Point Cloud Based Three-Dimensional Reconstruction and Identification of Initial Welding Position

Lunzhao Zhang, Yanling Xu, Shaofeng Du, Wenjun Zhao, Zhen Hou and Shanben Chen

Abstract Initial welding position guidance is necessary for vision-based intelligentized robotic welding. In this paper, we proposed a point cloud based approach to recognize working environment and locate welding initial position using laser stripe sensor. Calibrated laser sensor can achieve high accuracy in transforming from image coordinate system to camera coordinate system and to robot tool coordinate system with hand-eye calibration. Linear feature based image processing algorithm is developed to extract the position of laser stripe center in subpixel-level accuracy; then trajectory-queue based interpolation is implemented to convert down-sampled laser points to robot base coordinate system in real-time scanning. Identification of workpiece is implemented by segmenting workpieces from the point cloud data in the image. Before segmentation, KD-Tree based background model is constructed to filter out background points; then RANSAC fitting procedure rejects outliers and fits the correct workpiece plane model; and the welding initial position can be found along the weld seam which is the intersection of fitted planes. In verification experiment, workpiece planes and welding initial position can be correctly recognized despite the presence of abnormal noises.

Keywords Intelligentized welding · Welding initial position · Laser vision sensor Welding robot · Point cloud · KD-tree · Segmentation

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1 Introduction

In intelligentized welding applications, autonomous machines such as welding robot are used as executor. It is necessary to equip welding robot with machine vision sensor to handle uncertain and varying environment [1]. Therefore, machine vision techniques are widely deployed in robot welding application, such as guidance, tracking and quality assessment after weldment. Identification of initial position before welding is one scenario where vision sensor can map the welding environment and eliminate the uncertainty of workpiece location. Various machine vision methods can be divided into two main categories: passive vision sensing, which and active vision sensing. Extensive noise such as reflection and make active sensor a good candidate for weld environment. Besides tracking, guiding robot to initial position of weld seam is a vital procedure before weldment. It requires that robot can map the work piece and workspace environment and locate the desired relative to weld torch.

Some early works investigate passive-vision based localization on weld joint and welding initial position. Zhu and Lin used edge detection and template matching to locate weld seam and its intersection with workpiece edge. To accelerate process and boost precision, they adapt two-step match method, first in global and then in local area [2]. Similarly, Chen use "coarse-to-fine" method to find initial point of weld seam. A global curve is fitting to find the weld seam, which can then be narrowed down to a local window where search of intersection between weld seam and workpiece edge is performed. Three-dimensional position is given by dual-cameras measurement [3]. Stereo vision like dual-camera system are widely used in such weld joint localization scenario. Dinham and Fang propose a stereo approach to locate three-dimensional position of weld joints. In their method, background is subtracted by Hough line detection of workpiece edge, then edge detection is used to extract weld seam. Identification of weld joints cam achieve accuracy within ± 1 mm in three-dimensional space based on homography matching technique. Experiments in a working space verifies that this method can be implemented in industry [4]. Passive-vision methods are widely deployed in welding application, Xu et al. developed a welding seam tracking system using single passive vision sensor and achieve high tracking accuracy in real-time [5].

Compared to above-mentioned passive vision sensors, laser stripe based active vision sensor performs well in weld tracking applications, because external laser light can still be observed under intensive arc light. This good characteristic attracts many researchers with various investigations. To track weld seam in environment with intensive noise, Xinde Li and Xianghui Li utilize Kalman filter to track laser stripe after image preprocessing. They also build description model for weld joint profile in character strings. Comprehensive experiment in static precision, real-time and dynamic precision shows that their method outperforms others in static, dynamic precision and stability [6]. Ding and Huang utilized principle of triangulation to derive equations that transform image pixels to two spatial directions: X direction which is along the laser stripe and Z direction as dept. To detect weld joint feature, they propose a correlation coefficient based matching method which compare current frame with last frame's joint profile, and maintain a first-in-first-out queue for refreshing seam position during welding. Their matching algorithm enables detections of different groove types and no pre-defined model is needed [7].

Although tracking using laser stripe sensor is relatively mature, there is few explorations on localization of welding initial position based on laser-stripe sensor system, and stereo vision based localization approach requires extra hardware besides laser stripe sensor, which make system more complex. In this paper, three-dimensional reconstruction of working environment and localization of weld joint will be fulfilled using a spatial point cloud approach. After laser calibration and hand-eye calibration, laser-stripe sensor system mounted on robot end effector can scan the working environment, transform laser pixels to spatial space and identify workpiece and initial welding position before welding.

