Point Cloud Based 3D Matching and Identification of Welding Seam Using Genetic Algorithm

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Abstract. Welding seams identification is a challenging task in robotic welding process. In this paper, we present a method for the automatic identification and location of welding seams for robotic welding using handy 3D scanner. The method uses point cloud based local feature matching and continuous feature search algorithm, which aim at achieving an adaptive seam identification process that can work on similar work pieces with different sizes. The results together with the visual verification demonstrate that the proposed algorithms have ability to identify the welding seam from point cloud acquired by handy laser scanner.

1. Introduction

Up to now, arc welding robots are mainly applied to mass production such as automobile industry by using teach-and-playback mode. There are enough advantages to take a significant amount of time and expense to programme paths and optimize welding parameters for each new part. However, it cannot be justified for small volume manufacturing to do so. To bring benefits of robots to broader application scenarios, some issues that include welding seam identification and tracking need to be addressed. As one of the key issues, welding seam identification aims to find actual seams in the work piece.

Computer vision system can be used to detect the weld seams and provide a path to the robot to weld parts automatically. In some approaches, computer vision is used for approximation and reconstruction of the actual work piece geometry and then automatic generation of robot programs for each new work piece [2]. However, developing robust and efficient vision guided robotic systems can be a challenging task to accomplish when using 2D images that inherently only captures a projection of the 3D environment.

The recent introduction of the depth camera enables new methods for helping robots to make more useful decisions. A low cost 3D camera and CAD model data solution was developed in order to improve the process of offline programming a welding robot, by estimating a corrected pose of the
object to be welded [3]. However, the algorithms are highly dependent on the CAD model. When the size changes, the feature points and the pre-defined CAD template need to be rebuilt again. The process is therefore neither adaptive nor robust. The development of a flexible and accurate seam detection algorithm that is not limited to unique work piece is needed.

In order to tackle the above-mentioned challenges, a handy laser scanner was introduced to acquire field information for seam identification in this work. Point cloud based local feature matching and continuous feature search algorithm, which aim at achieving an adaptive seam identification process that can work on similar work pieces with different sizes, were proposed and implemented. Firstly, the GA (Genetic Algorithm) is used to optimize the pose transformation parameters, and the point cloud of ruler is aligned with the point cloud of work piece to identify local welding seam segment in the work piece. Secondly, the boundary of the ruler is then extended to search the remaining welding seam segments with the same feature in the work piece. When continuous search finished, the entire welding seam of the work piece can be extracted.

2. Related works
In [2] computer vision is used for reconstruction of the actual work piece geometry. The proposed method can automatically subtract the background from the images obtained from a robot mounted camera system. Reliable seam identification can then be achieved for welding of ferrous materials. The methods developed in [5] enables the robust identification of narrow weld seams for ferrous materials combined with reliable image matching and triangulation through the use of 2D homography. The goals of [6] are to recognition the butt welding joint for welding robot environments by using a new approach of background subtraction seam path process. Butt welding joint images were captured from CCD camera mounted on the top of the work bench then processed by the proposed approach method to extract and determine the weld seam path position in x-y coordinates. [7] presents a novel method that can autonomously identify fillet weld joints regardless of the base material, surface finish and surface imperfections such as scratches, mill scale and rust. The new method introduces an adaptive line growing algorithm for robust identification of weld joints regardless of the shape of the seam. Many studies like [8,9] focus on weld seam tracking using computer vision. [11] propose a new approach known as local thresholding for the segmentation process which consists of image pre-processing, noise reduction and edge region points generation for butt welding joint identification. The trends and new approaches have been indicated by [10] in order to provide a comprehensive source for researchers who are planning to carry out research related to the intelligent robot vision techniques for welding automation. These research can help improve flexibility of welding process and cut down tedious teach-in jobs. However the computation is both complex and difficult, since a lot of image-processing steps, such as binary threshold, edge detection, pattern matching, are needed for robust target recognition.

A system for automatic robotic welding based on offline programming using CAD data is presented in [3]. The welding paths are corrected before execution with 3D vision where the 3D image is aligned with the CAD model of the work piece to be welded. [4] utilizes a laser displacement sensor to acquire 3D point cloud of the workspace. The point cloud can provide a sparse outline of the work piece. This outline is then registered to correspond to the CAD model by estimating a transformation between them. In order to compute the actual gap geometry, a matching process is performed between computer-aided design model and a measured point cloud of the welding assembly using ICP algorithm [1]. But CAD models need to be configured for each piece work in these works, and point cloud alignment is also a time-consuming task.

