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An Identification and Localization Method for 3D Workpiece Welds Based on the DBSCAN Point Cloud Clustering Algorithm

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Abstract: With the development of robotic welding automation, there is a strong interest in welding seam identification and localization methods with high accuracy, real-time performance, and robustness. This paper proposed a 3D workpiece weld identification and localization method based on DBSCAN (density-based spatial clustering of applications with noise) to realize stable feature extraction for multiple joint types. Firstly, this method employs combinatorial filtering to effectively eliminate non-target point clouds, including outliers and installation platform point clouds, which can minimize the computational load. Secondly, DBSCAN is used to classify workpiece point clouds into different clusters, which can be used for point cloud segmentation of flat workpieces and curved workpieces. Thirdly, the edge detection and feature extraction methods are used to obtain joint gap and weld feature points while combining the information of point clouds for different types of welds. Finally, based on the identification and localization of the welds, welding path planning and attitude planning are implemented. Experimentation results indicated that the proposed method exhibits robustness across various types of welded joints, including butt joints with straight seams, butt joints with curved seams, butt joints with curved workpieces, and lap joints. Meanwhile, the average error of joint gap detection was 0.11 mm and the processing time of a 90 mm straight-seam butt joint is 701.12 ms.

Keywords: point cloud clustering; joint gap detection; welding seam extraction; weld planning; welding



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1. Introduction

Robotic welding technology, which has the significant advantages of high productivity, stable welding quality, and repeatability, is promising in automotive, shipbuilding, bridge-building, and other fields [1–4]. Due to the difficulty of guaranteeing the accuracy and efficiency of the teaching–playback mode [5,6], welding seam identification and localization have been selected as the main scope of research projects by many scholars. Ultrasonic sensors [7,8], arc sensing [9], vision sensors [10–12], laser vision sensors [13–16], contact sensors [17], and other assorted sensors have gradually been used in this scope.

Among them, the laser vision sensor is based on the triangulation principle; it captures the laser line information projected on the surface of the workpiece by the laser generator through the camera, and obtains the point cloud with the contour information of the workpiece surface. Because of its high accuracy and reliability, it is widely used in the field of welding [18–20], and realizes the seam identification and extraction of planar and curved components based on the local and global geometric features of the point cloud. Typically, welded components can be categorized into plane and curved components. The planar components mainly include planar butt joints, lap joints, and fillet joints, which are common in the industrial field. The curved components include round tubes, curved butt joints, and impellers, which have complex structures. In recent years, researchers have proposed many algorithms based on point clouds to realize the perception and recognition of the welded components.

For the plane components, Chen et al. obtained the inflection points by slicing the point cloud along the scanning direction and using the second derivative, and finally realized the weld center point extraction [21]. Zhang et al. used the second derivative and combined filtering to obtain the feature points of the weld groove, and then obtained the weld path through the NURBS fitting method and coordinate system transformation [22]. The method of weld extraction by the first- and second-order derivatives [21–23] uses the localized features of the point cloud, which is more suitable for workpieces with grooves. Yang et al. used the RANSAC algorithm to segment the workpiece surface and weld groove, and then obtained straight and curved welds for planar workpieces by calculating the distance from the point to the plane, and finally completed the welding planning [24]. Zhang et al. searched for the edge points based on the number of neighboring points, then segmented the edge lines by the RANSAC algorithm, and finally obtained the weld seams of multiple planar workpieces based on centroid positioning [25]. The above methods, by combining the RANSAC segmentation algorithm and the edge extraction method, can realize high-precision weld seam extraction, but cannot be applied to curved components.

For curved components, Geng et al. processed the pipe through a cylindrical fitting algorithm, and then computed parameters such as eccentricity and pinch angle, which were inputted into the established mathematical model to obtain the welding path [26]. Gao obtained the edge points of D-type pipes based on the point cloud normal [27]. Geng et al. planned the position and attitude of the robot so that the points on the impeller weld were farthest from the 3D surface scanning structured light camera, then screened the weld point cloud based on the z-value, and finally fitted the weld path by the least squares method [28]. Due to the complex structure of curved components, specific extraction methods are required to obtain welding seams, but these methods cannot be directly applied to planar components.

Currently, the research on weld seam recognition and extraction is mainly focused on the planar components, with less research on the curved components and those features applicable to both kinds of components. In addition, the current feature points extraction methods usually ignore the detection of the joint gap, while in some welding procedures, it is necessary to select the welding parameters and welding paths based on the joint gap. For example, laser welding needs to keep the laser and the weld aligned.

To address the above issues, this paper proposes a 3D workpiece weld identification and localization method based on the DBSCAN point cloud clustering algorithm, which can achieve joint gap detection and feature extraction for multiple-types of joints. In the proposed method, the DBSCAN (density-based spatial clustering of applications with noise) algorithm [29] clusters the point clouds into different clusters based on the density, which is applicable to both planar and curved components. In addition, weld edges and joint gaps are obtained based on the horizontal information (y-values) of the point cloud and finally, the weld extraction for both planar and curved components is realized.

2. Experimental Platform and Framework

2.1. Experimental Platform

As shown in Figure 1, the experimental platform included a welding robot system and a structured light vision system. The welding robot system consisted of a robot, robot controller, welding torch, and wire feeder. The structured light vision system consisted of a laser vision sensor and a personal computer (PC). The robot was an Erfurt ARC12-1400. The laser vision sensor was a SmartRay ECCO 95.040 with a resolution of 0.013 mm in the horizontal direction and a resolution of 0.00135 mm in the vertical direction.

The laser vision sensor was installed at the robot end-effector (the welding torch). The laser vision sensor scanned the workpiece placed on the installation platform to obtain the coordinate values of points in the X-axis, Y-axis, and Z-axis. Then, the point cloud dataset was relayed to the PC via the TCP/IP protocol. The proposed method was implemented based on a PC with 2.9 GHz and 16.0 GB memory. In addition, the data used in this paper were all obtained in the same experiment. The experiment was set up indoors with a 400 W

light source about 8 m above the installation platform, and no additional light source was added to irradiate the surface of the workpiece.