2 System Setup

As shown in Fig. 1, robotic welding vision system composites of a Fanuc M20-iA industrial robot as executor, which is equipped with weld torch as end effector, and other welding equipment like GMAW weld machine. In-house designed laser stripe

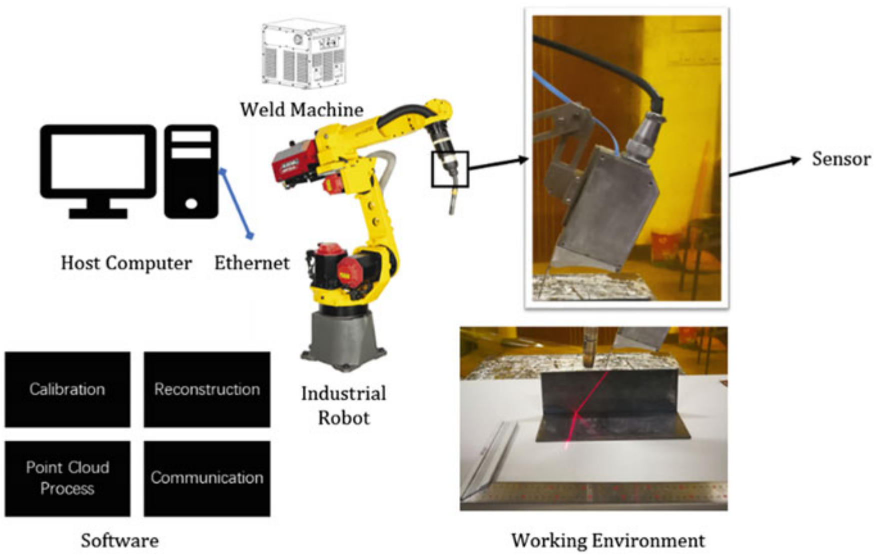


Fig. 1 Laser stripe vision system for reconstruction and localization of initial welding position

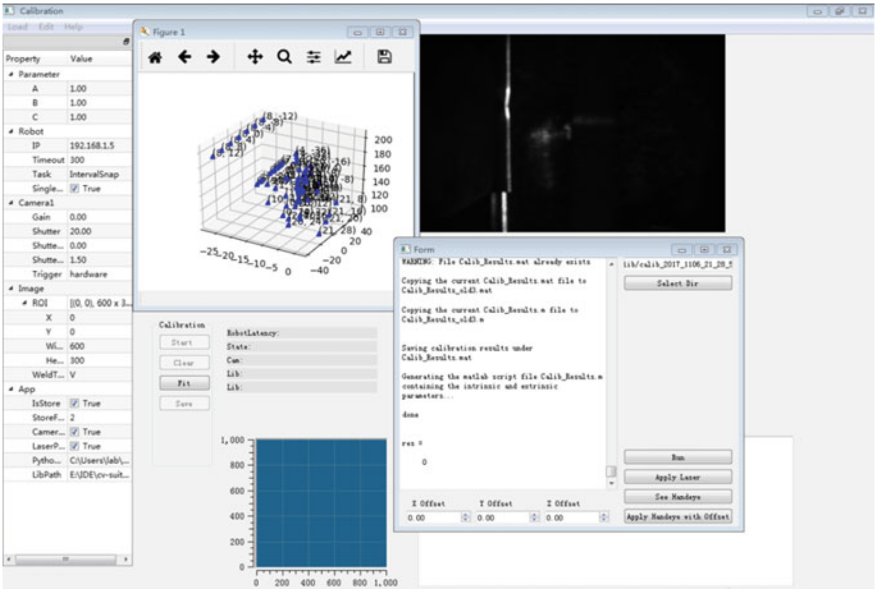


Fig. 2 Graphic user interface of calibration program

sensor is used and mounted in the weld torch. The host computer communicates with robot controller for exchanging robot information and with laser sensor for image data, both on Ethernet. It is the core of the whole system since data like image and robot position are processed by software components running in it.

The software part running on host computer includes communication interface with robot controller based on a protocol from vendor, calibration implementation which is the key part of spatial reconstruction, image processing algorithm designed for laser image, and point cloud processing. Procedure like initial position guiding and tracking is implemented in software, as well as an easy-to-use program for fast calibration, shown in Fig. 2.

3 Calibration

Laser stripe based active sensor can collect image with laser pattern, which can be recovered as three-dimensional information. The accuracy of stripe light sensor depends on calibration procedure. In presented system, it requires two stages of calibration: Laser plane calibration and hand-eye calibration. Both are combined into one by using a planar calibration plate with grid pattern.

Calibrating of laser plane targets at establish transform from two-dimensional image pixel to spatial space represented as a camera based frame. Calibrating the hand-eye matrix is the following steps to derive a matrix as transform from camera frame, as the eye of system, to tool frame, as the hand of system. Tool frame in robotic system is based on weld torch, and its TCP, Tool Center Point, is the weld wire tip. In this paper, these two steps are unified into one calibration procedure, which can be done by a single planar calibration plate. Figure 3 presents overall procedure of calibrating.

