensure that the laser is projected to the surface of the weld at any angle. As shown in Fig. 1, bracket 1 is used to install the motor and grinding wheel, with regular through holes on the left. Bracket 2 is designed with 3 U-shaped grooves, which can move in the Y and Z directions on bracket 1. Bracket 4 fixed with bracket 5 can rotate at any angle around bracket 3. The sensor laser head is fixed with the bracket 5 by 3 screws.
2.3 Hand-eye calibration

The hand-eye calibration is performed to obtain the transformation matrix between the sensor coordinate system and robot end coordinate system. In this paper, a high-precision standard ball was used as a fixed target to solve the hand-eye relationship by controlling the robot to move three times in translation and four times in any posture. After each movement, a line laser scanner installed on the robot end-effector was used to scan the standard ball to obtain a column of point clouds on the surface contour of the target ball (see Fig. 2). Then, the spherical center space coordinates of the target ball were obtained. Finally, the equation could be listed according to the constraint relationship, and the hand-eye relationship could be solved by singular value decomposition. We used a set of quaternions \((Q_1, Q_2, Q_3, Q_4)\) and \(T\) to represent the rotation matrix part and the translation matrix part, respectively. The calibration matrix \(X_s\) can be expressed as Eq. (1).

\[
X_s = \begin{bmatrix}
Q_1^2 + Q_2^2 - Q_3^2 - Q_4^2 & 2(Q_2 Q_3 - Q_1 Q_4) & 2(Q_2 Q_4 + Q_1 Q_3) & T_1 \\
2(Q_2 Q_3 + Q_1 Q_4) & Q_1^2 - Q_2^2 + Q_3^2 - Q_4^2 & 2(Q_3 Q_4 - Q_1 Q_2) & T_2 \\
2(Q_2 Q_4 - Q_1 Q_3) & 2(Q_3 Q_4 + Q_1 Q_2) & Q_1^2 - Q_2^2 - Q_3^2 + Q_4^2 & T_3 \\
0 & 0 & 0 & 0
\end{bmatrix}
\]  

(1)

Table 1 The laser vision sensor parameters

| Case | Parameters                  | Value                        |
|------|-----------------------------|------------------------------|
| 1    | Accuracy                    | 0.1% F. S                    |
| 2    | Sampling frequency          | 3.8 ms                       |
| 3    | Size (length*width*height) | 138(mm)*76(mm)*38(mm)        |
| 4    | Weight                      | 480 g                        |
| 5    | Measuring distance          | 200 mm                       |
3 Method of weld seam segmentation

When processing spatial point cloud data, there are common problems such as large amount of data, complex algorithm, and slow processing speed. In this paper, the processing of spatial point data cloud data is transformed into the processing of two-dimensional point cloud data. For this purpose, a method based on region segmentation is proposed to extract the contours of welds with unequal thickness steel plates (see Fig. 3). On the weld section, the plane point cloud is firstly segmented, then the slope point cloud data is further extracted. Finally, the weld seam point cloud is obtained through the model segmentation and stored in the data buffer. After scanning the whole welding seam, the 3D morphology of the complete welding seam is extracted by combining the robot coordinates. Compared with directly processing spatial point cloud data, this processing method is fast, efficient, and with a small data amount.

3.1 Model building

Figure 3 illustrates the butt welding formed by two types of steel plate with unequal height. Note that in order to strengthen the connection strength after welding, the groove is usually processed in the area to be welded. Hence, the welding surface includes four parts, which are the bead, the 1st type of base material, and the 2nd type of base material and groove area. When the laser scans the weld contour, the laser line can be divided into five areas, including two planes (A, B), two bevels (C, D), and irregular weld surfaces (E). Therefore, point cloud data is mainly composed of plane point cloud, bevel point cloud, and weld seam point cloud. Considering the complexity of weld shape, it is difficult to extract point cloud data directly by building model. Thus, if models can be found to represent the plane region and the bevel region respectively, the weld data can be used as outliers to segment the weld profile.

