Three-dimensional reconstruction of welding pool surface by binocular vision

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Title page

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ORIGINAL ARTICLE

Three-dimensional reconstruction of welding pool surface by binocular vision

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Abstract: Welding pool geometry includes plenty of welding quality information. The observation and reconstruction of the welding pool surface is the basis of developing intelligent control system for welding process to substitute skilled welders. The binocular vision system was ameliorated to capture images of welding pool surface by suppressing the strong arc interference during gas metal arc welding (GMAW). Combining and improving the algorithms of speeded up robust features, binary robust invariant scalable keypoints and KAZE, the feature information of points (i.e. RGB value, pixel coordinates and so on) was extracted as the feature vector of the welding pool surface. Based on the characteristic of welding images, the mismatch elimination algorithm was developed to increase the accuracy of image matching algorithms. The world coordinates of matching feature points was calculated to reconstruct the 3D shape of the welding pool surface. The effectiveness and accuracy of reconstruction for welding pool surface were verified by the experimental results.

Keywords: Surface reconstruction • Welding pool • Binocular imaging • Gas metal arc welding • Feature points matching

1 Introduction

Gas metal arc welding (GMAW) is widely applied in modern manufacturing industries. To improve the weld quality of manual GMAW, welders correct welding parameters or the position of welding gun based on the

information of welding pool surface acquired through their eyes and professional experience accumulated in long term working [1]. It means that welding pool surface includes important visual information for the skilled welders to control GMAW process. To decrease the workload and occupational risks of welders, lots of researches have been done to transfer the working experience of skilled welders into intelligent control system in the past few decades [2-6].

Andersen [7] developed a synchronous welding pool oscillation method for sensing the penetration of weld. Guu [8] utilized real-time radiography to control the depression of the welding pool. Song [9] measured the temperature of workpieces and set up a depth estimator system to closed-loop control the welding process. These methods mostly focused on the improvement of welding process by the information from one-dimensional or two-dimensional of the welding pool surface. It is clear that the 3D information of the welding pool surface can better reflect the weld quality.

The three-dimensional(3D) reconstruction method for welding pool can be categorized into 3D structured light method, shape from shading method and binocular stereo vision method [10-14]. To avoid the arc interference during measurement process, Zhang and his coworkers [15] proposed a novel structured laser vision system for reconstructing 3D welding pool surface. In their experiments, a structured laser was projected on the welding pool surface, and was specularly reflected to the preseted imaging plane. The images of the laser points on the plate were captured by camera. At last, the geometry of weld pool surface was reconstructed by Edge-point algorithm and One-point algorithm [16]. However, the depression of welding pool surface under the arc was disappeared in above reconstruction method. Zhao [17]

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introduced the SFS method into the extraction of height information of the welding pool surface. The smoothing constraint, boundary conditions, and grayness-weighting factor were combined with the SFS method to reconstruct surface height of welding pool. Statistical results show that the mean error was 0.04 mm and the maximum absolute error was over 0.5mm on the central height of object surface. Zhong [18] et al. put forward some measures to increase the effectiveness and accuracy of SFS method, such as smoothing process, strengthening boundary constraints. The improved algorithm was used to reconstruct the weld surface of aluminum alloy for gas tungsten arc welding (GTAW). However, the SFS method was difficult to be used in GMAW process as its spatters, arc interference, and welding stability were much worse than those in GTAW. The accurate and anti-jamming 3D reconstruction method for GMAW was still needed for the suppression of strong electromagnetic interference, high heat radiation interference, weld fumes, and so on.

Binocular stereo vision method is more accuracy and efficient to acquire reconstruction result. Mnich [19] tried to use this method to reconstruct welding pool of GMAW. The results showed that the binocular vision system needed to be improved as the extra bright area on welding pool surface could not be reconstructed. Richardson [13] used particle image velocimeter (PIV) to track the movement of oxide particles to determine the velocity field on the welding pool, and then transferred the above data into 3D fluid velocity by stereo vision method. Calibration process was the main factor that influenced the measurement precision during 3D reconstruction, the average distance error between the tested corner points was 0.14 mm. Liang [20] established a biprism stereo vision system to the state of weld penetration based on the geometry of welding pool surface under pulsed GMAW. A two-step stereo matching algorithm was proposed to reconstruct the 3D shape of welding pool surface. However, some region on the welding pool surface were discontinuous and the accuracy of this algorithm was not discussed. Xiong [21] also built up the biprism stereo vision system to reconstruct welding pool geometry in GMAW. The global-based iterative matching algorithm and triangle measuring method were optimized. The results were validated by a reconstructed standard cylinder with clear checkboard and the maximum height error was 4.15%. It was shown that the accuracy and usability of global-based iterative matching algorithm for GMAW process without checkboard still needs to be verified and improved.