To fit laser plane equation in three-dimensional space, at least three non-collinear points are required. These points data can, be achieved using calibration target with specific geometry feature in calibration process, like a calibration target with perpendicular planes, which is difficult to manufacture. In this paper, proposed calibration procedure requires only a simple planar calibration plate which is common in camera calibration. Well-known camera calibration method, proposed by Zhang, is widely adapted in camera calibration. Although laser calibration and hand-eye calibration will not directly depend on result of camera calibration. The external parameter of camera can be used to generate non-colinear data for laser calibration, so that a simple plane can be used as calibration plate, as long as camera take multiple pictures from different view. In summary, points on laser are computed

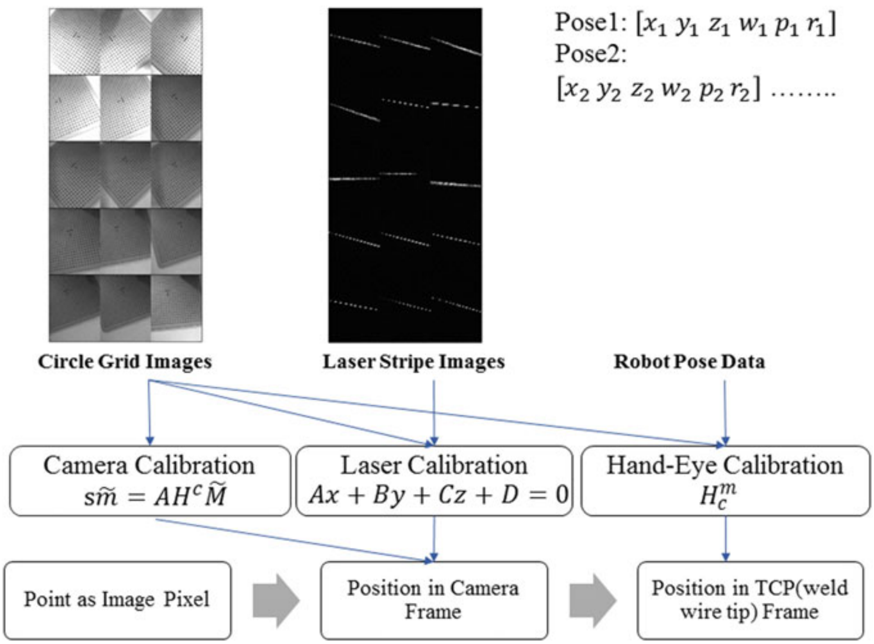


Fig. 3 Overall calibration procedure

from intersection of laser line and circle grid pattern. These points from different image at different orientations are all transformed by external parameters into camera frame, and then there are enough non-colinear laser points to fit laser plane equation $Ax + By + Cz + D = 0$. Zhou proposes this method to calibrate laser stripe sensor. Laser plane equation can be combined with camera model to derive relation between two-dimensional laser pixels and three-dimensional position in camera frame. In this paper, a 4 * 3 conversion matrix M_i^c is used to represent this linear transform. The deduction of this conversion matrix is followed Huynh's method, which use homography between laser plane and image plane to derive this linear transform after laser plane is fit [8]. Hand-eye calibration aims at transform from camera frame to tool frame. In this paper, a third-party toolbox is used for computing hand-eye matrix, which is developed by Wengert as a fully automated hand-eye toolbox [9].

Calibration program implement a Graphic User interface which facilitate data acquisition and computing of calibration model. To acquire both laser stripe image and calibration plate image at one pose, program can automatically adjust camera shutter and toggle laser to capture two images once it receives a capture command, one in lower shutter and laser on as laser image, another in higher shutter and laser off as circle grid calibration image. Utilizing the planar calibration target with circle grid pattern, the intersections of laser stripe and extracted circle grid can be calculated and transformed into camera frame. Robot position information is provided by robot controller and recorded for Hand-eye calibration.

In summary, once calibration is finished, the laser pixel in image can be transformed to camera frame, then to tool frame with hand-eye calibration. Then position in robot base frame can be achieved with current robot position. The whole transform can be expressed as follows:

$$P = H^0 H_c^m M_i^c P_i \tag{1}$$

P_i is the homogeneous form of pixel coordinate, like $\begin{bmatrix} x & y & 1 \end{bmatrix}^T$, M_i^c is the 4*3 conversion matrix from laser calibration, H_c^m is the hand-eye matrix from hand-eye calibration, H^0 is the transform between tool frame and robot base, and usually offered by robot controller as robot position value.

Error both laser calibration and hand-eye calibration. To measure the error, the reprojection method, which use calibrated transform to recalculate the data points, is used. Fig. (4) show the reprojection error of laser plane calibration. For hand-eye calibration, the same reprojection method is used by hand-eye toolbox and result shows that error of approximately 1 mm can be achieved in hand-eye transform, which means hand-eye calibration is the major source of measurement error.

