# Type Identification and Feature Extraction of Weld Joint for Adaptive Robotic Welding

**Ran Li, Manshu Dong, Xiaochao Zhang and Hongming Gao**

**Abstract** In recent years, intelligent robotic welding has been an active research area. Vision sensors have been widely used in robotic welding systems for information collection and processing. For better welding quality and efficiency, it is necessary to achieve accurate and fast information processing and intelligent decision-making for welding robot. For weld joint information processing, most of the reported works focus on the feature extraction of weld joint concerning a specific type or a regular shape. In this chapter, an algorithm is proposed to identify joint type and extract relevant feature values by extracting three feature lines and two key turning points. Three types of weld joints are inspected and the results indicate that the algorithm is of high efficiency and robustness.

**Keywords** Laser vision sensor · Type identification · Feature extraction
Adaptive robotic welding

## 1 Introduction

Nowadays, with the development of modern manufacturing technologies and shortage of skilled manual welders, automatic welding becomes an inevitable trend. However, most of the welding robots applied in the automatic manufacturing are still primary teaching-playback robots. Their welding path and parameters are set in advance. The use of welding robots requires sufficient preparation of working conditions. But in practice, the positions and shapes of weld joint usually vary due to the workpiece distortion, changing misalignment and changing gap which are mainly caused by production error, assembly error and welding heat respectively.

R. Li · M. Dong · X. Zhang · H. Gao (✉)
State Key Laboratory of Advanced Welding and Joining,
Harbin Institute of Technology, Harbin, China
e-mail: gaaohm@hit.edu.cn

M. Dong
Ningxia Tiandi Benniu Industrial Group Co., Ltd, Shizuishan, China



S. Chen et al. (eds.), *Transactions on Intelligent Welding Manufacturing*,
Transactions on Intelligent Welding Manufacturing,
https://doi.org/10.1007/978-981-10-7043-3_14

Therefore, this type of welding robots cannot meet the enterprises' requirements on high quality and efficiency [1]. In order to address these issues, new welding robot should have the functions of real-time seam tracking and welding parameter adjustment to achieve adaptive robotic welding [2]. In an adaptive robotic welding system, the sensor system gets the information of the weld joint in advance and then extracts relevant feature values so as to determine the welding path and parameters [3].

Laser vision sensors are the most widely used sensors in welding manufacturing because such sensors are insensitive to electrical and magnetic interferences and robust even in the presence of extreme noise [4]. The principle of laser vision sensors is primarily based on triangulation technique. The camera captures the image of target weld joint with the projection of structured light. Then, the captured stripe is processed to extract the geometrical information of the weld joint.

Although feature extraction has been researched extensively [5–9], most of the works focus on the specific joint type with horizontal surfaces. The surface unevenness and misalignment are not considered, while they are inevitable in practice. The conventional feature values extracted are the trace coordinates used for path correction and the welding area used for parameter adjustment. These methods are exclusively applied to specific and well-assembled weld joint, so there is a need for an intelligent algorithm that can identify joint type (butt, lap or fillet joint) and extract relevant features even with big noise.

An algorithm for information processing of laser sensors in adaptive robotic welding is described in this chapter, and it can be used to identify the joint type and then calculate the relevant feature values in real time for most plate welding.

## 2 Experimental System

The experimental system (see Fig. 1a) consists of a six-axis industrial robot (Motoman, HP20D), a smart laser system (META, 50V1), a three-axis motion platform and a computer. All the components are interconnected by a hub. The sensor head fixed at the end effector of the robot, in front of the welding torch (see Fig. 1b), is 65 mm away from the workpiece surface with a 50 mm field of view. The built-in camera gets an image with a laser stripe projected on the surface. This image indicates the shape of joint. After interior operation, the joint information in the form of a series of relative coordinate values is sent to the computer.