![Fig. 3 Weld surface profile model](image-url)
According to the above analysis, the laser cloud data are orderly arranged based on the A-C-E-D-B region. In butt welding, the base metal in a certain area on both sides of the weld is considered to be an ideal flat. The region (A, C, D, B) can be represented by a first-order polynomial, respectively.

\[
\begin{bmatrix}
  y_{Ai} \\
  y_{Ci} \\
  y_{Bi}
\end{bmatrix} =
\begin{bmatrix}
  a_A \\
  a_C \\
  a_B
\end{bmatrix} \cdot x_i +
\begin{bmatrix}
  b_A \\
  b_C \\
  b_B
\end{bmatrix}
\]

where \((y_{Ai}, y_{Ci}, y_{Di})\) is the distance between the laser sensor and the region of \((A, C, D, B)\) at the location of \(x_i\), \(x_i\) is laser point position, and \((a_A, a_C, a_B, b_A, b_C, b_B)\) are the polynomial parameters fitted by least square method (LSM). The distance between the point cloud and the fitting function is then represented as follows:

\[
d_i = y_i - y
\]

\[
(x_i, y_i) = \begin{cases} 
\text{Outlier} & d_i > d_S \\
\text{Interior point} & d_i < d_S 
\end{cases}
\]

where \(y_i\) is the value predicted from Eq. (2), \(y\) is the measured value (between the laser sensor and workpiece surface), and \(d_S\) is the threshold to split the outliers.

### 3.2 Point cloud segmentation

On the weld section, the data collected by the sensor is arranged in an orderly manner. Starting from the first point of the data, 10 points were randomly selected with a certain range and fitted by the least square method. The point cloud in region A was separated by Eqs. (2)–(4). When the continuous data was greater than the threshold value, it was regarded as region C. Then, 10 points were selected and fitted by the least square method to extract data from region C. At this moment, the starting point of the weld could be obtained.

Through the above process, regions A and C can be separated. Then, as shown in Fig. 4, in order to search from the last point in the data, the least square method is used to fit the degree polynomial to divide the region B and D.

After the above process, the 2D weld profile of the section is extracted and stored in the data buffer. Combined robot coordinate system synchronously, the three-dimensional morphology of the weld seam can be obtained by scanning the whole weld section profile. The flow chart of weld extraction based on model segmentation is shown in Fig. 5.

The algorithm is aimed at the extraction of welds of steel plates with unequal thicknesses, and the premise is to obtain ordered weld point cloud data. Firstly, the weld section model is established, and different areas are divided according to the section characteristics. Then, the LSM based on threshold comparison is utilized to extract the weld contour according to the order of \(A - C - B - D\).

To extract the weld seam accurately, it is the key to set the appropriate threshold \(d_i\). Whether the threshold value is too large or too small will affect the judgment of the region. Therefore, before the actual grinding, the right \(d_i\) by experiment need to be confirmed. As shown in Figs. 6, 7 and 8, \(a\) is actual weld profile, and \(b\)–\(e\) are the profile extracted according to different \(d_i\) that are preliminarily set as 0.05 mm, 0.15 mm, and 0.25 mm.

The experimental results show that the size of the threshold has a greater impact on the accuracy of weld extraction. When the threshold value is 0.05 mm (see Fig. 6), areas C and D are easily misjudged, failing to extract the weld contour. When the threshold value is 0.25 mm (see Fig. 8), it is difficult to accurately judge the starting and ending point of the weld. According to the experimental results, the extraction accuracy is satisfied when \(d_i = 0.15\) (see Fig. 7).

### 3.3 Feature information extraction

In order to accurately track the weld seam, the height, width, and normal vector of the weld seam need to be further calculated. The process can be expressed as follows.