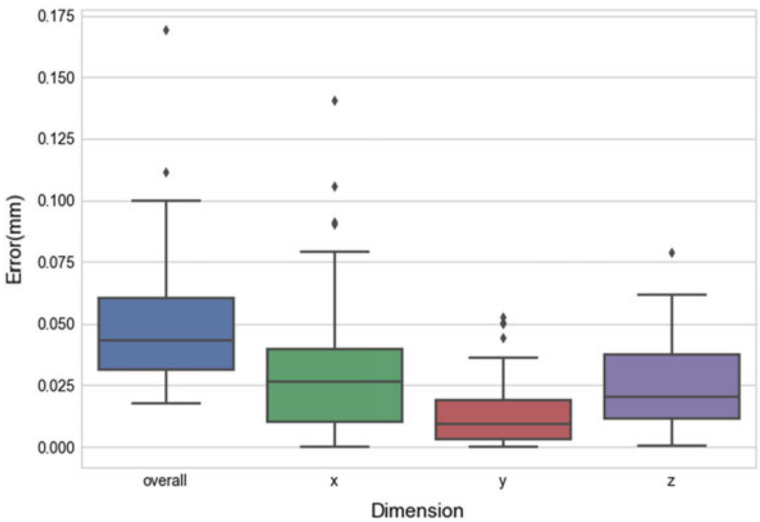


Fig. 4 Reprojection error of laser plane calibration

4 Image Process and Reconstruction

Extraction laser point in two-dimensional image is widely discussed and various methods are proposed. Most of them are based on column-scanning, iterating over the column which is perpendicular to laser line direction and find out the laser point on each column by lightness pattern, like centroid of lightness and gaussian fitting of gray value. Reference [10] proposed a laser stripe peak detector based on FIR filter. Such method's accuracy will easily deteriorate in presence of weld noise, since arc light are far more intense than laser light. Beyond column scanning approach, Steger proposes a robust method to extract linear feature in images, based on Hessian Matrix which describe the property of second-order derivative of image gray values. Du utilize same idea to extract laser stripe in reflective and uneven metallic surface [11]. This hessian-matrix based ridge detect shows good robustness against various noise, and high accuracy at sub-pixel level. This paper will not cover the mathematical intuition behind this method in depth. To extract linear feature, images should be convolved with gaussian kernel, so that 2 * 2 hessian matrix of each pixel can be achieved. If I is a gray-value image and $r(x;\sigma) = g(x;\sigma) * I$ is convolution operation on I, with $*$ denote convolution operator and $g(x;\sigma) = \frac{1}{\sqrt{2\pi}\sigma}\exp^{-\frac{-x^2}{2\sigma^2}}$ as Gaussian kernel. Hessian matrix can be represented by:

$$H = \begin{bmatrix} r_{xx}(x;\sigma) & r_{xy}(x;\sigma) \\ r_{xy}(x;\sigma) & r_{yy}(x;\sigma) \end{bmatrix} \quad (2)$$

Obviously four convolutions with different gaussian derivative kernel can compute a Hessian matrix in each pixel. From Hessian matrix, line strength N of each pixel can be computed as follow:

$$N = \frac{\sigma^{\gamma}}{2}\left|r_{xx} + r_{yy} - \sqrt{(r_{xx} - r_{yy})^2 + 4r_{xy}^2}\right| \tag{3}$$

Using a threshold, linear feature can be extracted.

Extracted pixels has rich information of laser stripe and can be recovered to three-dimensional profile information which represents the intersection of laser plane and scanned object. However, since reconstruction in three-dimensional space requires a set of images acquired while scanning, the capture frequency is the bottleneck of scanning procedure. For example, if the robot scans at speed of 50 mm/s and the sensor capture speed is at 14 frames per second, the distance between two images is about 3.6 mm which is sparse compared to extracted continuous laser stripe on each image. This unbalanced data distribution can be utilized to reduce its size, which means discarding some information on each image without loss of too many details. Based on this intuition, Down-sample technique is proposed, which will sample laser pixels on each image per M pixels after extraction of laser center pixels. Fig. (5) shows the result of laser extraction without down-sample (M = 1), and the result after down-sample with M = 5. The laser stripe pixels after down-sample can still retain most of details.

M is the only parameter of down-sample parameter and decides the final data volume. Appropriate M can reduce volume of data with little loss of surface information. In experiment of workspace scanning, M at 20 can still retain most information of workpieces but the total data size is rapidly reduced.

While scanning, robot with sensor will capture a series of images which are discrete both in time and space. To reconstruct these images into three-dimensional robot base frame, it is important to get the precise position where each image captured while scanning, so that we can transform the data from single image to robot base frame. Acquisition of precise robot position where each image captured cannot be done directly since we can only achieve robot position data from controller at a fixed finite frequency, 50 Hz for example. The solution is to maintain a trajectory queue which can linearly interpolate position by time once an image is acquired at certain timepoint.

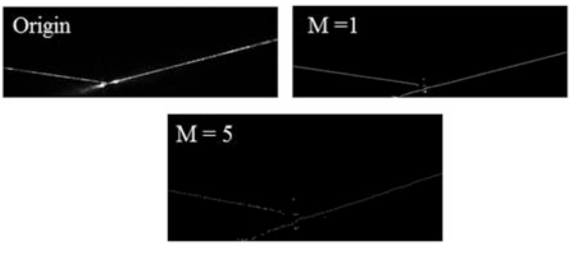


Fig. 5 Extracted laser center in different M

As input of reconstruction, images and robot position are separately handled by host computer but they will both be recorded using a millisecond-level timestamp once program successfully receive these data. However, timestamp like this is the timepoint when communication is finished, not the timepoint when data is generated. For image data from sensor, communication cost is non-trivial and must be considered. This delay can be estimated by image size and ethernet bandwidth. For system in this paper, the image size is 1200 * 1600 * 8bit, and the ethernet connection between host computer and sensor has a bandwidth of 50 Mbit/s, so the communication cost, the timestamp should minus, is about 27.32 ms. As for robot position data streaming, due to its relatively high frequency and unknown internal mechanism, its communication delay is not considered.