## 3 The Proposed Method

The traditional methods extract feature points through calculating derivative [6] or turning angle [8]. The number and type of the turning points extracted determine the type of weld joint [10]. These methods depend highly on the precision of

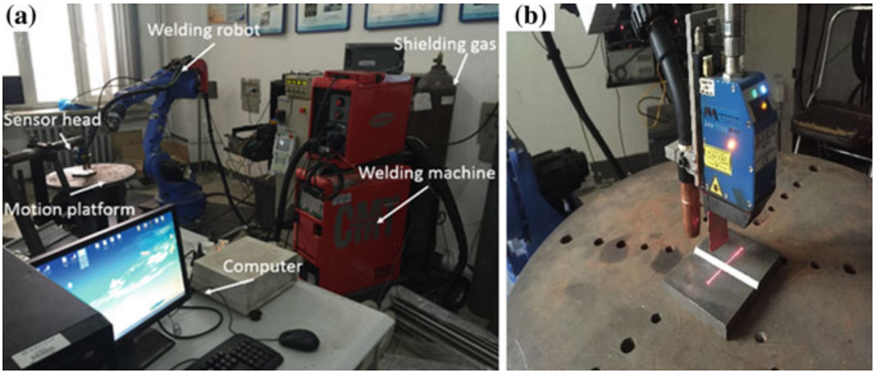



**Fig. 1** Experimental system (**a**) and sensor head (**b**)

extraction of laser stripe, and most of them are applicable to a specific or regular joint. When the weld joint is irregular or the laser stripe is noisy, these methods may be not suitable. In order to adjust the welding parameters more sensitively, the adaptive welding robot system needs to extract feature values as soon as possible. Therefore, there is a need for an algorithm to quickly identify joint type and extract relevant feature values.

In practice, the surface of workpiece except the joint is usually flat. Due to the continuity of seam, the joint part is usually in the middle of the laser stripe. Therefore, two feature lines which indicate the surfaces of two workpieces can be extracted from the points at two ends of the laser stripe. Then, the two key turning points are extracted by calculating the deviation values from points to each line in the $y$-axis. The third feature line is extracted by connecting the two key turning points. The angle values among three feature lines and the distance between two key turning points determine the joint type, and the relevant feature values are then calculated according to the joint type. The detailed steps are shown below.

## 3.1 Type Identification

There is some noise in raw data sent from the laser sensor system due to specular reflection and arc light. These noise points should be removed first. The laser sensor system sends 1024 points in order of $x$-axis, so the valid data $(X_i, Y_i)$ should meet this criterion: (1) $X_{i-1} < X_i < X_{i+1}$; (2) $-40 < Y_i < 40$, if $Y_{i-1} < Y_i > Y_{i+1}$ or $Y_{i-1} > Y_i < Y_{i+1}$, $|Y_i - Y_{i-1}| < 3$ and $|Y_i - Y_{i+1}| < 3$. The relevant thresholds are obtained through test. Because of edge distortion, the points at two ends are usually invalid. Therefore, the former ten points and the last ten points are removed.

The valid data contain nearly 1000 points. Two feature lines $L_1$ and $L_2$ are extracted from 200 points of both ends first by least square method. $K_1$ and $K_2$ are the slope values of $L_1$ and $L_2$ in $y$-axis respectively. $D_1$ and $D_2$ are the max deviation values of $L_1$ and $L_2$ in $y$-axis respectively. Let $L_1$ be the feature line indicating the surface of left workpiece and $L_2$ be the feature line indicating the surface of right workpiece. Then, the deviation values in $y$-axis are consecutively calculated from the point 201 to the point 800. When the deviation values of ten consecutive points are beyond $D_1$, the last point close to these points in the left is regarded as the key turning point $A$. The point $B$ is got by the same method. $L_3$ is then extracted by connecting $A$ and $B$. The slope of $L_3$ is $K_3$. Through $K_1$, $K_2$ and $K_3$ and the distance between $A$ and $B$, the type of weld joint can be identified.