3. Point cloud preprocess
In contrast to capture methods mentioned above, a handy laser scanner was introduced to acquire point cloud of work piece. The handy laser scanner can provide point cloud data with a 3D position accuracy of within 0.04mm which is suitable for most industrial applications.
These points measured by the handy laser scanner can be divided into three categories: background, target work piece, and noise. To facilitate later process, background and noise should be eliminated to refine point cloud quality, and number of points also should be reduced to control point cloud density and improve computation speed. In the first step, we perform a pass through filter along a specified dimension, that is, to remove points whose values fall inside/outside a user given interval. In the second step, for each point, we compute the mean distance from it to all its neighbors. By assuming that the resulted distribution is Gaussian with a mean and a standard deviation, all points whose mean distances are outside an interval defined by the global distances mean and standard deviation can be considered as outliers and trimmed from the dataset. Thirdly, by using the voxel grid filter which can be regarded as a set of tiny 3D boxes in space over the input point cloud data, we can down sample point cloud uniformly to reduce the number of points. Scanning and the result of preprocess for point cloud data are shown in Fig. 1.

![Fig. 1 Work piece scanning and point cloud after preprocess](image)

**4. Localization**

To locate welding seam on work piece, a template ruler is designed to adapt to a work piece spectrum with similar features and different sizes. In this paper, we focus on fillet welding seam whose angle of the intersecting faces is 90 degree, which can be seen from Fig. 2.

**4.1 template ruler**

A ruler model should be defined to adapt to similar work pieces, so that there is no need to build different models for each work piece. As shown in Fig.2, the CAD model of template ruler contains specific information such as feature faces, welding seam, and pose of mark point. At the boundary of the template ruler, we established the local coordinate system where unit vector $e$ represents seam direction, unit vector $h$ is normal to vertical feature face, and unit vector $v$ is normal to horizontal feature face. Here, $e$, $h$ and $v$ are expressed in coordinate form as Eq. (1) respectively.

$$
\begin{align*}
  e &= (x_e, y_e, z_e) \\
  h &= (x_h, y_h, z_h) \\
  v &= (x_v, y_v, z_v)
\end{align*}
$$

The origin of the local coordinate system is also considered to be mark point whose orientation can be derived by Eq. (2). The orientation of tool like welding gun can be similarly calculated through Eq. (2).

$$
\begin{align*}
  X_{[tool]} &= e \\
  Z_{[tool]} &= -(v + h) \\
  Y_{[tool]} &= (-v + h) \times e
\end{align*}
$$

![Fig. 2 Template ruler and point cloud](image)
4.2 local matching

To align point cloud of template ruler with point cloud of work piece is to let feature faces on the template ruler coincide with feature faces on the work piece. Once the ruler is properly located in the point cloud of work piece, later identification of entire seam can be achieved by continuous search proposed in this work. Here, we adopt well-known ICP and GA algorithms to perform ruler location.

Assumed that \( P = \{ p_i \} \) \( (i = 1, 2, \cdots, N_p) \) represents points on the ruler surface, and \( Q = \{ q_j \} \) \( (j = 1, 2, \cdots, N_q) \) denotes point cloud data from scene, the location can be regarded as pose transform matrix optimization whose objective is to minimize distances between source point cloud and target point cloud. Hence, the objective function is to minimize Eq. (3), and the variables include rotational matrix \( R \) and translational matrix \( T \) respectively.

\[
\begin{align*}
    f(R, T) &= \frac{1}{N_p} \sum_{i=1}^{N_p} \left\| R p_i + T - q_i \right\| \\
    R_{3 \times 3} &= R_x(\alpha)R_y(\beta)R_z(\gamma) \\
    T &= \begin{bmatrix} t_x & t_y & t_z \end{bmatrix}^T
\end{align*}
\]

Where:

\[
R_{3 \times 3} = R_x(\alpha)R_y(\beta)R_z(\gamma)
\]

\[
T = \begin{bmatrix} t_x & t_y & t_z \end{bmatrix}^T
\]

As given by above equations, there are six variables, since \( R \) and \( T \) are dependent on \( \alpha, \beta, \gamma, t_x, t_y, t_z \) which correspond to Euler angles and translational components respectively.

In the objective function above, \( p_i \) is a point on the model surface, \( q_i \) is the scene destination point. For each new iteration, the destination point \( q_i \) corresponds to the nearest scene point to model point \( p_i \) transformed in the last iteration.