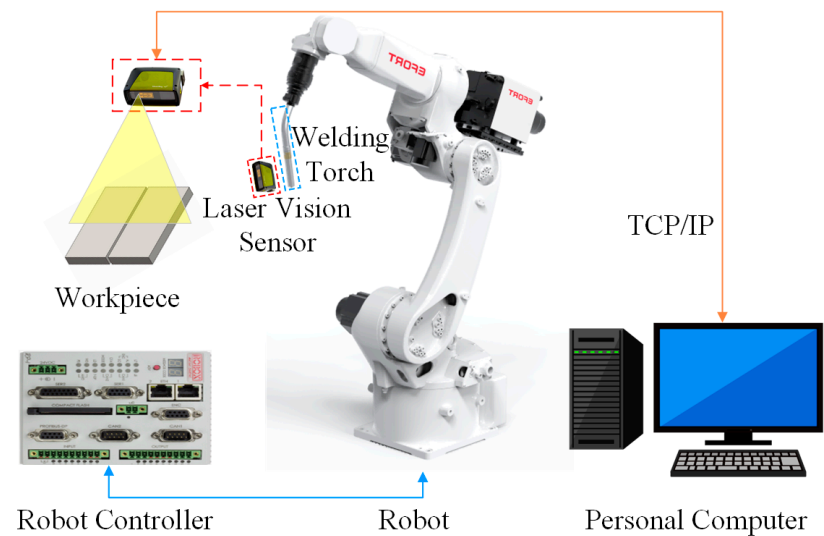


Figure 1. The composition of the experimental platform.

2.2. The Framework of the Proposed Method

The framework of the proposed method is shown in Figure 2.

- (1) Data collection: The motion speed of the robot was set to 20 mm/s with reference to the actual welding scene. At the same time, in order to ensure the integrity of the workpiece point cloud, the starting point of the scanning path was set at the front of the workpiece. Then, the camera scanned the workpiece along the welding direction to obtain the point cloud.
- (2) Data preprocessing: In general, external factors in the collection process will bring noise. To eliminate the interference of noise and reduce the cost of calculation, the point clouds were preprocessed by using several filtering methods and setting the ROI (region of interest).
- (3) Joint gap detection and welding seam extraction: The point cloud was divided into different clusters using the DBSCAN algorithm. Then, the welding path points were extracted based on the clustering results and the type of the welded joint.
- (4) Welding planning: Welding planning includes path planning and attitude planning. After welding planning, the feature points obtained in the previous step could be used to guide the actual welding production.

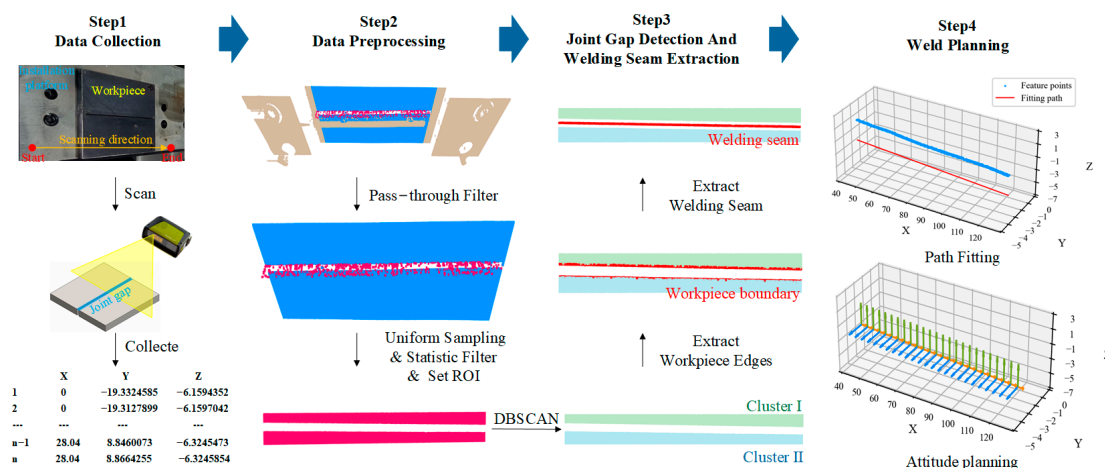


Figure 2. System framework.

3. Feature Extraction

3.1. Point Cloud Preprocessing

As shown in Figure 3a, external interference such as light and vibration caused noise during the scanning process. In addition, there were a large number of installation platform point clouds in the data, as the scanning path length was longer than the workpiece length. In order to remove the noise generated by the external environment and human factors, various filters were used to preprocess the data.

It can be observed that the noise was divided into dense point clouds of the installation platform and outliers in the middle of the joint gap. Because the distance between the installation platform and the sensor detection plane was larger than the distance between the workpiece plane and the sensor detection plane, the pass-through filter was used to remove the point clouds of the installation platform based on the height information of the point cloud. The filtering result is shown in Figure 3b.

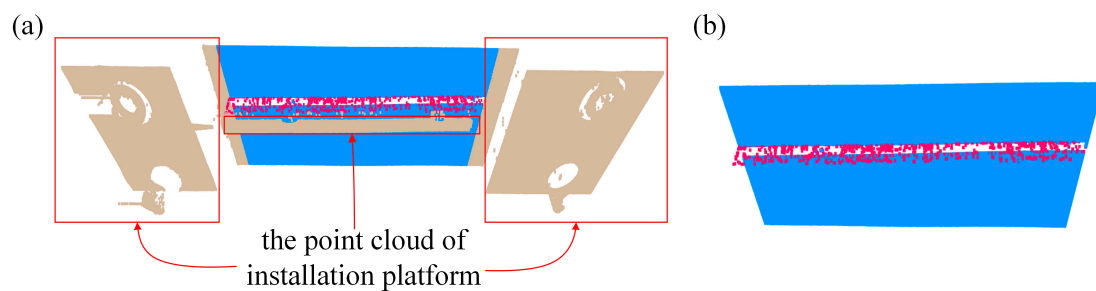


Figure 3. Pass-through filtering. (a) Raw point cloud. (b) Point cloud pass-through filtering.

