A Weld Line Detection Method Based on 3D Point Cloud for Automatic NDT

Zhaoxuan Dong, Jianchang Huang, Shiqi Yin, Yuenong Fei*

College of Mechatronics and Control Engineering, Shenzhen University, Shenzhen 518060, China

*Corresponding author e-mail: zhaoxuand@gmail.com

Abstract. The quality of welding is often checked by ultrasonic waves. Manual testing is costly and inefficient, and manual testing is not possible in some extreme environments. Automatic non-destructive testing (NDT) technology uses robots to carry ultrasonic devices for automatic detection. Machine vision is one of the important methods to achieve navigation, that is, capturing the weld line through the camera, planning the optimal path through visual analysis and processing, and also based on structured light. Although the navigation method can solve the problem of rust and stain to a large extent, it is less robust in dealing with problems such as rust, light interference and stain. This paper proposes a navigation method based on 3D point cloud, which can effectively improve its robustness.

1. Introduction

Non-destructive testing (NDT) of weld seams is important in guaranteeing the safe operation of industrial equipment including oil pipelines, storage tanks, and wind turbine towers. In recent years, the rapid development of robot and image-processing technology has inspired widespread study of automatic NDT systems. Such systems automatically track weld lines to complete testing, thereby significantly improving the quality and efficiency of NDT. Unlike indoor welding, automatic NDT is usually performed in the field, with moving platforms, unplanned routes, and unconstrained illumination. Therefore, the biggest challenge in developing automatic NDT systems is the quick and accurate detection and tracking of weld lines under multiple interfering conditions.

Concerning weld line navigation, some approaches have been proposed based on the weld visual features, artificial tracks, and structured light sensors. With the development of depth camera technology, depth data has begun to be widely used, such as face recognition, gesture detection, background segmentation, and the like. This paper proposes a NDT robot that uses depth data for navigation. Compared with the traditional navigation method, the accuracy of the new method is significantly improved. Because the frame rate of the depth camera is very high, and the algorithm structure is simple and efficient, there is no delay. In short, after a large number of tests, robots based on 3D depth data navigation have higher reliability and accuracy than traditional 2D visual navigation methods.
2. Devices
There are many mature depth sensors, such as Microsoft's Kinect series, Intel's Realsense series, and so on, as shown in Figure 1. The main applied technologies are Lidar imaging, TOF principle, structured light principle, active infrared binocular vision and so on. In this paper, the sensor uses Intel realsense D415, 99mm*20mm*23mm, which makes it easy to install on the wall-climbing robot, which can fully meet the requirements of this paper.

![Figure 1. Depth camera](image)

The non-destructive testing robot needs to advance parallel along the edge of the weld to detect the welding quality. The control parameters required for the moving process include the advancing angle $\theta$ and the relative distance $d$, as shown in the figure. The 3D sensor mounted above the robot captures the weld 3D information and processes it to obtain the required control parameters, as shown in Figure 2.

![Figure 2. Robot structure](image)

3. Algorithm
Positioning is performed in three steps, first determining the range, second determining the angle, and finally determining the distance.

3.1. Determine the scope
The original data captured by the camera is more serious. Since the motion parameters of the robot can only be determined by the middle part of the field of view, the range of 60mm x 60mm in the field of view can be directly obtained by the shearing algorithm, as shown in Figure 3.

![Figure 3. Point cloud after narrowing down](image)
3.2. Angle acquisition

The angle parameter is an index that determines the direction of the non-destructive detection of the robot. The commonly used method is mainly the 2D image analysis method based on the principle of computer vision. However, 2D images have higher requirements on the quality of images. The 3D point cloud based detection method proposed in this paper can completely avoid the problems of the 2D image method.

Determining the depth image of the range is shown in Figure 4. To determine the angle between the motion path of the robot and the weld line, the geometric features of the 3D point cloud need to be analyzed. Since the weld is higher than the plane to be measured, this feature can be used to remove the useless portion of the bottom surface. Methods include thresholding, clustering, support vector machines, and so on.