To perform optimization, local match can be achieved as shown in Fig. 3. The match process includes two steps. The first step is to implement center based alignment between ruler (in red) and work piece (in green). On the basis of step one, the ruler (in blue) is accurately located through pose transformation whose values are optimized by using genetic algorithm.

5. Continuous search

Recognition of entire welding seam from field point cloud dataset acquired by a handy laser scanner is implemented by using continuous search, an approximation method, which is different from other methods presented in previous literatures.

5.1 boundary extension

In order to realize continuous search for welding seam, we proposed boundary extension conception illustrated in Fig. 4. There are two situations which mean that one changes at horizontal plane, and another changes at vertical plane. Let boundary point cloud data of ruler expressed by matrix \( B \) with \( 3 \times n \) elements.

![Fig. 3 Local match](image-url)
Where \( b_i = [x_i, y_i, z_i] \), \( x_i, y_i, z_i \) are spatial coordinates respectively.

When horizontal direction changes, unit extension direction \( f \) can be expressed by equation

\[
f = \cos \phi e + \sin \phi h
\]  

When vertical direction changes, unit extension direction can be expressed by equation

\[
g = \cos \psi e + \sin \psi v
\]  

If \( B_f, B_s \) denote new boundary point cloud, \( b_i' = [x_i', y_i', z_i'] \), \( b_i'' = [x_i'', y_i'', z_i''] \), each point in \( B_f \) and \( B_s \) can be calculated by equation as follows.

\[
B_f = \begin{bmatrix} x_1' & x_2' & \cdots & x_N' \\ y_1' & y_2' & \cdots & y_N' \\ z_1' & z_2' & \cdots & z_N' \end{bmatrix} = \begin{bmatrix} b_1' & b_2' & \cdots & b_N' \end{bmatrix}
\]

\[
B_s = \begin{bmatrix} x_1'' & x_2'' & \cdots & x_N'' \\ y_1'' & y_2'' & \cdots & y_N'' \\ z_1'' & z_2'' & \cdots & z_N'' \end{bmatrix} = \begin{bmatrix} b_1'' & b_2'' & \cdots & b_N'' \end{bmatrix}
\]

\[
b_i' = b_i + \Delta \begin{bmatrix} \cos \phi x_i + \sin \phi y_i \\ \cos \phi y_i + \sin \phi x_i \\ \cos \phi z_i + \sin \phi z_i \end{bmatrix}
\]

\[
b_i'' = b_i + \Delta \begin{bmatrix} \cos \psi x_i + \sin \psi y_i \\ \cos \psi y_i + \sin \psi x_i \\ \cos \psi z_i + \sin \psi z_i \end{bmatrix}
\]

Where \( \Delta \) is step length with 6mm for value in this case study.

5.2 continuous search

Continuous search is repeatedly to optimize extension direction that makes distance between new boundary point cloud of the template ruler and work piece point cloud smallest. Therefore, the whole welding seam can be step by step approximated by extending ruler boundary along optimal direction. Here, boundary point cloud is used other than ruler point cloud, doing so computational burden can be decreased without accuracy loss of seam identification. Objective function of optimal boundary extension can be modeled as follow.

\[
f(\phi, \psi) = \frac{1}{N_q} \sum_{j=1}^{N_q} \| q_j - h \|
\]

Where \( \phi, \psi \) are variables which determine extension directions, \( B' = \{ b_i \} \) \((i=1,2,\ldots,N_b)\) denotes boundary point set after extension, and \( Q = \{ q_j \} \) \((j=1,2,\ldots,N_q)\) is still point cloud of work piece. Similarly, the above mathematical model is solved by GA. Details are described as follows.
Step 1 is to read point cloud data of work piece, boundary point coordinates of template ruler, and so on. Step 2 initializes population. Fitness value is to be calculated in Step 3. Step 4 checks termination condition, and if number of iteration exceeds maximal number of generations then goes to Step 6, else goes to Step 5. Step 5 is to perform genetic operators, then goes to Step 3. Step 6 exports optimal solution $x^* = [\phi^*, \psi^*]$ and $f_{\text{best}}(\phi^*, \psi^*)$. Terminating condition verification is implemented in the Step 5, if objective function value which is derived by using $\sigma = f_{\text{best}}(\phi, \psi) - d_{\text{max}}$ is smaller than given value for deviation $d_{\text{max}}$, store and update boundary, then go to Step 2, else finish entire search.