Since the density of outliers was smaller than the density of the workpiece point cloud, a statistical filter [30] was used to remove outliers. It filtered out the points that did not meet the requirements by statistically analyzing the neighborhood of each point. As shown in Figure 4, the removal of outliers by using statistical filtering worked well. Meanwhile, the edges of the workpiece were not recognized as noise, and hence the workpiece edges retained intact.

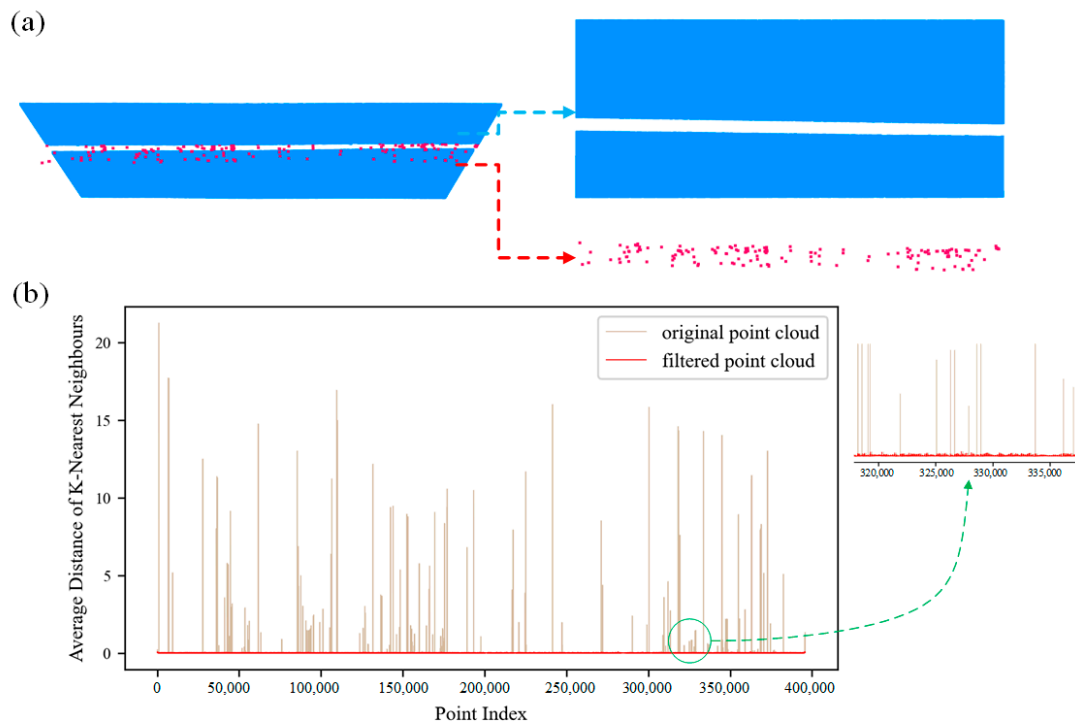


Figure 4. Statistical filtering. (a) Point cloud statistical filtering. (b) Average distance to KNN (K-nearest neighbor) before and after filtering.

In addition, due to scanning frequency and the precision of equipment, the number of collected point clouds was huge. For example, the laser vision sensor obtained more than seven million points by scanning a common butt joint. It was computationally intensive and time-consuming to process the collected points directly. Consequently, a uniform sampling filter was used before the statistical filtering to reduce the number of points involved in the calculation and to retain the main features and shape information. In addition, a pass-through filter was used to extract the ROI, which further reduced the number of points. The ROI of the point cloud is shown in Figure 5.



Figure 5. The ROI of the point cloud.

3.2. DBSCAN-Based Point Cloud Clustering and Joint Gap Detection

Generally, a butt joint consists of two plates after clamping. In order to accurately extract the welding seam, it is necessary to segment or cluster the point cloud according to the physical entity. Common methods use plane-fitting algorithms to segment the workpiece plane and the mounting plane and then use distance formulas or other judgment formulas to extract the edge of the workpiece. These methods can accurately extract welding seam, but plane-fitting algorithms are time-consuming and can only be applied to plane welding seams. In manufacturing, it is necessary to weld both plane welds and curved welds, so the DBSCAN [31,32] point cloud clustering algorithm is used to cluster the collected point cloud into different clusters.

DBSCAN is a density-based clustering algorithm. It does not need to set the number of clusters in advance, and it can be applied to point clouds of any shape; therefore, it works well for both flat and curved workpiece surfaces. The implementation steps of the DBSCAN algorithm are as follows:

- (1) Calculate the number of neighbors within the *eps* radius: Set the appropriate value of *eps* based on the k-distance graph, and then count the number of neighbors for each point within the *eps* radius. The “*eps*” parameter is utilized to define the neighborhood around each data point. Specifically, if the distance between two points is less than or equal to “*eps*”, they are deemed neighbors.
- (2) Mark core points: Set the appropriate value of *MinPts*, and then mark a point as a core point if its neighbors are more than or equal to “*MinPts*” within the *eps* radius. The points that do not meet the condition are marked as noise. *MinPts* refers to the minimum number of neighbors within the radius of *eps*.
- (3) Cluster point cloud: Begin with any core point, locate all density-connected points, assign them to the corresponding cluster, and iterate this process until all core points are labeled as belonging to clusters.
- (4) Process noise: Assign all the noise to independent clusters.