Basically, there are three types of weld joints: butt joint, lap joint and fillet joint (see Fig. 2). For butt joint with groove, $L_1$, $L_2$ and $L_3$ are almost parallel. So, the angle values $\theta_{12}$, $\theta_{13}$ and $\theta_{23}$ should be less than a certain value which is 30° in this chapter. For butt joint without groove, if $L_1$ and $L_2$ are almost coincident or the turning points are very close to each other, it is hard to find the accurate turning points. In this case, the turning points can be got by calculating the max deviation value in $x$-axis of consecutive points. If the max deviation value is more than a certain value which is 1 mm in this chapter, the two consecutive points are regarded as the turning points. If the max deviation value is less than 1 mm and the two feature lines are almost coincident, the joint is regarded as flat. If $L_1$ and $L_2$ are not coincident, the identification criterion is the same as that of butt joint with groove. For lap joint, $L_1$ and $L_2$ are almost parallel and $L_3$ is almost vertical to $L_1$ and $L_2$. So, the angle values $\theta_{13}$ and $\theta_{23}$ should be more than a certain value which is 60° in this paper. The angle value $\theta_{12}$ should be less than a certain value which is 30° in this paper. For fillet joint, $L_1$ and $L_2$ are almost vertical and the points $A$ and $B$ are almost coincident. So, the angle value $\theta_{12}$ should be more than a certain value which is 60° in this paper. And the distance between $A$ and $B$ should be less than a certain value which is 1 mm in this chapter. As the turning points $A$ and $B$ are almost coincident, $\theta_{12}$, $\theta_{12}$ and $L_3$ are not considered. Figure 3 shows the block diagram of the whole algorithm.

## 3.2 Feature Extraction

As the joint type is identified, a series of feature values are then calculated according to actual demand. For lap joint and fillet joint, the main feature values are tracepoint and torch direction. The key turning point located at a low position is the

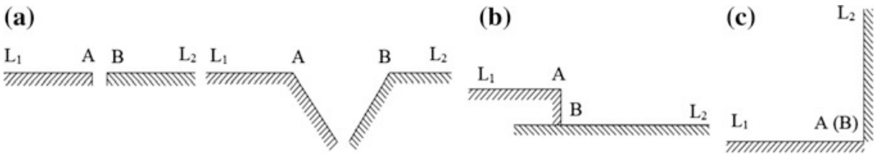



**Fig. 2** Three main types of weld joint: **a** butt joint; **b** lap joint; and **c** fillet joint

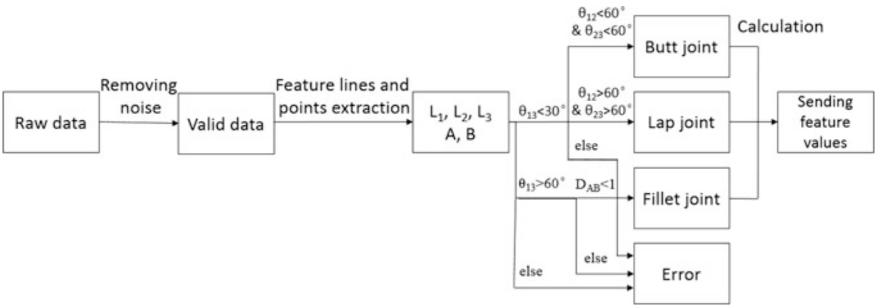



**Fig. 3** Block diagram of the algorithm

tracepoint, and the relevant feature line which the tracepoint belongs to is the baseline. For lap joint, the torch vector is between baseline and $L_3$. For fillet joint, the torch vector is between $L_1$ and $L_3$. For butt joint, the tracepoint is the midpoint of gap. And the welding area is calculated by summing up the area of the trapezium composed by every two consecutive points between $A$ and $B$ and their vertical intersection points with $L_3$. The misalignment value is got by calculating the distance from the higher turning point to the line through the lower point.

## 4 Results and Discussion

Three types of weld joints are inspected to examine the performance of this algorithm.

A butt joint is tested and the raw data are plotted (see Fig. 4a). It is obvious that there are some distortion points at two ends. After data filtering, valid data are obtained (see Fig. 4b). Two feature lines are then calculated from 200 points at two ends by least square method, i.e. $L_1$ ($y = -0.1240x - 2.6884$) and $L_2$ ($y = -0.0360x - 2.0666$) which are the green and yellow lines in Fig. 4c respectively. The max deviation values are got: $D_1 = 0.0662$ and $D_2 = 0.0808$. By calculating the deviation values from other points to these two feature lines in sequence, the turning points $A$ and $B$ are extracted: $A$ (−4.117, −2.265) and $B$ (8.462, −2.46) shown in Figs. 4d and e. Then, the feature line $L_3$ is got: $L_3$ ($y = -0.0155x - 2.3288$). The angle values are calculated: $\theta_{12} = 5.0063°$, $\theta_{23} = 1.4035°$ and $\theta_{13} = 6.4075°$. According to the above block diagram, this joint is identified as a butt joint.