Because the least squares method is small in calculation, it can meet the demand well. In this paper, the least squares method is used for cutting, as shown in Figure 5, and the formula is as follows.

The equation of the spatial plane can be represented by \(Ax+By+Cz+1=0\), and when there are \(n\) points, it is represented by a matrix.

\[
\begin{bmatrix}
    x_1 & y_1 & z_1 \\
    \vdots & \vdots & \vdots \\
    x_n & y_n & z_n
\end{bmatrix}
= \begin{bmatrix}
    A \\
    B \\
    C
\end{bmatrix} \begin{bmatrix}
    1 \\
    1 \\
    1
\end{bmatrix}
\]

(1)

\[
\begin{bmatrix}
    x_1 & y_1 & z_1 \\
    \vdots & \vdots & \vdots \\
    x_n & y_n & z_n
\end{bmatrix} = \begin{bmatrix}
    x_1 & y_1 & z_1 \\
    \vdots & \vdots & \vdots \\
    x_n & y_n & z_n
\end{bmatrix}^T
\]

(2)

\[
\begin{bmatrix}
    x_1^2 & x_1y_1 & x_1z_1 \\
    \vdots & \vdots & \vdots \\
    x_n^2 & x_ny_n & x_nz_n
\end{bmatrix} = \begin{bmatrix}
    A \\
    B \\
    C
\end{bmatrix}
\begin{bmatrix}
    1 \\
    1 \\
    1
\end{bmatrix}
\]

(3)

\[
\begin{bmatrix}
    A \\
    B \\
    C
\end{bmatrix} = \begin{bmatrix}
    \sum x_i^2 & \sum x_iy_i & \sum x_iz_i \\
    \sum x_iy_i & \sum y_i^2 & \sum y_iz_i \\
    \sum x_iz_i & \sum y_iz_i & \sum z_i^2
\end{bmatrix}^{-1}
\begin{bmatrix}
    -\sum x_i \\
    -\sum y_i \\
    -\sum z_i
\end{bmatrix}
\]

(4)
After determining the values of A, B, and C, the dividing plane of the weld can be drawn, and the weld point cloud above the dividing plane is retained, and the weld point cloud below the dividing plane is removed, and the weld point cloud can be obtained. As shown in Figure 6.

The cut point cloud is flattened to obtain its two-dimensional data, as shown in Figure 7. There are many ways to fit a weld line on a two-dimensional plane, such as support vector machine, least squares, neural network regression, and so on. This article uses the least squares method to meet the demand.

Figure 5. Space plane least squares fitting

Figure 6. Part of the weld after cutting

Figure 7. Fitting of weld direction
3.3. Distance acquisition
Define k=12, step=(max(x) - min(x))/k, and select a segment in the middle, as shown in Figure 8.

![Figure 8. Point cloud segmentation](image)

Let the value of the X coordinate in the point cloud after cutting be 0. Due to the geometric nature of the point cloud, there may be coincident point clouds in the X-axis direction, and the coincidence points need to be found for de-duplication. After obtaining the point cloud after planarization, it is necessary to find the weld boundary point. The commonly used methods include the sliding window area method, the derivative extreme value method, the geometric feature method, and the like.

This paper uses the most suitable sliding window area method. Starting from the rightmost pixel of the image, C=30 points are selected to the left, and the average of the heights of the ordinates of the C points is calculated as the height h of the sliding window reference line, as shown in Figure 9.

\[
h = \frac{\sum_{i=1}^{C} y_i}{C}
\]  

![Figure 9. Sliding window area method](image)

After determining the height of the sliding window, the area threshold of the sliding window is defined as s=5, and the sliding window slides point by point along the baseline to the left. The integrated area of each point from the baseline of the sliding window is calculated, and the sliding stops when the area is s. The center point coordinate of the current sliding window is the distance parameter d, as shown in Figure 10.