After setting *eps* and *MinPts* reasonably, DBSCAN can automatically divide the data points into different clusters according to the shape of the point cloud. As shown in Figure 6,

the DBSCAN point cloud clustering algorithm ($eps = 0.15$, $MinPts = 1$) is used to divide the collected point cloud into Cluster I and Cluster II, which represent the two plates that make up the welded joint.

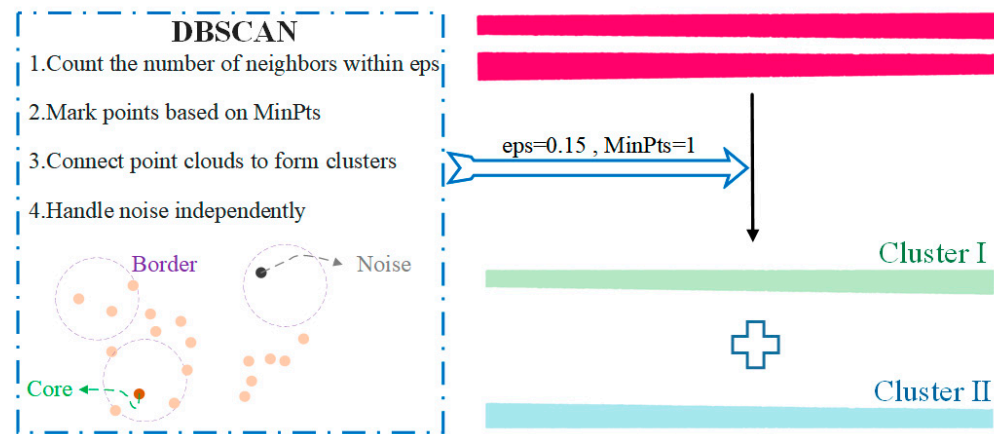


Figure 6. Point cloud clustering.

In order to obtain the joint gap and feature points, the edges of the workpieces must be detected and extracted. It can be observed that a workpiece has two edge lines along the scanning direction, so it is also necessary to identify the required edges after extracting the edges.

The detailed process of welding seam edge extraction is shown in Figure 7. Firstly, the edges of the workpieces are detected by setting the x-value as the key of the dictionary (dictionary is a data type in Python, this article used version 3.8 of Python), storing the two clusters in two dictionaries based on the key, finding the points with the largest and smallest y-value in each key, and storing their index values. The inner edges of the workpieces contain the weld information so it is then necessary to identify the joint edge according to the y-value. The y-means of the two clusters are calculated separately, and then the cluster with a smaller mean is labelled as Cluster I and the other one as Cluster II. For Cluster I, the point with the maximum y-value is used as the edge point in each point cloud profile, while for Cluster II, the opposite is done. Here, the edges are extracted and recognized by using Equation (1):

$$p_i = (x_i, y_i, z_i) = \begin{cases} P_{y_{max}} & \text{cluster I} \\ P_{y_{min}} & \text{cluster II} \end{cases} \quad (1)$$

where P is the point cloud dataset obtained by preprocessing and i is the point cloud contour index.

In welding production, the joint gap is one of the important factors affecting the quality of welding, and it is of great significance in guiding the setting of welding parameters. Consequently, after edge extraction, the joint gap is calculated by using Equation (2):

$$a = y1_i - y2_i \quad (2)$$

where a is the joint gap, $y1$ is the y-value of the edge point in cluster I, $y2$ is the y-value of the edge point in cluster II, and i is the point cloud contour index.

3.3. Feature Extraction for Multiple-Types of Joints

Commonly welded joints are divided into two types, one is the open joint which has gaps and the other is the closed joint, without gaps. In this paper, different methods are used to obtain feature points for different types of welded joints.

For open joints, the feature point cannot be obtained directly. They are obtained indirectly through the weld edge by using Equation (3):

$$p_i = \frac{p1_i - p2_i}{2} \quad (3)$$

where $p1$ is the edge points in cluster I and $p2$ is the edge points in cluster II.

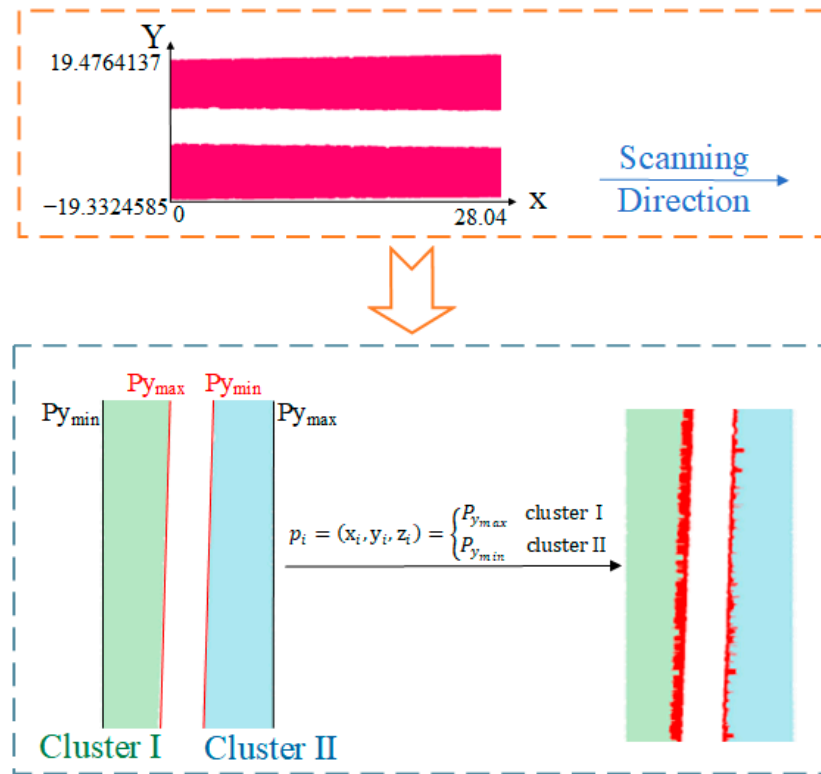


Figure 7. Welding seam edge extraction.