1. Obtain starting and ending position \(p_1(x_1, y_1), p_2(x_2, y_2)\) of the weld seam based on model segmentation.
2. Calculate the distance between \(p_1\) and \(p_2\) to obtain the weld width value according to Eq. (5)

\[
D_w = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}
\]

3. Fit the polynomial according to the starting and ending points \(p_1\) and \(p_2\) based on LSM.
4. Calculate the distance from the point to the polynomial by a point-by-point search.
5. Find the maximum distance to obtain the weld height data (see Figs. 9 and 10).

### 4 Grinding path planning

#### 4.1 Grinding path fitting

To ensure good grinding quality, the grinding path must be smooth to avoid the vibration caused by the discontinuous speed and acceleration of the robot. The traditional trajectory fitting methods include three polynomial fitting [28] and five polynomial fitting [29], which have low fitting accuracy. In
In this paper, the U-direction utilized a spline function to fit the grinding trajectory based on the obtained weld profile, which is expressed as Eq. (6). In the actual grinding process, the grinding step in U-direction is obtained by the isometric method. Under the condition of ensuring the grinding efficiency and accuracy at the same time, it is more appropriate to set the step as 15 mm according to experimental experience.

\[
C(u) = \sum_{i=0}^{n} N_{ik}(u)P_i, \quad 0 \leq u \leq 1
\]  

where \( C(u) \) is a vector function of the B-spline curve, \( N_{ik}(u) \) is the k order spline basis function, which can be obtained by Eqs. (7) and (8), \( P_i \) is the known feature point, and \( u \) is the sequence of parameters.
The International Journal of Advanced Manufacturing Technology (2022) 121:7627–7641

Fig. 5 Flow chart of weld extraction based on model segmentation

\[ N_{i,k}(u) = \frac{u - u_i}{u_i - u_i} N_{i,k-1}(u) + \frac{u_{i+k+1} - u}{u_{i+k+1} - u_i} N_{i+1,k-1}(u) \] \quad (7)

\[ N_{i,0}(u) = \begin{cases} 1, & u_i \leq u < u_{i+1} \\ 0, & \text{else} \end{cases} \] \quad (8)

Fig. 6 Weld segmentation result graph. a Actual weld profile. b–e The weld profile extracted according to \( d_z = 0.05mm \)
The end pose of the robot is a key factor affecting the quality of grinding. The surface topography of the weld seam is reconstructed and the normal vector can be obtained. Then, the pose of the grinding wheel can be calculated according to the normal vector value.

The pose model of the weld seam is established in Fig. 10, which includes direction vectors, normal vectors, and proximity vectors. The starting and ending points $P_a(x_{a}, y_{a}, z_{a})$

---

**Fig. 7** Weld segmentation result graph. **a** Actual weld profile. **b–e** The weld profile extracted according to $d_z=0.15\text{mm}$

**4.2 Calculation of end pose**

The end pose of the robot is a key factor affecting the quality of grinding. The surface topography of the weld seam is reconstructed and the normal vector can be obtained. Then, the pose of the grinding wheel can be calculated according to the normal vector value.

The pose model of the weld seam is established in Fig. 10, which includes direction vectors, normal vectors, and proximity vectors. The starting and ending points $P_a(x_{a}, y_{a}, z_{a})$

---

**Fig. 8** Weld segmentation result graph. **a** Actual weld profile. **b–e** The weld profile extracted according to $d_z=0.25$
and $P_b(x_b, y_b, z_b)$ have been obtained, so the direction vector can be written as Eq. (9).

\[ \vec{a}(x_a, y_a, z_a) = \frac{\frac{df_k}{dt}i + \frac{df_j}{dt}j + \frac{df_i}{dt}k}{\sqrt{\left(\frac{df_k}{dt}\right)^2 + \left(\frac{df_j}{dt}\right)^2 + \left(\frac{df_i}{dt}\right)^2}} \]  

(9)

\[ \vec{m} = (\vec{p}_{c1} \cdot \vec{p}_{c2}) \times (\vec{p}_{d1} \cdot \vec{p}_{d2}) \]  

(10)

\[ \vec{n} = \vec{m} \times \vec{a} \]  

(11)

where $\vec{m}$ is the proximity vector, $\vec{n}$ is the normal vector, and $\vec{a}$ is a proximity vector.