For robot position (x_n, y_n, z_n) at timepoint t_n, it is inserted into a trajectory queue after received. This trajectory queue is ordered by timepoint and contains robot position in a fixed duration, such as 500 ms. The purpose of maintaining such a queue is to estimate robot position of arbitrary timepoint.

As shown in Fig. (6), when an image is received and is to be reconstructed in robot base frame, robot position (X_n, Y_n, Z_n) where this image is captured remains unknown. To estimate this position, the timepoint T_n when image is captured is used to interpolate an estimated (X_n, Y_n, Z_n), in following steps:

1. In trajectory queue, use binary search to find the first timepoint t_i which is larger than T_n, now T_n is between t_{i-1} and t_i.
2. Calculate the averaged velocity V_i between t_{i-1} and t_i:

$$\Delta t = (t_i - t_{i-1})$$

$$\begin{cases} V_{xi} = \frac{(X_i - X_{i-1})}{\Delta t} \\ V_{yi} = \frac{(Y_i - Y_{i-1})}{\Delta t} \\ V_{zi} = \frac{(Z_i - Z_{i-1})}{\Delta t} \end{cases} \tag{4}$$

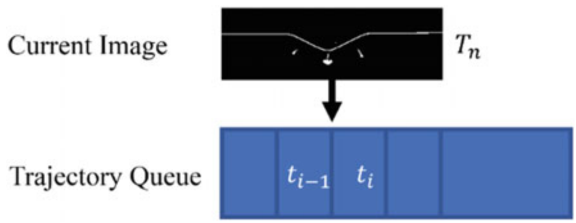


Fig. 6 Interpolation using trajectory queue

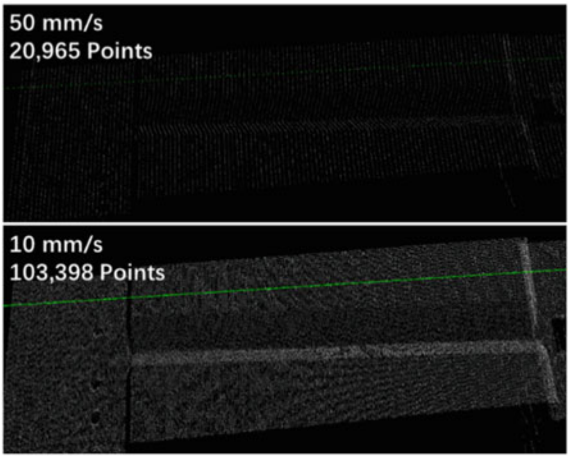


Fig. 7 Reconstruction result with different scanning speed

3. Linearly interpolate corresponding position at T_n:

$$\begin{cases} X_n = V_{xi} * (T_n - t_i) + x_i \\ Y_n = V_{yi} * (T_n - t_i) + y_i \\ Z_n = V_{zi} * (T_n - t_i) + z_i \end{cases} \tag{5}$$

Such interpolation based position estimation can recovery robot position in arbitrary timepoint. Therefore, once the timepoint when image is captured is known, the robot position of this image timepoint can be calculated based on the above method, and then the reconstruction in robot base frame, which depends on robot position, can be done by recovery accurate spatial position of a series images captured along scanning direction. This trajectory-queue based interpolation can handle online scanning and reconstruction at various scanning speed. Figure 7 shows reconstructed point cloud after down sampled with $M = 10$ and scanning speed = 50 and 10 mm/s respectively. The green dot is the estimated position where camera captures each image. It is obvious that scanning at 50 mm/s constructs a sparser point cloud, because the camera's capture speed is fixed. Thanks to trajectory queue based interpolation, varying speed will not affect the reconstruction accuracy.

5 Point Cloud Processing

Based on above-mentioned components. Industrial robot mounted with laser sensor can scan welding workspace and acquire three-dimensional point cloud data set in robot coordinate. To further process these points, we utilize PCL (Point Cloud Library), a C++ library for point processing algorithms, to process generated point cloud data.

Robot must move to search before localizing the workpieces. To prevent potential collision between weld torch and work pieces while moving, robot should conform pre-determined search policy. Here is the proposed search scheme: the robot program requires two pre-taught position as its begin and end of search. The search area is defined by the distance between these two points and the field of view of laser sensor, which is affected by laser stripe length and field of view of camera.

In search area, points can be divided into three categories: background, target workpiece and abnormal noise, as shown In Fig. 8. Only workpiece is the interest of later process. Therefore, background and abnormal noise should be eliminated to improve accuracy of identification. Background is what keep static in space, so it will not change in multiple scanning over time. Filtering out these background points can utilize this static feature to construct a background model.

A background model defines geometry of background, and can be used to check whether one point belong to background environment or not. The general ideal is to search every point's nearest k neighbors in background and use distance threshold to reject points that has a high possibility to belong to background, this can be named as kNN distance criterion. To accelerate query of kNN, background model will be constructed as KD-Tree, a data structure offering fast kNN query operation.