For closed joints, the intersection of the workpiece surface and the workpiece side plane is the welding seam, i.e., the welding seam is one of the edge lines extracted in the previous subsection. For the collected lap joint point clouds, in this paper, welds are identified based on the 3D structure of the welded joints. As shown in Figure 8, the welding seam is an edge line away from the inspection plane of the laser vision sensor; therefore, the edge line with the smaller z -mean is selected as the weld seam by comparing the z -means of the extracted edge lines.

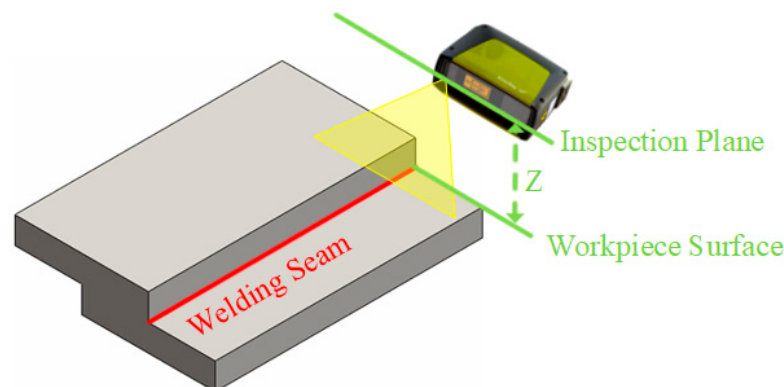


Figure 8. Welding seam of closed joints.

4. Welding Path and Attitude Planning

4.1. Welding Path Planning

After the coordinate system transformation, if the feature points extracted are transmitted directly to the robot, it will cause the robot to jitter, for the reason that the motion

path based on feature points is not smooth enough. Therefore, it is necessary to plan the weld path to reduce the jitter during the welding process by smoothing the weld path.

In manufacturing, the weld path usually consists of simple straight lines or curves. In this paper, the least squares method is employed for fitting the features of the weld. The objective function is

$$\delta = \sum_{i=1}^n (Y_i - y_i)^2 = \sum_{i=0}^{n-1} (\varphi(x_i) - y_i)^2 \quad (4)$$

where δ is the sum of squared deviations, Y_i is the fitted values, and y_i is the observed value.

In order to obtain the regression coefficients of the fit function when δ is minimum, it needs to take the partial derivatives of the objective function and make the partial derivatives equal to zero, and then, after simplification, a series of equations can be obtained. These equations are expressed in the form of the matrix, as shown in Equation (5):

$$\begin{bmatrix} n & \sum_{i=1}^n x_i & \cdots & \sum_{i=1}^n x_i^k \\ \sum_{i=1}^n x_i & \sum_{i=1}^n x_i^2 & \cdots & \sum_{i=1}^n x_i^{k+1} \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{i=1}^n x_i^k & \sum_{i=1}^n x_i^{k+1} & \cdots & \sum_{i=1}^n x_i^{2k} \end{bmatrix} \begin{bmatrix} p_0 \\ p_1 \\ \vdots \\ p_k \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^n y_i \\ \sum_{i=1}^n x_i y_i \\ \vdots \\ \sum_{i=1}^n x_i^k y_i \end{bmatrix} \quad (5)$$

where $(p_0, p_1 \dots p_k)$ are regression coefficients.

4.2. Welding Attitude Planning

In order to ensure that the welding is carried out in a stable manner, it is also necessary to plan the welding attitude. The calculation of the unit vector along the welding direction by using Equation (6) ensures that the direction of the welding torch is correct:

$$\vec{r} = \frac{\frac{\partial x}{\partial t} \vec{i} + \frac{\partial y}{\partial t} \vec{j} + \frac{\partial z}{\partial t} \vec{k}}{\left\| \frac{\partial x}{\partial t} \vec{i} + \frac{\partial y}{\partial t} \vec{j} + \frac{\partial z}{\partial t} \vec{k} \right\|} \quad (6)$$

Furthermore, in order to maintain a consistent angle between the welding torch axis and the workpiece plane throughout the welding process, it is imperative to compute the vector $\vec{\gamma}$. This crucial calculation ensures stability during welding. As shown in Figure 9, the vector $\vec{\gamma}$ can be obtained by using Equation (7):

$$\vec{\gamma} = \frac{\vec{m} + \vec{n}}{\left\| \vec{m} + \vec{n} \right\|} \quad (7)$$

where $\vec{m}$ and $\vec{n}$ are the normal vectors of the planes that make up the welding seam.

Based on the right-hand rule, the vector $\vec{\sigma}$ can be obtained by using Equation (8):

$$\vec{\sigma} = \vec{\gamma} \times \vec{r} \quad (8)$$

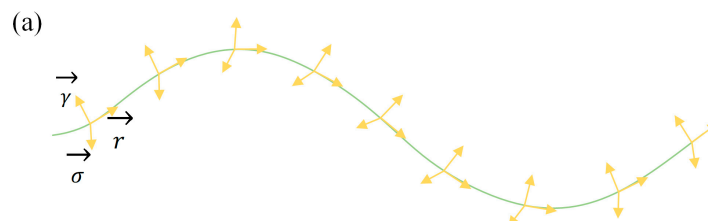


Figure 9. Cont.