In this paper, an improved binocular vision system was developed to observe the welding pool surface. An

automatic 3D reconstruction method was proposed to suppress arc interference on welding pool information. The mathematical models including detection, description and matching of feature points were established to effectively and robustly calculate the world coordinates of weld pool surface against different welding conditions. This study was foundation of on-line intelligent control of welding pool behavior for GMAW process.

2 Experimental system

The binocular vision system was given in Figure 1. Two Basler acA2000-165uc cameras (color) were used and their CMOS sizes were both 2 / 3 ". The focal length of camera lens was 35 mm with 650 nm cut-off filter and 7# welding goggle. The aperture was F/5.6. Two cameras were connected with a synchronizer trigger to generate two synchronous images. The frequency of sampling was 200 frames/s with a resolution of 600 × 500 pixels, and the exposure time was 40 μs.

Figure 1 Binocular vision system

The weld workpiece was fixed on a moveable workbench. Bead-on-plate welding tests were carried out on Q235 mild steel plates with a dimension of 250.0 × 70.0 × 5.0 mm. The welding wire material was H08Mn2Si with a diameter of 1.2 mm. The distance between welding wire tip and workpiece surface was 18.0 mm. The chemical compositions of the welding wire and base metal are presented in Table 1. Direct current electrode negative was used and the distance from wire tip to workpiece was 18.0 mm. Other welding parameters are listed in Table 2. The torch and the cameras were stationary during the welding process. The workpiece and workbench were moved at a preset welding speed.

Table 1 Chemical compositions of welding wire and base metal (wt-%).

Composition (%)	C	Si	Mn	P	S
Wire(H08Mn2Si)	0.11	0.65	1.80	0.030	0.030
Q235	0.17	0.15	0.30	0.015	0.035

Table 2 Welding parameters

Welding Current (A)	Arc Voltage (V)	Welding Speed (m/min)	Shielding Gas (L/min)
240-280	33.0	0.5-0.8	20(Ar)

3 Calibration system

In order to effectively avoid errors caused by perspective distortion and lens distortion (including radial distortion, centrifugal distortion and prism distortion), the preset coordinate system for camera calibration [22] was used to establish the corresponding relationship between the world coordinates and the image coordinates by a calibration target with point matrix at different positions. For example, the two cameras were fixed on the tripod as shown in Figure1. Figure 2 shows that the target paper was moved along the y direction from $y = 0.0 \text{ mm}$ to $y = 20.0 \text{ mm}$, the moving step length was 0.5 mm for each time and the target paper was captured by two cameras at each position. The red dot on target paper meant the coordinate origin of point matrix. O_{xyz} and $O_{x_0y_0z_0}$ were the world coordinate system and pixel coordinate system respectively.

The world coordinates of black dots in each target image were calculated by the distance from red dot. That is, when the black dot P_b is located in the a row to the left of the red dot, its world coordinate is $x_d = a \times 1 \text{ mm} = a \text{ mm}$; when the black dot is located in the b row above the red dot, its world coordinate is $z_d = b \times 1 \text{ mm} = b \text{ mm}$, as shown in Figure 3. It can be seen that the world coordinates of the black dots are $[x_d, y_d, z_d] = [a, y_m, b]$. When the world coordinates of all grid points on the graph are assigned, the world coordinate system of the calibration system is successfully constructed.

Figure 2 The 3-dimensional point array **Figure 3** Captured images of the calibration target by two cameras at y_m

It is assumed that a point P_a was located in the area of calibration and it was captured by two cameras as shown in Figure 4. The word coordinates of P_a could be reconstructed from the following procedure:

(1) The image coordinates of P_a were $P_1(X_1, Y_1)$ in camera 1 and $P_2(X_2, Y_2)$ in camera 2. The four nearest neighbors of P_1 in the captured image were $A(x_A, y_A)$, $B(x_B, y_B)$, $C(x_C, y_C)$, and $D(x_D, y_D)$. Their word coordinates which was calibrated before were $A'(x_A, y_p, z_A)$, $B'(x_B, y_p, z_B)$, $C'(x_C, y_p, z_C)$, and $D'(x_D, y_p, z_D)$. $P'(x'_{yp}, y_p, z'_{yp})$ could be calculated by the four nearest neighbors of P_1 as follows:

$$\begin{bmatrix} x_A & x_B & x_C & x_D \\ z_A & z_B & z_C & z_D \end{bmatrix} \times \begin{bmatrix} X_A & X_B & X_C & X_D \\ Y_A & Y_B & Y_C & Y_D \end{bmatrix}^{-1} \times \begin{bmatrix} X_1 \\ Y_1 \end{bmatrix} = \begin{bmatrix} x'_{yp} \\ z'_{yp} \end{bmatrix} \quad (1)$$

Similarly, all the corresponding world coordinates of P_2 at 41 planes can be obtained as $P''(x''_{yp}, y_p, z''_{yp}) (y_p = 0.5i, i = -20, -19, \dots, 19, 20)$.