A lap joint is tested (see Fig. 5). The feature lines and feature points are got: $L_1$ ($y = -0.1223x - 4.9181$), $L_2$ ($y = -0.1279x + 1.4444$), $L_3$ ($y = 26.7265x - 112.4126$), $A$ (4.005, −5.373) and $B$ (4.239, 0.881). The max deviation values and angle values are: $D_1 = 0.1804$, $D_2 = 0.4259$, $\theta_{12} = 0.3159°$, $\theta_{13} = 85.17°$ and $\theta_{23} = 84.854°$. According to the above block diagram, this joint is identified as a lap joint.

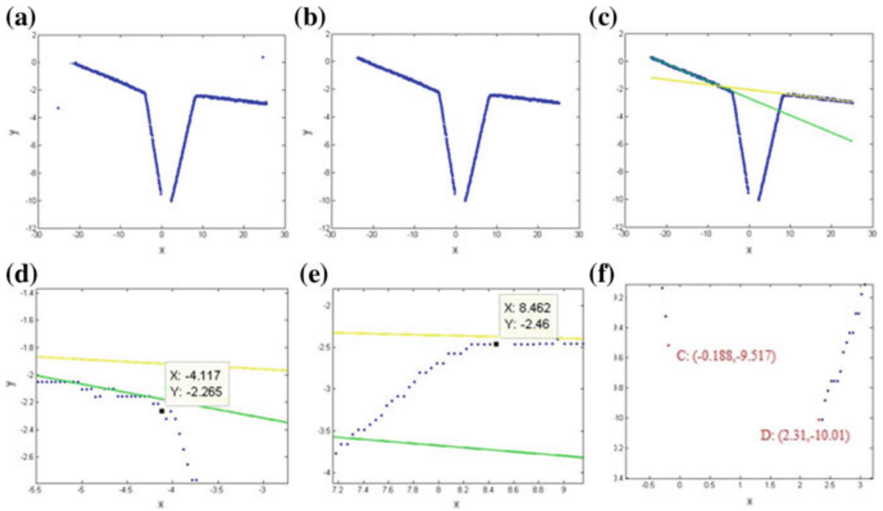
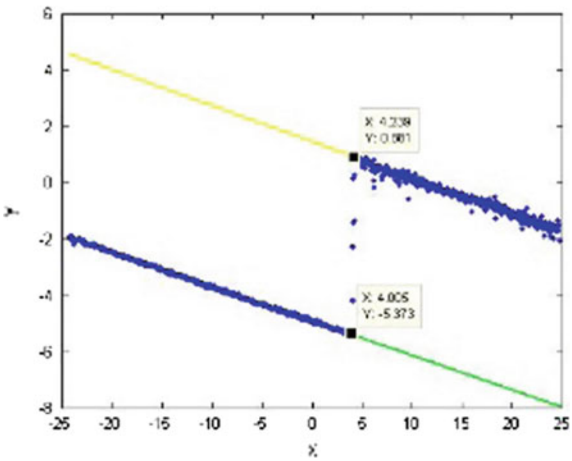



**Fig. 4** Feature extraction of butt joint: **a** raw data; **b** valid data; **c** feature lines; **d** the point *A*; **e** the point *B*; and **f** gap points

**Fig. 5** Feature extraction of lap joint




A fillet joint is tested (see Fig. 6). The feature lines and feature points are got: $L_1$ ($y = -0.3988x - 11.0133$), $L_2$ ($y = 2.6580x - 45.5687$), $A$ (11.17, −15.34) and $B$ (11.404, −14.919). So, the angle value of $L_1$ and $L_2$ and the distance between $A$ and $B$ are got: $\theta_{12} = 88.875°$ and $D_{AB} = 0.482$. According to the above block diagram, this joint is identified as a fillet joint.