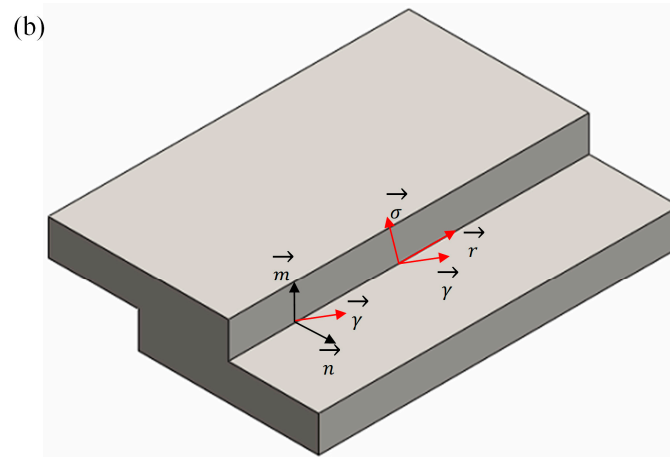


Figure 9. The basic vectors of the welding seam. (a) The attitude of discrete points on the welding path. (b) The basic vectors of the weld.

5. Experimentation and Analysis

Welding usually involves multiple types of welded joints, which requires that the welding seam identification and localization method is not only applicable to plane welding seams, but also has the ability to handle curved welding seams reliably. In order to verify the proposed method, the point cloud datasets of multiple-types of welded joints, including butt joints with straight seams, butt joints with curved seams, butt joints with curved workpieces, and lap joints, were obtained based on the built experimental platform. The four types of joints are shown in Figure 10.

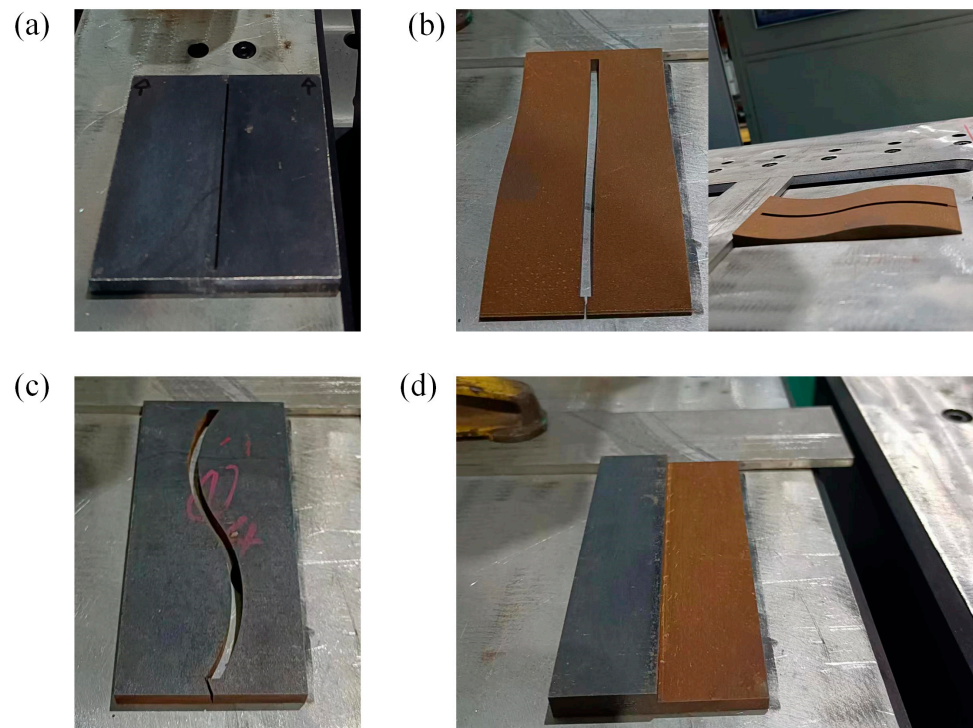


Figure 10. The four types of joints. (a) Butt joint with straight seam. (b) Butt joint with curved workpieces. (c) Butt joint with curved seam. (d) Lap joint.

5.1. Welded Joint Experiments

In order to test the robustness of the proposed method, open and closed joints were tested. In this paper, three types of open joint point clouds were collected based on the constructed experimental platform, including butt joints with straight seams (Figure 10a), butt

joints with curved seams (Figure 10c), and butt joints with curved workpieces (Figure 10b). For the open joints, a comparative test experiment of plane and curved workpieces was set up. As shown in Figures 11d and 12d, the proposed method not only solved the clustering of plane point clouds but also solved the clustering of curved point clouds.

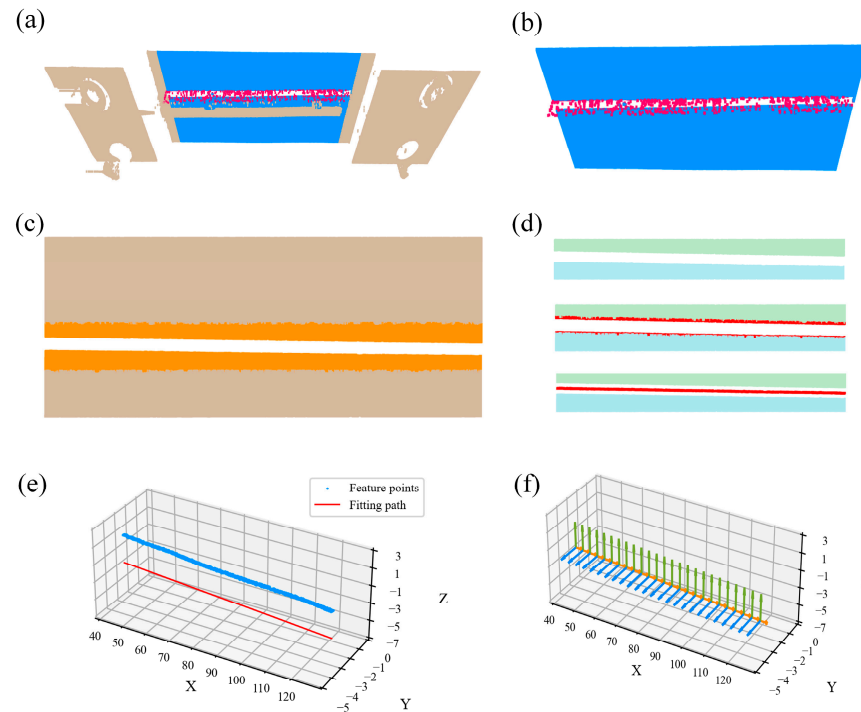


Figure 11. Butt joint with straight seam. (a) Raw point cloud. (b) Pass-through filtering. (c) Statistical filtering, uniform sampling filtering, and ROI operation. (d) Edge detection and feature extraction. (e) Welding path planning. (f) Welding attitude planning.