According to the D-H method, six joint coordinate systems of the robot were constructed, and the end-tool coordinate system $\{G\}$ and the laser coordinate system $\{L\}$ were also considered. The transformation matrices between $\{G\}$ and $\{L\}$ can be expressed as $G_T^L$. The end pose of robot can be determined by Euler angles (see Fig. 11), which is calculated by Eqs. (12)–(15).

\[ \cos(\theta) = \frac{n_{P_y} \cdot P_z}{|n_{P_y}| \cdot |P_z|} = \frac{x_{n2} \cdot P_z}{\sqrt{x_{n1}^2 + y_{n1}^2}} \]  

(12)

\[ \cos(\gamma) = \frac{n_{P_y} \cdot \vec{a}}{|n_{P_y}| \cdot |\vec{a}|} = \frac{x_{n1} \cdot x_a + x_{n2} \cdot y_a + x_{n3} \cdot z_a}{\sqrt{x_{n1}^2 + y_{n1}^2 + z_{n1}^2}} \cdot \sqrt{x_a^2 + y_a^2 + z_a^2} \]  

(13)

\[ \cos(\phi) = \frac{\vec{n} \cdot P_z}{|\vec{n}| \cdot |P_z|} = \frac{z_a \cdot P_z}{\sqrt{x_a^2 + y_a^2 + z_a^2}} \]  

(14)

\[ W_G^T = w_1^T \cdot \frac{1}{3} \cdot \frac{1}{4} \cdot \frac{1}{5} \cdot \frac{1}{6} \]  

(15)

where $\{W\}$ is world coordinate system, $P_x, P_y, P_z$ are robot base coordinate system, and $n_{P_z}$ is the projection of $\vec{n}$ onto the plane $p_{o_x}p_{o_y}$, $n_{P_x}$ is the projection of $\vec{n}$ onto the plane $p_{o_x}p_{o_y}$, $\theta, \gamma, \phi$ are Euler angles. Before the robot grinding, the transformation relationship between coordinate system
and coordinate system \( \{L\} \) is calculated by hand-eye calibration, and the end pose is adjusted by the Euler angel. The calculation process of the above trajectory and pose is obtained by MATLAB calculation (see Fig. 12) and realized by OrageEdit programming.

5 Experiment

5.1 Experimental platform

A grinding platform based on a KUKA robot was constructed [30] (see Fig. 1). The platform integrates weld extraction and automated grinding systems according to the proposed method, which specifically included KUKA KR210R2700 industrial robot, multi degree of freedom bracket, Keyence LJ-G500 sensor, IPC (610 I7-3770), electrical machinery (AC motor D-RE100M2/FL/LN), frequency converter (MTA11A-503-S623-D01-00), switches (Siemens SCALANCE X108PoE), alumina grinding wheel, force sensor (FC3D120-1KN), and Keyence LJ-G500 sensor (see Table 1).

5.2 Weld extraction experiment

In order to verify the effectiveness of the welding seam extraction and reconstruction method, the feature extraction experiment was carried out on the welds of unequal-thickness steel plates. As shown in Fig. 13a, the width and height values were obtained with vernier calipers at five different positions. The feature data were extracted by the model segmentation algorithm and compared with the actual values. To evaluate the accuracy of the algorithm, five extraction experiments were carried out at five different positions (see Fig. 13c, d). The error range of the extraction width was \( \pm 0.7 - \pm 1.4 \text{mm} \), and the error range of height was \( \pm 0.15 - \pm 0.5 \text{mm} \). The reason for the large width error is due to the influence of external environmental factors, resulting in the weld seam boundary not obvious. However, the extraction results can meet the error requirements. Finally, the extracted weld data was stored in the cache area to reconstruct the three-dimensional morphology of the weld. The reconstruction results are shown in Fig. 13b.