The results indicate that all three types of weld joints are successfully identified. As shown in Fig. 6, even if the data have some big noise, this algorithm can still find the appropriate key turning points according to the max deviation values.

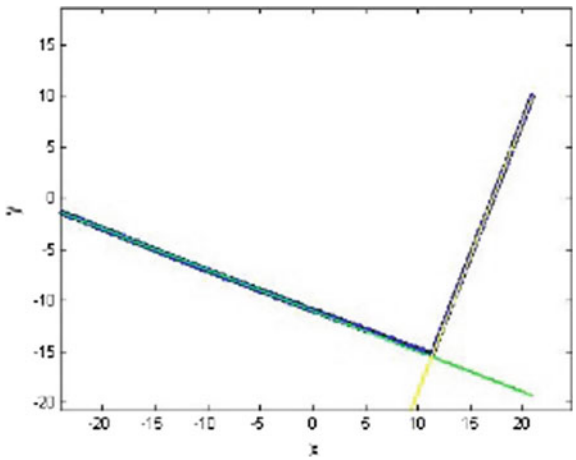



**Fig. 6** Feature extraction of fillet joint

In order to test the accuracy of this algorithm, a standard V-groove is tested with given dimension (see Fig. 2). The groove is 10 mm wide and 5 mm deep after machine work. The algorithm identifies the joint type and then gives the feature values as follows: the groove width is 10.076 mm, the groove depth is 4.932 mm, the welding area is 25.696 mm$^2$, the misalignment value is 0.02 mm and the angle value of workpiece is 0.22. In consideration of the lateral resolution of the laser system, which is 0.05 mm, the errors of these values are acceptable.

## 5 Conclusion

An algorithm for type identification and feature extraction of irregular weld joints is presented in a practical and reliable way. The following conclusions can be made. The proposed algorithm can quickly identify the joint type according to the extracted three feature lines and two key turning points and the amount of computation is comparatively small due to the simple criterion. Even if the data noise is big, the set of max deviation value and consecutive deviation point number ensures the reliability and robustness of the algorithm. This algorithm can give fairly accurate feature values. And the error is within one-half of the lateral resolution of the laser system.

**Acknowledgements** This work is supported by the National Key Technology R&D Program of China (2015BAF01B01).

## References

1. Xu YL (2013) Research on real-time tracking and control technology of three-dimension welding seam during welding robot GTAW process based on vision sensor and arc sensor. Dissertation, Shanghai Jiao Tong University, China
2. Chen SB, Lv N (2014) Research evolution on intelligentized technologies for arc welding process. J Manufact Process 16(1):109–122
3. He YS, Chen YX, Xu YL et al (2016) Autonomous detection of weld seam profiles via a model of saliency-based visual attention for robotic arc welding. J Intell Rob Syst 81 (3–4):395–406
4. Wu J, Smith JS, Lucas J (1996) Weld bead placement system for multi-pass welding. IEE Proc Sci Measur Technol 143(2):85–90
5. Shi YH et al (2007) Adaptive robotic welding system using laser vision sensing for underwater engineering. In: Proceedings of IEEE International Conference on Control and Automation. IEEE, Guangzhou, pp 1213–1217
6. Manorathna RP, et al (2014) Feature extraction and tracking of a weld joint for adaptive robotic welding. In: Proceedings of 13th international conference on control automation robotics & vision. IEEE, Singapore, pp 1368–1372
7. Zhang LG, Ye QX, Yang W et al (2014) Weld line detection and tracking via spatial-temporal cascaded hidden Markov models and cross structured light. IEEE Trans Instrum Meas 63 (4):742–753
8. Sung K, Lee H, Choi YS et al (2009) Development of a multiline laser vision sensor for joint tracking in welding. Weld J 88(4):79–85
9. Lei ZL, Lv T, Chen YB et al (2013) Features extraction for weld image of scanning laser sensing. Trans China Weld Inst 34(5):54–58
10. Muhammad J, Altun H, Abo-Serie E (2017) Welding seam profiling techniques based on active vision sensing for intelligent robotic welding. Int J Adv Manuf Technol 88 (1–4):127–145