KD-Tree is a binary tree data structure, with nodes specifies an axis and splits the set of points based on comparison of their coordinate along and certain value. Once constructed, KD-Tree can be used to queried one point's nearest K points at a time cost of $O(\log N)$, with N for number of points inside tree, which indicates a substantial gain in efficiency. Utilizing kNN (k Nearest Neighbor) query, point can be verified whether it belongs to a background model, by checking its' kth neighbors inside KD-Tree. This distance method is named as kNN Distance method. With a constructed KD-Tree background model, every point in point cloud is checked with kNN Distance criterion. If one point's kNN Distance is smaller than threshold, it will be subtracted from point cloud. Details of kNN Distance are shown in Fig. 9.

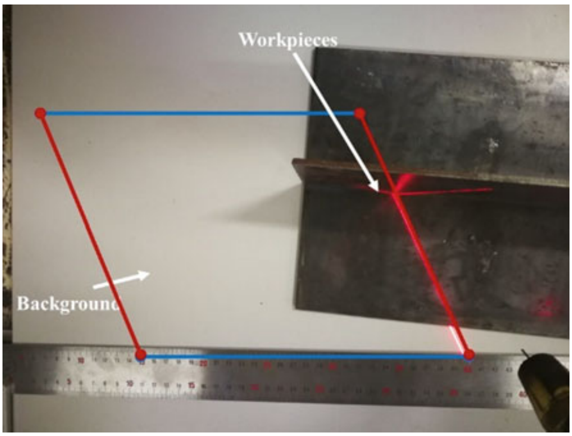


Fig. 8 Search area and working environment

Fig. 9 Filtering based on kNN distance threshold

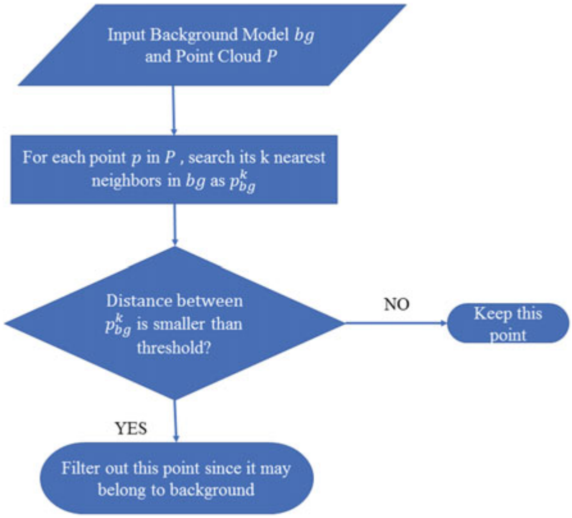
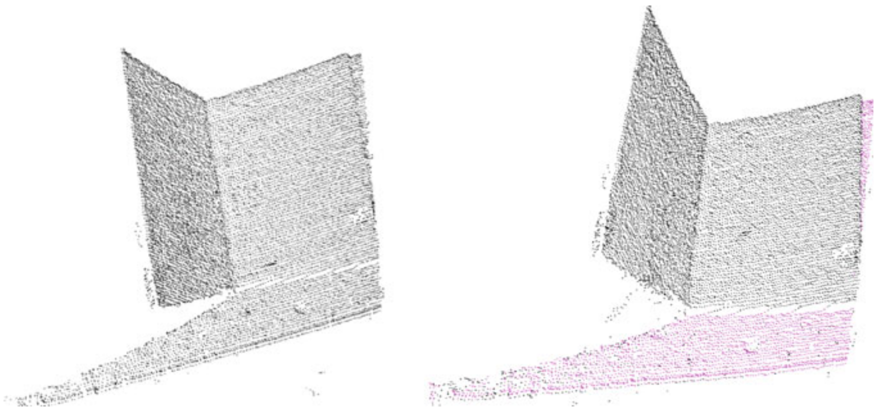


Figure 10 shows effect of background subtraction. The background in working environment is a coarse planar surface and has been constructed before workpiece is put into environment. Then every scanned point cloudas Fig. 10a shown, will use this KD-Tree as input to query every point's kNN Distance in this point cloud. Points in purple in Fig. 10b represents points that have a smaller kNN Distance than threshold so they are marked as background point and will be filtered before later fitting process.



(a) Original Point Cloud Point

(b) Point Cloud with Back-ground Subtraction

Fig. 10 Effect of background substraction

Introduction of KD-Tree based background model and kNN Distance criteria can finish effective background subtraction, eliminate noise for later process.

To locate welding initial position from large point cloud data set, algorithms should be designed to fit different workpieces with different joint profile. The process that separate points belong to workpieces from other points is called segmentation. Segmentation can be based on workpieces' geometry feature. In 3d estimation problem, planar model is a good pattern to fit. Fortunately, most work pieces in welding production and can be describe by composition of different planar model. Therefore, identification of workpieces can be described as a problem of fitting multiple plane model from point cloud data. In this paper, Tee joint with workpieces perpendicular to each other is chosen to as target of recognition.