5.3 System grinding quality experiment

Weld grinding experiments were carried out based on the above methods of weld extraction and trajectory planning. As shown in Table 3, the alumina grinding wheel speed is kept as 10.46 m/s during the grinding process, the robot feed speed is 20 mm/s, and the grinding depth is set as 1.25 mm. The diameter and width of alumina grinding wheel are 200 mm and 20 mm, respectively. Through grinding parameters shown in Table 3, the measured normal grinding force fluctuates around 50 N (see Fig. 14).

The grinding track and pose were calculated by MATLAB, and the robot grinding trajectory was programmed in OrageEdit. After grinding, 10 points were selected equidistantly to measure the weld surface roughness by the surface roughness tester (TR200) with the evaluation length of 0.8 mm. As shown in Fig. 15, the average roughness value can reach 0.382 \( \mu \text{m} \), which completely satisfied the request of industry. Due to the instability of grinding starting point, the roughness value at the initial position is relatively high, which reaches 0.532 \( \mu \text{m} \) (see Fig. 15c). Subsequently, the grinding process tends to be stable and the weld surface roughness decreases.

To fully characterize the grinding quality, the weld height was extracted respectively based on the proposed method before and after grinding (see Fig. 16). The average height of the weld before grinding was 1.25 mm while was 0.098 mm after grinding. In order to observe the grinding quality more intuitively, the three-dimensional shape of weld surface was reconstructed based on hand-eye calibration (see Fig. 17). After grinding, the weld bead has been completely removed, the weld seam and base metal transition smoothly, and the weld seam surface is flat and smooth without obvious damage and crack, which proves that the system is reliable.

5.4 Grinding system efficiency experiment

To test the working efficiency of the system, the grinding experiment was carried out both in the manual teaching way and the method introduced in this article through the welds of unequal thickness steel plate with the same material,
Fig. 13 Feature extraction experiment. a Unequal thickness steel plate weld; b 3D reconstruction; c results of weld width extraction; d results of weld height extraction
shape, and length (40 cm). The grinding time was recorded under the same grinding parameters. The traditional teaching method had low efficiency and poor quality due to complicated procedures and large teaching errors, which took 7 min to grind (see Fig. 18a). The proposed system guaranteed the grinding quality and improved the polishing efficiency through accurate and efficient welding seam extraction and path planning methods, which only took 3 min to grind. The surface consistency after grinding was good, and the average roughness can reach 0.382 μm (see Fig. 18b). The specific experimental comparison effect is shown in Table 4.

Table 3  Grinding process parameters

| Process parameters | Linear velocity (m/s) | v_feed (mm/s) | a_p (mm) | Width (mm) | Diameter (mm) |
|--------------------|-----------------------|---------------|----------|------------|--------------|
| Value              | 10.46                 | 20            | 1.25     | 20         | 200          |

Fig. 16  Weld height after grinding

Fig. 14  Normal grinding force

Fig. 15  Grindng experiment. a Surface after grinding; b roughness measuring instrument; c roughness value
Fig. 17 Surface topographies of the weld seam. a Surface topography before grinding. b Surface topography after grinding

Fig. 18 Grinding efficiency and surface roughness experiment. a The traditional way for grinding. b The system for grinding
Table 4 Comparison of the grinding efficiency experiment

|                        | An efficient robot automatic grinding | Manual teaching |
|------------------------|---------------------------------------|----------------|
| Surface quality        | Smooth                                | Rough          |
| The average Ra value   | 0.382μm                               | 1.457μm        |
| The average height after grinding | 0.1 mm                                | 0.15 mm        |
| Grinding time          | 3 min                                 | 7 min          |

6 Conclusion

In order to achieve high-quality and efficient welding seam grinding, a simple but effective method of welding seam feature extraction was proposed. A robot automatic welding seam grinding system was built to solve a series of problems in manual grinding. The experimental results proved that the system was reliable and efficient. The main contributions of this paper are as follows.

