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# Weld bead recognition using laser vision with model-based classification

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A B S T R A C T

Weld bead recognition is important for providing information for automatic control of welding process and also for post-weld inspection. Bead geometry profiles can be measured by a laser-line profile sensor projecting a laser line onto the welding surface and receiving the reflection to calculate the height of the surface. As the bead is usually very small, it may be easily covered by the sensor noise or distorted by the bending of the work pieces after welding. In addition, it is difficult to estimate the parameters of bead width and bead height while moving the laser sensor to cover a 3D surface, since the movement may cause unstable measurements. This work investigates using a model-based classification method to automatically segment the bead from the welding surface regardless of the distance and the angle of the scanner to the welding surface. It firstly uses a polynomial model together with the Expectation-Maximisation (EM) algorithm fitting into the distance profiles measured by the laser sensor, and then automatically removes the surface curvature. Consequently the shape of the bead can be easily extracted from the welding surface by applying a small value of threshold depending on the noise level of the data. Experimental results show that the Butt welding bead parameters of bead width and height can be extracted successfully. The method is robust to the bending of the welding surface and the unstable movement of the laser sensor.



## 1. Introduction

Automatic welding has been widely applied in modern manufacturing industry. The welding process can be automated either simply using a “teach-and-go” robot to follow a given path, or using an online tracking algorithm to enable the robot to plan its own path along the actual welding line [1–5]. The welding quality is one of the most important issues in welding industry, since unsatisfied welding beads could reduce the mechanical properties of the welding joints, shorten the lifetime of the products, and even cause a collapse of the structure [6]. The welding quality could be affected by the welding parameters of welding voltage, welding speed, torch angle etc. Previous studies have developed various models, such as mathematical models [7,8] and neural networks [9–12], to predict and control the welding quality (or the geometry of the weld bead height and width) using the welding parameters of welding voltage, wire feed rate, torch angle, welding speed and nozzle-to-plate distance etc. as inputs. The use of the above models is an indirect mode to relate the bead geometry with the welding parameters which are easier to be measured. However it is still necessary to measure and recognise the bead geometry using a direct method, either for providing feedbacks to control the welding quality during welding, or for weld beads inspection during regular maintenance.

Ultrasonic sensing is one of the direct methods used to measure weld bead geometry [13–15]. It is based on the time of flight of the echo travels back from the measurement object so its cost is relatively low. However its ranging accuracy is low and may be easily affected by the surrounding conditions such as the temperature change of the environment. Vision sensors including passive and active systems are more popular. The passive vision system usually uses a camera to capture an image and then analyses the image to detect the location of the weld joints, such as using local thresholding to identify weld joints for butt welding [16] and using adaptive line growing method to detect weld joints for fillet welding [17]. To measure the bead width and bead height respectively, two cameras are usually applied, e.g. one camera fixed to the rear of the welding gun for measuring bead width and another camera fixed on the side of the welding gun for measuring bead height [18]. The use of a single camera fixed parallel to the welding direction for simultaneously measuring bead width and height is also reported. As the accuracy of the bead width and height measurements highly depends on the angle between the camera optical axis and the work piece plane, the camera has to be precisely aligned [19,20]. In an active vision system, an external illumination source, e.g. an infrared laser, is used to illuminate the weld pool to produce high quality images with lower noise by using a narrow bandwidth optical filter to filter out the interference of the strong visible welding light. Although detailed images can be captured, the active vision system is not widely used due to its additional lighting source and system complexity [19]. In addition, recent studies by Aviles-Viñas et al. [11] and Rios-Cabrera et al. [12] used a laser beam projected to

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the bead with an angle of 45° to create a deformation proportional to the width and the height of the bead, and hence the geometry of the bead can be measured by detecting the bead edges such as using Canny edge detection.

In recent days, the laser vision based on the principle of laser triangulation has been more popular in welding industry, since both bead width and bead height can be measured simultaneously and precisely. The sensor projects a laser line onto the work pieces surface and observes the triangulation angle of the scattered light on a CCD camera [21]. Thus the 2D distance between the sensor and the laser line on the work piece surface can be captured at the same time without any complicated moving scanning. It has been used for seam tracking, e.g. detecting the precise position of the seam for automatic welding control [22–24], and also for 3D bead inspection by using a gantry or a robot to move the laser sensor along a straight line or the path of the bead to produce a 3D bead profile [6,25–27]. However, it is still difficult to extract the precise bead parameters (bead width and bead height) from the 3D bead profile measured. The first reason is that the gantry or robot will be reinstalled at different locations for different bead measurement. It will bias the relative position between the robot and the work pieces. While moving the laser sensor, the position errors introduced from the gantry can also cause range deviations between the gantry and the work pieces. The second is that the work pieces in Butt welding may not be strictly on the same plane. In addition, the high temperature during arc welding may cause the work pieces distorted or bended, leading to a slightly curved or angled range profile (see the figures shown in later sections). Simple segmentation methods such as using a threshold are difficult to calculate the bead width and bead height due to the uneven and bended base metals. Previous research by Wang et al. [28] demonstrated a method to recognise a cubically modular part by using edge and corner detection and line fitting to the laser-stripe-based range data, but it is not suitable for bead recognition due to the complexity of the bead shape. It is also reported that the quadratic surface measured by a 3D laser scanner can be automatically segmented by using the boundary information extracted from the top view images acquired by two cameras on the top of the surface [29]. In addition, recent work by Chu [6] used the RANSAC algorithm to fit lines to the left and the right base metals respectively to remove the displacement between the base metals. However it is still difficult to deal with the curved base metals.