(2) The distance D_{yp} between $P'(x'_{yp}, y_p, z'_{yp})$ and $P''(x''_{yp}, y_p, z''_{yp})$ at all the y -planes was calculated as follows:

$$D_{yp} = \sqrt{(x'_{yp} - x''_{yp})^2 + (z'_{yp} - z''_{yp})^2}, (y_p = 0.5i, i = -20, -19, \dots, 19, 20) \quad (2)$$

When P_a was in a certain y -plane ($y = 0.5i$), P' and P'' were overlapping, D_{yp} was 0. Then $x'_{yp} = x''_{yp}$ and $z'_{yp} = z''_{yp}$; the world coordinates of P_a is (x'_{yp}, y_p, z'_{yp}) . Otherwise, P_a was located between two adjacent plane matrices where the sum of D_{yp1} and D_{yp2} was the minimum. If $y_{p1} = 0.5i$ and $y_{p2} = 0.5(i+1)$, the world coordinate was as follows:

$$x = \frac{1}{2}(x''_{yp1} + x'_{yp1}) \quad (3)$$

$$y = \frac{(z'_{yp2} - z''_{yp2}) \times y_{p1} + (z''_{yp1} - z'_{yp1}) \times y_{p2}}{(z'_{yp2} - z''_{yp2}) + (z''_{yp1} - z'_{yp1})} \quad (4)$$

$$z = \frac{(z'_{yp2} - z''_{yp2}) \times z'_{yp1} + (z''_{yp1} - z'_{yp1}) \times z'_{yp2}}{(z'_{yp2} - z''_{yp2}) + (z''_{yp1} - z'_{yp1})} \quad (5)$$

Where, P'_{yp1} and P'_{yp2} are points captured by camera 1 and their world coordinates are $(x'_{yp1}, y_{p1}, z'_{yp1})$ and $(x'_{yp2}, y_{p2}, z'_{yp2})$, respectively. Similarly, P''_{yp1} and P''_{yp2} are points captured by camera 2 and their world coordinates are $(x''_{yp1}, y_{p1}, z''_{yp1})$ and $(x''_{yp2}, y_{p2}, z''_{yp2})$, respectively. Then the world coordinates of point P_a is successfully achieved. The verification experiment showed that the maximum relative error between the recovered and measured results was less

than 0.6% [22]

Figure 4 A schematic of the mapping between the two image coordinates and their world coordinates

4 Pre-preprocessing of welding pool image

The size of the welding pool under the arc is small, and there are various noises in the process of image acquisition and quantification. In addition, the existence of strong arc will also affect the extracting and matching processes of feature points, which decreases the accuracy of 3D reconstruction. Therefore, image processing algorithms, which mainly includes gray-level transformation, image filtering and edge detection, are needed to pre-process the welding pool images [23]. Figure 5 shows the original images of the welding pool under the arc. Figure 6 shows the processed images which can be used for the feature points detection.

Camera 1

Camera 2

Figure 5 Captured images of the welding pool under the arc (240A, 33V, 0.6m/min)

Camera 1

Camera 2

Figure 6 Pre-processed images of the welding pool under the arc (240A, 33V, 0.6m/min)

5 SURF-BRISK-KAZE feature point matching algorithm

It is a high priority of the welding pool surface reconstruction to find the matching feature points accurately and efficiently. The algorithms need to adapt to various requirements such as small scale of weld pool, affine transformation of camera angles, noise interference of spatter and arc electromagnetism, severe illumination of arc, and image nonlinear distortion.

5.1 SURF Feature point detection

For a couple of welding pool images captured by the cameras 1 and 2, the box filters [24] was used to replace the Gaussian second order derivatives approximately. The different box filters were selected to establish the scale space for feature points detection. The feature points were extracted by Hessian matrix and a threshold on each scale space layer. For an image $I(x, y)$, Hessian matrix with scale σ at point (x, y) is defined as follows:

$$H = \begin{bmatrix} L_{xx}(x, y, \lambda) & L_{xy}(x, y, \lambda) \\ L_{yx}(x, y, \lambda) & L_{yy}(x, y, \lambda) \end{bmatrix} \quad (6)$$

L_{xx} is the convolution of the Gaussian second order partial derivative (Gaussian filter) and the input image $I(x, y)$ at point (x, y) , the Gaussians is defined as

$$g(\lambda) = 0.5 \exp\left(-\frac{x^2 + y^2}{2\lambda^2}\right) / (2\pi\lambda^2) \quad (7)$$

The meaning of L_{xy} , L_{yy} and L_{yx} are the same as L_{xx} .