![Figure 10. Distance result](image)

Performing the same operation on the remaining k-1 parts yields k points, each separated by a step, as shown in Figure 11.
Figure 1. Detection effect

After mapping k points to the bottom surface, you can get the distribution map of the discrete points, as shown in the figure 12.

Figure 12. Two-dimensional image of discrete points

By fitting the series of points using the least squares method, a straight line can be obtained. As shown in the figure 13, the midpoint of the line is selected as the distance parameter of the robot.

Figure 13. Distance parameter acquisition

4. Conclusions
Compared with the traditional 2D image navigation method, due to the difference of the principle, various problems of 2D image navigation, such as oil stain, ambient light interference, rust, etc., can be completely overcome. Depth information is an intrinsic property of an object. The navigation method in this paper relies only on depth information, so it is highly immune to external environmental interference. However, the robots in this paper also have some shortcomings. When the welding material is too smooth for some reasons, the specular reflection problem occasionally occurs, so that the local information will be missing, and the loophole can be filled by an algorithm.
Compared with the traditional navigation method, the depth data-based navigation robot has improved the fault tolerance by 25% and the detection speed by 10%.

References

[1] Zhang, L.; Sun, J.; Yin, G.; Zhao, J.; Han, Q. A cross structured light sensor and stripe segmentation method for visual tracking of a wall climbing robot. Sensors 2015, 15(6), 13725-13751.

[2] Zou, Y.; Du, D.; Zeng, J.; Zhang, W. Visual method for weld seam recognition based on multi-feature extraction and information fusion. Trans. China Weld. Inst. 2008, 34, 33-36.

[3] Du, D.; Wang, S.; Wang, L. Study of vision sensing technology in seam recognition based on analyzing target feature. Trans. China Weld. Inst. 2008, 29, 108-112.

[4] Krämer, S.; Fiedler, W.; Drenker, A.; Abels, P. Seam tracking with texture based image processing for laser material processing. In Proceedings of the International Society for Optics and Photonics, High-Power Laser Materials Processing: Lasers, Beam Delivery, Diagnostics and Applications III, San Francisco, CA, USA, 20 February 2014; Volume 8963, p. 89630P-1-9.

[5] Liu, X.; Xu G.; Fei Y. Image processing algorithm for intersecting line weld inspection robot. Transducer and Microsystem Technologies 2017, 36(7), 146-153.

[6] Li, X.; Li, X.; Ge, S.; Khyam, M. O.; Luo, C. Automatic welding seam tracking and identification. IEEE Transactions on Industrial Electronics 2017, PP(99), 1-1.

[7] Zeng, J.; Chang, B.; Du, D.; Wang, L.; Chang, S. Peng, G., et al. A weld position recognition method based on directional and structured light information fusion in multi-layer/multi-pass welding. Sensors 2018, 18(1).

[8] Molleda, J.; Usamentiaga, R.; Garcia, D. F.; Bulnes, F. G.; Ema, L. Shape measurement of steel strips using a laser-based three-dimensional reconstruction technique. IEEE Transactions on Industry Applications 2011, 47(4), 1536-1544.

[9] Molleda, J.; Usamentiaga, R.; Bulnes, F. G.; Granda, J. C.; Ema, L. Uncertainty propagation analysis in 3-d shape measurement using laser range finding. IEEE Transactions on Instrumentation & Measurement 2012, 61(5), 1160-1172.

[10] Usamentiaga, R.; Molleda, J.; Garcia, D. F. Fast and robust laser stripe extraction for 3d reconstruction in industrial environments. Machine Vision & Applications 2012, 23(1), 179-196.

[11] Duran, O.; Althoefer, K.; Seneviratne, L. D. Automated pipe defect detection and categorization using camera/laser-based profiler and artificial neural network. IEEE Transactions on Automation Science & Engineering 2007, 4(1), 118-126.

[12] Liang, L.; Ordonez, C.; Jr, E. G. C.; Coyle, E.; Palejiya, D. Terrain surface classification with a control mode update rule using a 2d laser stripe-based structured light sensor. Robotics & Autonomous Systems 2011, 59(11), 954-965.