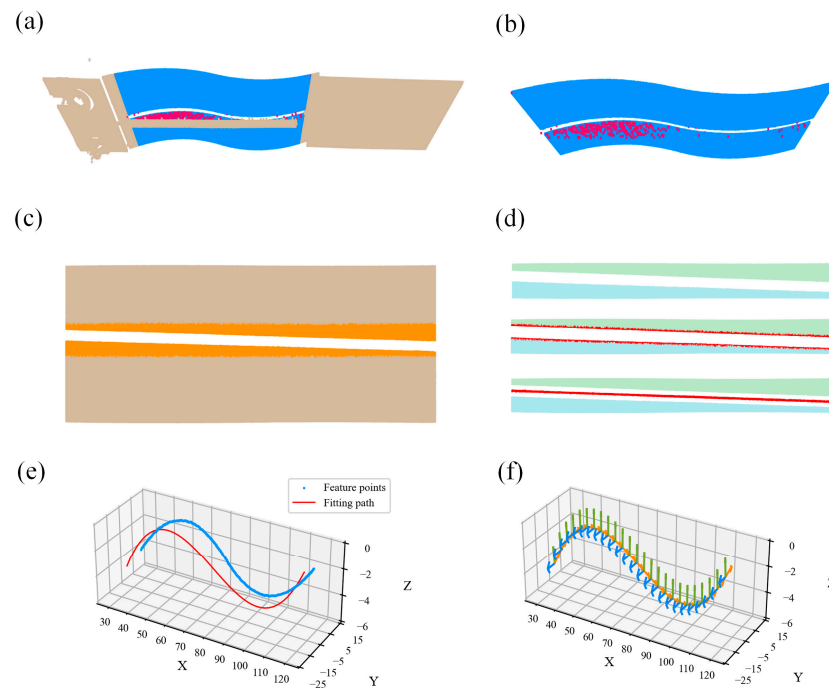


Figure 12. Butt joint with curved workpieces. (a) Raw point cloud. (b) Pass-through filtering. (c) Statistical filtering, uniform sampling filtering, and ROI operation. (d) Edge detection and feature extraction. (e) Welding path planning. (f) Welding attitude planning.

In addition, comparative test experiments were conducted on straight welds (Figure 10a) and curved welds (Figure 10c). Due to the welding requirement that the welding gun has to be aligned to the center of the joint gap, it was necessary to perform feature extraction based on the detected workpiece edges. This gave practical meaning to the feature points. Meanwhile, the least squares method was employed for fitting the straight welds and curved welds. As shown in Figures 11e and 13e, in order to facilitate the observation of the fitting results, an offset was set for the z-value of the fitted path. In summary, the comparative test experiments verified the ability of weld extraction and path fitting.

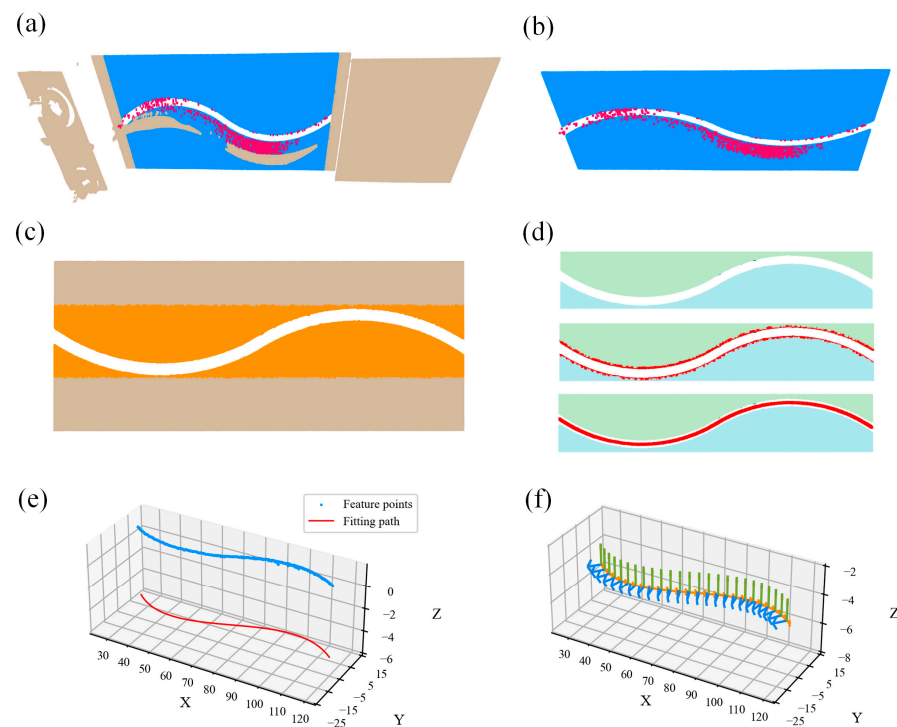


Figure 13. Butt joint with curved seam. (a) Raw point cloud. (b) Pass-through filtering. (c) Statistical filtering, uniform sampling filtering, and ROI operation. (d) Edge detection and feature extraction. (e) Welding path planning. (f) Welding attitude planning.

For closed joints, the point clouds of the lap joint were collected for testing. As shown in Figure 14, the extraction of edges based on the point cloud width information and the identification of the welding seam based on the height information were achieved.