From Fig. 5, it can be seen that entire welding seam is identified by extending the ruler boundary along optimal directions through continuous search. Once the boundary extension comes to the start or end of the welding seam, the objective function value will exceed given deviation. At this point the continuous search stops and the entire seam line has been identified. It should be noted that identification in this work may miss the start or end point of realistic welding seam due to fixed step length used, variable step length will be considered in future work.

Fig. 5 Continuous search

It should be suggested that the actual welding seam of sample piece may not be a circular arc due to manufacturing errors. However the actual welding seam is assumed to be a circular arc for the purpose of conducting comparative analysis. 3D plots are illustrated in Fig. 5 where blue curve represents theoretical or ideal path line and those points in red are calculated by presented algorithms in this paper. To confirm the accuracy of algorithms, the calculated points are compared to the ideal path. As shown in Fig. 5, the calculated points scatter near the ideal path. For each point, the position error is calculated by the Euclidean distance between the calculated points and ideal seam. It can be seen that results in Fig. 6 and Fig 7 show that the maximal position error is within 2mm. These results together with the visual verification demonstrate that the proposed algorithms have ability to identify the welding seam from point cloud acquired by a handy laser scanner.

Fig. 6 Calculated points and ideal circular arc

Fig. 7 Distance between calculated points and offline path

6. Conclusion
In this paper, in order to achieve a reliable and accurate seam identification process that can work on similar work pieces with different sizes, a point cloud based method is developed.
(1) A handy laser scanner is introduced to acquire point cloud of work piece. The handy laser scanner can provide point cloud data with a 3D position accuracy of within 0.04mm which is suitable for most industrial applications.

(2) A template ruler is designed to adapt to a work piece spectrum with similar features and different sizes. Thus, well-known ICP and GA algorithms are adopted to perform ruler location locally.

(3) After local point cloud matching, the whole welding seam is step by step approximated by extending ruler boundary along optimal direction. The results demonstrate that the proposed algorithms have ability to identify the welding seam from point cloud acquired by handy laser scanner.

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References
[1] Besl, P.J., McKay, N.D. (1992) A method for registration of 3-d shapes. IEEE Transaction on Pattern Analysis & Machine Intelligence. 14(2): 239–256.
[2] Dinham, M., Gu, F. (2012) Weld seam detection using computer vision for robotic arc welding. In: IEEE International Conference on Automation Science and Engineering(CASE), Seoul. pp. 771–776.
[3] Njaastad, E.B., Olav, E. (2016) Automatic Touch-Up of Welding Paths Using 3D Vision. IFAC-PapersOnline, 49(31) 73-78.
[4] Rajaraman, M., Dawson-Haggerty, M., Shimada, K., and Bourne, D. (2013) Automated workpiece localization for robotic welding. In: IEEE International Conference on Automation Science and Engineering(CASE), Madison. pp. 681–686.
[5] Mitchell, D., Gu, F. (2013) Autonomous weld seam identification and localisation using eye-in-hand stereo vision for robotic arc welding. Robotics and Computer-Integrated Manufacturing, 29(5): 288–301.
[6] Shah, H.N.M., Sulaiman, M., Shukor, A.Z., Rashid, M.Z.A. (2017) Recognition of butt welding joints using background subtraction seam path approach for welding robot. Robotics and Computer-Integrated Manufacturing. 17: 57-62.
[7] Mitchell, D., Gu, F. (2014) Detection of fillet weld joints using an adaptive line growing algorithm for robotic arc welding. Robotics and Computer-Integrated Manufacturing, 30(3): 229–243.
[8] Chen Y.Q., Gao X.D., Huang J.Y., et al. (2012) Detection of Weld Seam Position Based on Infrared Image during High Power Fiber Laser Welding[J]. Advanced Materials Research, 2013: 1007-1011.
[9] Ding, Y.Y., Huang, W., Kovacevic, R. (2016) An on-line shape-matching weld seam tracking system. Robotics and Computer-Integrated Manufacturing. 42: 103-112.
[10] Muhammad, J., Altun, H., Abo-Serie, E. (2017) Welding seam profiling techniques based on active vision sensing for intelligent robotic welding. The International Journal of Advanced Manufacturing Technology, 88(1-4): 127–145.
[11] Shah, H. N. M., Sulaiman, M., Shukor, A.Z., Kamis, Z., Rahman, A.A. (2018) Butt welding joints recognition and location identification by using local thresholding. Robotics and Computer–Integrated Manufacturing, 51: 181–188.