This work investigates using a novel model-based classification method for bead recognition on the 3D bead profile measured by a laser vision sensor. A polynomial function is introduced to model the base metals, and the bead shape is expected to be excluded from the model. An expectation-maximization algorithm is introduced to automatically exclude the bead data points and select the base metal data point to estimate the model parameters. The whole classification process is fully unsupervised without any prior information or manual labelling to the data. It can also remove the range bias caused by the unstable movement of the laser sensor during 3D scanning.

## 2. Method

### 2.1. Modelling the welding surface

Butt welding is one of the most common welding types, which joins two pieces of base metals on the same plane. The welding surface includes two parts: the bead and the base metals (work pieces). In unsupervised pattern recognition, models have to be used to represent different classes. The shape of the bead is hard to be properly represented by an analytical model due to its shape complexity. Since there are only two classes (the bead and the base metal) to be separated in this case, the data can still be classified successfully if one class is modelled analytically and another class is treat as outliers. Thus if a model can be found to represent the base metal, the bead can be treated as a set of outlier data and hence can be recognised.

In Butt welding, the base metal is ideally flat to produce a straight line in the 2D distance profile measured by a 2D laser scanner. However in practice the distance profile on the laser scan line is slightly curved and angled due to the uneven base metal surface. This work uses a polynomial function to model the base metal plane to accommodate or compensate for its curvature. The advantage of using the polynomial function is that the parameter estimation can be solved effectively by the Least Squares Method (LSM). The polynomial function can be expressed as,

$$y_i = a_0 + a_1 x_i + a_2 x_i^2 + \cdots + a_n x_i^n \tag{1}$$

or it can be rewritten as,

$$y_i = A X_i' \tag{2}$$

where $X_i = [1,\ x_i,\ {x_i}^2,\ \ldots,\ {x_i}^n]$ and $A = [a_0, a_1, a_2, \ldots, a_n]$. $A$ is the parameter vector of the polynomial function, $n$ is the order of the polynomial function, $y_i$ is the distance between the sensor and the base metal at the location of $x_i$ along the laser scan line.

### 2.2. Model parameter estimation

Since the classification will be solely based on the polynomial model in Eq. (1) to represent the base metal, the bead will be recognized as a set of outliers to the model. Thus the model parameter estimation has to use the data points belonging to the class of the base metal and exclude the data points of the bead. However, the classification of data points is unknown until the model parameters are estimated. This is called the missing data problem [30] and can be solved by the Expectation-Maximization (EM) algorithm [31].

The parameters of a polynomial in Eq. (1) can be estimated using the least squares method (LSM). For the missing data problem solved by the EM algorithm, the least squares method will be replaced by a weighted least squares method. The parameters can be estimated by minimising the weighted least squares errors,

$$A = \operatorname{argmin}\left\{ \sum_{i=1}^{I} w_i \left(y_i - y_i^*\right)^2 \right\} \tag{3}$$

and the weight is calculated by,

$$w_i = \exp\left[ -\frac{\left(y_i - y_i^*\right)^2}{2\sigma^2} \right] \tag{4}$$

where $A$ is the parameter vector to be estimated. $y_i$ is the value predicted from the model in Eq. (1). $y_i^*$ is the $i$th measurement (distance between the sensor and the welding surface) at the location of $x_i$ along a laser scan line. $I$ is the total number of the measured data points. $w_i$ is the weight to adjust the contribution of the data fitting to the model. $\sigma$ is the coefficient to control the relation between the fitting error and the weight.

The following Pseudo-Code illuminates the iteration of the EM algorithm step by step:

*Pseudo-Code*:
INIT $w_i = 1$
COMPUTE $A = \operatorname{argmin}\{\sum_{i=1}^{I} w_i (y_i - y_i^*)^2\}$
IF *the fitting error* $\sum_{i=1}^{I} w_i (y_i - y_i^*)^2 >$ *pre-set value* THEN
  COMPUTE $y_i = A X_i'$
  UPDATE $w_i = \exp[-(y_i - y_i^*)^2/(2\sigma^2)]$
  UPDATE $A = \operatorname{argmin}\{\sum_{i=1}^{I} w_i (y_i - y_i^*)^2\}$
ELSE
  OUTPUT $A$
ENDIF