5.2. Precision Analysis of Joint Gap Detection

To confirm the precision of gap detection, firstly, open joints with gaps of 1 mm, 2 mm, and 3 mm were obtained by wire cutting and the joint gaps were measured by using a micrometer. The calculated values were compared with the measured values, and the results of the joint gap detection and the detection error are shown in Table 1.

Table 1. The detection error of the joint gap.

Case	Joint Type	Measured Value (mm)	Computed Value (mm)	Error (mm)
1	Butt joint with straight seam	1.39	1.18	0.21
2		2.41	2.30	0.11
3		3.39	3.34	0.05
4	Butt joint with curved seam	1.25	1.27	−0.02
5		2.25	2.39	−0.14
6		3.29	3.42	−0.13

Based on the data in Table 1, the maximum error calculated was 0.21 mm, while the minimum error computed at 0.02 mm, and on average, the error stood at 0.11 mm. The calculated gap value could be used to guide the selection of welding parameters.

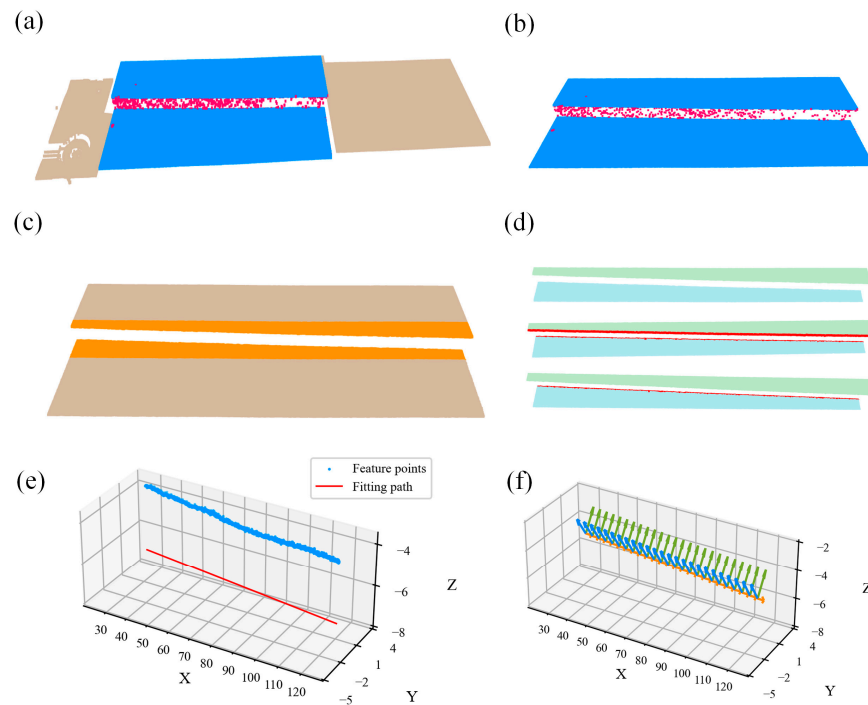


Figure 14. Lap joint. (a) Raw point cloud. (b) Pass-through filtering. (c) Statistical filtering, uniform sampling filtering, and ROI operation. (d) Edge detection and feature extraction. (e) Welding path planning. (f) Welding attitude planning.

5.3. Efficiency Analysis

In the manufacturing field, the runtime is one of the key considerations; therefore, the proposed method's running time was computed for a butt joint with a 90 mm straight weld, aiming to evaluate the algorithm's performance. The runtime of each step is shown in Table 2.

Table 2. The runtime of each step.

Case	Steps	Runtime (ms)
1	Point cloud preprocessing	540.55
2	Point cloud clustering	80.78
3	Feature extraction	74.80
4	Path fitting	4.99
5	The total time	701.12

Based on the results in Table 2, the proposed method in this paper took 701.12 ms, and the data preprocessing had the longest running time of 540.55 ms, which was due to the large number of raw point clouds. However, the number of point clouds was greatly reduced after preprocessing, which greatly reduced the running time of the subsequent procedures.

In addition, the proposed method in this paper was compared with Ref. [33]. Table 3 shows the operation elapsed time of the two methods, and the difference in elapsed time between the two methods is relatively small. Moreover, Ref. [33] requires a lot of time for 3D reconstruction before point cloud processing, so the proposed method is easier to implement. Meanwhile, Ref. [33] is only applicable to planar components such as lap joints and butt joints, while the proposed method is applicable to both planar and curved components, which is more adaptable.

Table 3. Algorithmic efficiency of the two methods.

Case	Steps	The Proposed Method (ms)	Ref. [33] (ms)
1	Point cloud clustering/segmentation	80.78	123.67
2	Welding seam extraction	74.80	1.00
3	The total time	155.58	124.67

6. Conclusions

In this paper, a 3D workpiece weld identification and localization method based on the DBSCAN algorithm is proposed. This method has the advantages of performing well with arbitrary-shaped clusters without specifying the number of clusters beforehand. This method can also quickly obtain weld information, including joint gap and weld feature points, for multiple types of welds, and its accuracy, real-time performance, and robustness were verified by different structural components. Some conclusions can be drawn as follows:

- (1) The proposed method is applicable to multiple shapes of workpiece point clouds and multiple types of welded joints based on the DBSCAN point cloud clustering algorithm, which is applicable to planar components, curved components, open joints, and closed joints.
- (2) The proposed method uses workpiece 3D information for edge detection, which achieves joint gap detection and weld feature point extraction. The maximum error calculated was 0.21 mm, while the minimum error was computed at 0.02 mm, and on average, the error stood at 0.11 mm.
- (3) The proposed method's running time was 701.12 ms for processing a 90 mm straight-seam butt joint. The pre-processing took a longer time of 540.55 ms due to the large number of raw point clouds.

The method proposed in this paper can achieve the detection of weld feature points for planar and curved components, which have gaps. In the future, we will continue our in-depth research to solve components without gaps.

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Data Availability Statement: The data that support the findings of this study are available from the corresponding author, [L.S.], upon reasonable request.

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