1. A multi-degree of freedom bracket for weld seam feature extraction is designed, which can ensure that the laser is projected to the weld surface at any angle. Based on this, a grinding equipment and a laser sensor are integrated at the end of the robot to realize a robot weld automatic grinding platform. The grinding efficiency is increased by 50%.

2. A simple but effective weld extraction algorithm based on model segmentation is proposed to transform the calculating process of spatial point cloud into a two-dimensional point cloud calculating process.

3. The mathematical model of the weld surface is established, then the attitude angle of the robot end grinding is calculated based on the reconstructed 3D surface of the weld seam, which ensured the integrity of the grinding surface.

Author contribution Jimin Ge: conceptualization, investigation, writing-original draft, writing–review and editing. Zhaohui Deng: writing–review and editing, funding acquisition. Zhongyang Li: writing–review and editing. Wei Li: review and editing. Hua Zhang: funding acquisition. Jiaxu Nie: review and editing.

Funding This work was supported by the municipal joint Fund for Natural Science of Hunan Provincial (grant number 2021JJ50116). The Special Fund for the Construction of Hunan Innovative Province (grant number. 2020GK2003). The General Project of Hunan Provincial Education Department, China (grant number. 20C0830).

Availability of data and material We confirm that data is open and transparent.

Declarations

Ethical approval We confirm that the manuscript has not been submitted to any other journal. The submitted work is original and has not been published elsewhere in any form or language.

Consent to participate We confirm that all authors agree with the content and give explicit consent to submit.

Consent for publication If the article is accepted, we grant the Publisher an exclusive license to publish the article.

Conflict of interest The authors declare no competing interests.