Although background pints have been subtracted, there is still much noise in point cloud data. To fit a model from noise-polluted data set, a robust fitting algorithm is needed. In this paper, RANSAC (Ransom Sample Consensus) algorithm is used to fit planar workpiece out of point cloud. RANSAC is an iterating method which samples minimum data points from data set to fit model in each iteration, such as three points for plane model. Iteration will terminate if most of data points fit in this sampled model, and outliers can be rejected since they are far from true model. For point cloud data set, noise as outliers will mislead common fitting algorithm such as least-square fitting. Rejecting outliers using RANSAC can improve fitting accuracy greatly by rejecting these outlies over iteration. Fitted plane model can be represented as $Ax + By + Cz + D = 0$, with $\begin{bmatrix} A & B & C \end{bmatrix}^T$ as normal vector of plane.

Tee joint is composed of two workpieces which can be abstracted geometrically as perpendicular planes, and the perpendicular relation is a valuable constraint for fitting procedure: once we find one plane, the other can be easily found by explicitly choose a plane whose normal vector is perpendicular to the previous. This constraint can be expressed as angle θ, which is 90° in perpendicular Tee joint, as the ideal angle relation between two planes, and angle ε as the maximum allowed deviation. Real angle of planes can be computed as angle between two normal vectors of two planes. Real angle and ideal angle can determine whether these planes form a correct weld joint. Criterion is as follows:

$$\left|\cos^{-1}\frac{n_1 * n_2}{n_1 n_2} - \theta\right| < \varepsilon \tag{6}$$

In summary, fitting procedure of Tee joint includes:

1. RANSAC fitting for the first plane P_1 with normal n_1. Subtract all points belong to P_1
2. While fitting the second plane P_2 in RANSAC iteration, reject all fitted planes not satisfied with Eq. (6) using normal vector n_2. Subtract all points belong to P_2
3. For points belong to P_1 and P_2, apply static noise approval to further filter out outliers, then two points clouds represent two planes are achieved.

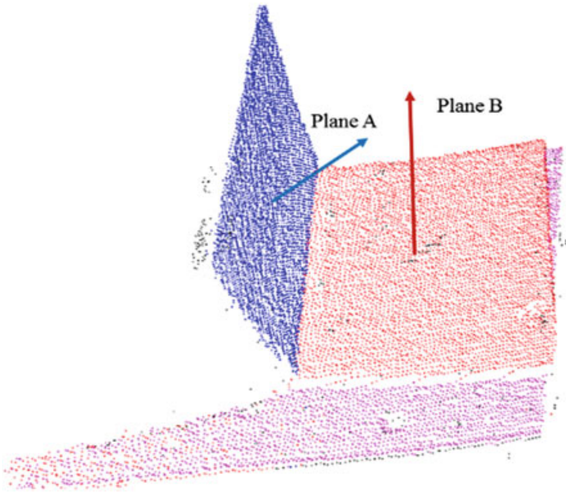


Fig. 11 Fitting planes of tee joint

Figure 11 shows the result of Tee joint fitting. Now since planes are segmented from original point cloud, it is simpler to find out weld seam and weld initial position.

The weld seam can be computed as intersection of two plane once planes' coefficients are estimated. Another interested feature, initial welding position, can be figured out along the weld seam. This is a one-dimensional search along intersection. To suppress random noise, compute the centroid of the first x valid point along the seam as the initial position of weld seam. Green line in Fig. (12) represents the weld seam, which is the intersection of two workpieces as Tee joint, and the green dot is the desired initial welding position.