References

1. Zhu Y, Mu W, Cai Y, Xin D, Wang M (2021) A novel high-efficient welding technology with rotating arc assisted by laser and its application for cryogenic steels. J Manuf Process 68:1134–1146
2. Baijun W, Jack HS, Lei S, Theodor F (2020) Intelligent welding system technologies: state-of-the-art review and perspectives. J Manuf Syst 56:373–391
3. Moritz B, Xiru W (2021) A review of fatigue test data on weld toe grinding and weld profiling. Int J Fatigue 45:106073
4. Fu Z, Ji B, Kong X, Chen X (2017) Grinding treatment effect on rib-to-roof weld fatigue performance of steel bridge decks. J Constr Steel Res 129:163–170
5. Wang Q, Wang W, Zheng L, Yun C (2021) Force control-based vibration suppression in robotic grinding of large thin-wall shells. Robot Comput-Integr Manuf 67:102031
6. Zhu D, Feng X, Xu X, Yang Z, Li W, Yan S, Ding H (2020) Robotic grinding of complex components: a step towards efficient and intelligent machining–challenges, solutions, and applications. Robot Comput-Integr Manuf 65:101908
7. Lin F, Lv T (2005) Development of a robot system for complex surfaces polishing based on CL data. Int J Adv Manuf Technol 26(9–10):1132–1137
8. Bedaka AK, Lin CY (2018) CAD-based robot path planning and simulation using OPEN CASCADE. Procedia Comput Sci 133:779–785
9. Comas T, Diao C, Ding L, Williams S, Zhao Y (2017) A passive imaging system for geometry measurement for the plasma arc welding process. IEEE Trans Industr Electron 64(9):7201–7209
10. Wu C, Gao J, Liu X, Zhao Y (2003) Vision-based measurement of weld pool geometry in constant-current gas tungsten arc welding. Proc Inst Mech Eng Part B J Eng Manuf 217(6):879–882
11. Charrett T, Bandari Y, Michel F, Ding J, Williams S (2018) A non-contact laser speckle sensor for the measurement of robotic tool speed. Robot Comput-Integr Manuf 53:187–196
12. Huang S, Niklas B, Yamakawa Y, Senoo T, Ishikawa M (2017) Robotic contour tracing with high-speed vision and force-torque sensing based on dynamic compensation scheme. IFAC-PapersOnLine 50(1):4616–4622
13. Wang Y, Ding W, Mei D (2021) Development of flexible tactile sensor for the envelop of curved robotic hand finger in grasping force sensing. Measurement 180:109524
14. Segreto T, Karam S, Treti R, Ramsing J (2015) Feature extraction and pattern recognition in acoustic emission monitoring of robot assisted polishing. Procedia CIRP 28:22–27
15. Wang N, Zhong K, Shi X, Zhang X (2020) A robust weld seam recognition method under heavy noise based on structured-light vision. Robot Comput-Integr Manuf 61:101821
16. Liu J, Fan Z, Olsen S, Christensen K, Kristensen J (2015) Boosting active contours for weld pool visual tracking in automatic arc welding. IEEE Trans Autom Sci Eng 14(2):1096–1108
17. Xu Y, Fang G, Lv N, Chen S, Zou J (2015) Computer vision technology for seam tracking in robotic GTAW and GMAW. Robot Comput-Integr Manuf 32:25–36
18. Ye Z, Fang G, Chen S, Dinham M (2013) A robust algorithm for weld seam extraction based on prior knowledge of weld seam. Sens Rev 33:125–133
19. Xu Y, Yu H, Zhong J, Tao L, Chen S (2012) Real-time seam tracking control technology during welding robot GTAW process based on passive vision sensor. J Mater Process Technol 212(8):1654–1662
20. Xue K, Wang Z, Shen J, Zhen Y, Liu J, Wu D, Yang H (2021) Robotic seam tracking system based on vision sensing and human-machine interaction for multi-pass MAG welding. J Manuf Process 63:48–59
21. Yang L, Liu Y, Peng J, Liang Z (2020) A novel system for off-line 3D seam extraction and path planning based on point cloud segmentation for arc welding robot. Robot Comput-Integr Manuf 64:101929
22. Xiao R, Xu Y, Hou Z, Chen C, Chen S (2019) An adaptive feature extraction algorithm for multiple typical seam tracking based on vision sensor in robotic arc welding. Sens Actuators A 297:111533
23. You DY, Gao XD, Katayama S (2014) Review of laser welding monitoring. Sci Technol Weld Join 19(3):181–201
24. Shao W, Huang Y, Zhang Y (2018) A novel weld seam detection method for space weld seam of narrow butt joint in laser welding. Opt Laser Technol 99:39–51
25. Zhang L, Ye Q, Yang W, Jiao J (2013) Weld line detection and tracking via spatial-temporal cascaded hidden Markov models and cross structured light. IEEE Trans Instrum Meas 63(4):742–753
26. Iakovou D, Aarts R, Meijer J (2005) Sensor integration for robotic laser welding processes. Int Congress Appl Lasers Electro-Opt 2005(1):2301. Laser Institute of America
27. Ye G, Guo J, Sun Z, Li C, Zhong S (2018) Weld bead recognition using laser vision with model-based classification. Robot Comput-Integr Manuf 52:9–16
28. Lin C, Chang P, Luh J (1983) Formulation and optimization of cubic polynomial joint trajectories for industrial robots. IEEE Trans Autom Control 28(12):1066–1074
29. Boryga M, Graboś A (2009) Planning of manipulator motion trajectory with higher-degree polynomials use. Mech Mach Theory 44(7):1400–1419
30. Ge J, Deng Z, Li Z, Li W, Lv L, Liu T (2021) Robot welding seam online grinding system based on laser vision guidance. Int J Adv Manuf Technol 116(5):1737–1749

Publisher’s note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.