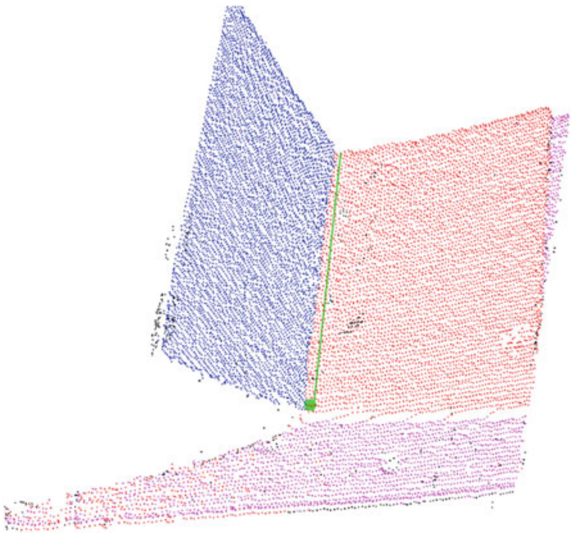


Fig. 12 Identification of weld seam and weld initial position

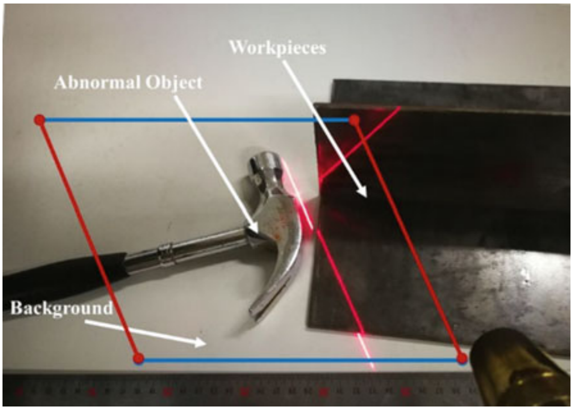


Fig. 13 Working environment with abnormal object as noise

6 Experimental Verification

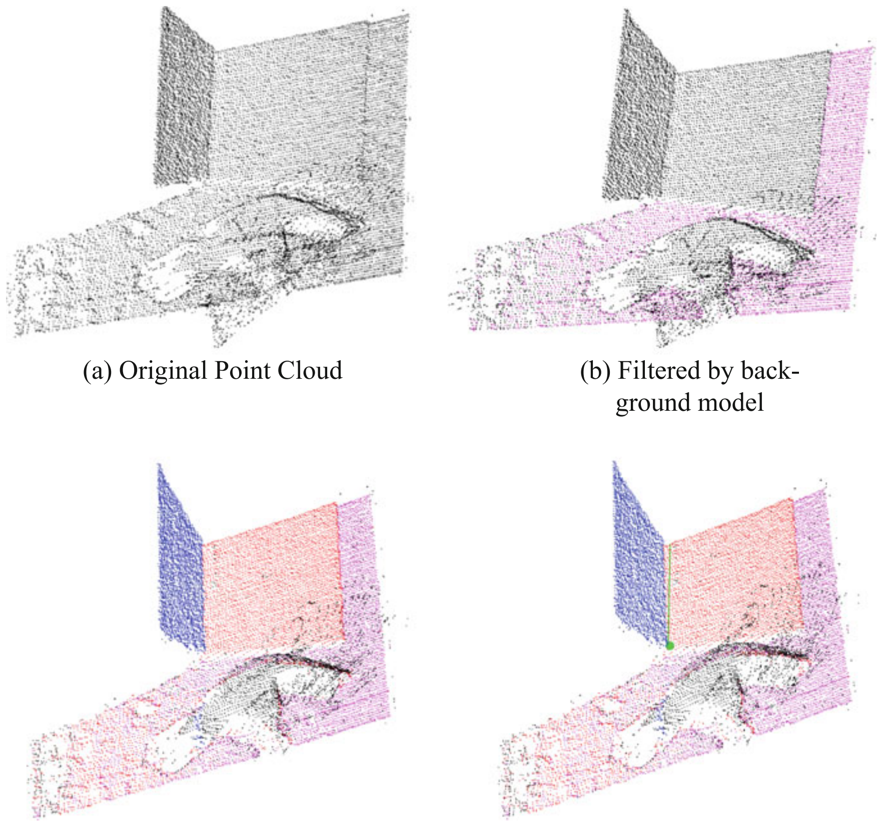
To verify performance and robustness of proposed algorithm in environment with unexpected noise, experiment is performed to simulate scenario where both workpiece and irrelevant object exists. As shown in Fig. 13, a working space with abnormal object is set up, composed of background, abnormal object and workpieces. As abnormal object, tool is arbitrarily put around workpiece. To search such a working space, search length is set to 150 mm and search speed is at 50 mm/s.

Before searching, background without other objects is scanned as background scanning, and KD-Tree model is constructed for kNN Distance based background filtering, with $K = 3$ and distance threshold of 1.5 mm. In reconstruction procedure, the down sample is performed at $M = 15$. Recognition result are shown in Fig. 14. From original point cloud to weld seam and welding initial position, algorithm presented in this paper can robustly filter out background points and abnormal object, which shows good practical performance in production environment.

7 Conclusion

In this paper, welding workspace reconstruction and identification of initial welding position using laser stripe sensor are studied. A robotic welding vision guiding system is proposed and be tested in noisy working environment. Related works including:

1. Fast and unified calibration procedure for laser plane and hand-eye conversion is proposed and programed as utility software. Laser plane calibration can achieve high reconstruction accuracy with approximately 0.1 mm reprojection error, and error in hand-eye matrix conversion is about 1.0 mm.



(a) Original Point Cloud

(b) Filtered by back-ground model

(c) Plane Estimation

(d) Weld Seam and start position

Fig. 14 Fitting and identification in noisy environment

2. Extracting algorithm for laser stripe center is developed to extract linear feature from images with subpixel-level accuracy. Hessian matrix based line extractor have good performance in noisy metallic surface.
3. Online reconstruction scheme suitable for moving robot arm is designed with two steps: down sample on single image and interpolation based estimation for position where image is captured. Three-dimensional Reconstruction from a series of images are finished online at different scanning speed.
4. Point cloud based workpiece segmentation is implemented. To segment work-pieces out of point cloud, KD-Tree background model and k Nearest Neighbor Distance criterion are used to filter out background points, and RANSAC based plane fitting approach can fit planes and reject noise. Certain angle relation between workpieces is utilized to multiple planes fitting. After workpiece segmentation, initial position can be found along the weld seam, which is the intersection of fitted planes.

5. Experimental verification shows system can recognize work pieces and initial position against noise like abnormal object. Robustness of the whole system is proved, and system can be deployed in industrial production environment.

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