To facilitate the calculation, the convolution D_{xx} , D_{xy} and D_{yy} of the box filters and the input image was used to replace L_{xy} , L_{yy} and L_{yx} to construct the fast Hessian matrix. The box filters in size 9×9 were substituted by the Gaussian filter when parameter λ was 1.2. The relationship between D_{xx} , D_{yy} and L_{xx} , L_{yy} is as follows:

$$\omega = \frac{\|L_{xy}(1.2)\|_F \|D_{xx}(9)\|_F}{\|L_{xx}(1.2)\|_F \|D_{xy}(9)\|_F} \approx 0.9 \quad (8)$$

$\|\cdot\|_F$ is Frobenius norm, ω is used to balance the relative weights in the expression for the Hessian's determinant. In practical application, 0.9 was adopted to

obtain approximate Hessian matrix determinant:

$$\det(H_{\text{essian}}) = D_{xx}D_{yy} - (0.9D_{xy})^2 \quad (9)$$

A threshold was needed to estimate the feature points detected by Hessian matrix. When the value of Hessian's determinant for the test point was greater than this threshold, a non-maximum suppression in a $3 \times 3 \times 3$ neighborhood was applied. When the value of test point was greater than that of 26 neighbor points, it can be selected as the optimal feature points. When the maxima detected by Hessian matrix was less than the threshold, this maxima was be excluded, so the speed of maxima detection was accelerated. Figure 7 shows the feature points extracted by SURF algorithm. It can be seen that the SURF feature points (red dots) were evenly distributed in the welding pool and it had the advantage of affine invariance. However, it cannot fully reflect the edge profile.

Figure 7 SURF feature points of the welding pool image under the arc (240A, 33V, 0.6m/min)

5.2 BRISK feature point detection

In order to obtain the characteristic of scale invariance on the edges of welding pool, the scale space was composed of four inner layers c_i and four middle layers $d_i(i=0,1,2,3)$ in the frame structure of brisk feature detection [25]. Each inner layer image was obtained by 0.5 times down sampling of the previous inner layer image, where the original image was corresponded to the c_0 layer. Each intermediate layer d_i was located between two adjacent inner layers c_i and c_{i+1} . The first intermediate layer d_0 was obtained by 1.5 times down sampling of the original image c_0 , and the remaining intermediate layers were obtained by 0.5 times down sampling of the previous intermediate layer. It was assumed that δ represented the scale, then $\delta(c_i)=2^i$ and $\delta(d_i)=1.5 \times 2^i$.

After the scale space of BRISK was constructed, the feature points were extracted on each scale. The extreme

points detected in the spatial domain and the scale domain were regarded as feature points, so the BRISK corner points had scale invariance for the welding pool edges. BRISK feature point detection can be determined by the following equation:

$$N = \sum |I(x) - I(R)| < \varepsilon \quad (10)$$

Where, $I(R)$ is the gray value of the central pixel R , and $I(x)$ is the gray value of the pixel points surrounding P . ε is the threshold which is 0.00001 in this study. If N was greater than ε , the candidate point was the feature point. BRISK feature points on the welding pool images are shown in Figure 8. It can be seen that the BRISK feature points reflected the edge profile well. However, the resolution on each layer of scale space calculated by the SURF and BRISK algorithms was blurry, which affected the accuracy of feature points. It also affects the number of feature points detected in the blurry area which was created by the welding pool oscillation.

Figure 8 BRISK feature points of the welding pool image under the arc (240A, 33V, 0.6m/min)

5.3 KAZE feature point detection

The additive operator splitting algorithm and the variable conductance diffusion method were used to construct nonlinear scale space in this study. The logarithmic steps were used in nonlinear scale space to generate O group and S group [26]. Different groups and layers were identified by group index o and layer index s , respectively. The corresponding relationship between group, layer and scale parameter σ is expressed as follows:

$$\sigma_i(o, s) = \sigma_0 2^{o+s/S}, o \in [0, \dots, O-1], \quad (11)$$

$$s \in [0, \dots, S-1], i \in [0, \dots, O \times S-1]$$

Where σ_0 is the initial scale parameter, which flattens the original image to reduce the image noise induced by arc

magnetic field. The relationship between time parameter t and scale parameter σ_i is:

$$t_i = \frac{1}{2} \sigma_i^2, i \in [0, \dots, O \times S - 1] \quad (12)$$

The nonlinear scale space is expressed as:

$$L^{i+1} = (I - (t_{i+1} - t_i) \cdot \sum_{i=1}^m A_i L^i)^{-1} L^i \quad (13)$$

Where, L is the luminance of the image. A_i is a matrix that encodes the image conductivities for each dimension.

Combining Eqs (11) and (13), the KAZE feature points on a couple of images captured by cameras 1 and 2 are shown in Figure 9. The results show that this method was effective to extract feature points from smooth surfaces with small brightness difference, especially for the white dotted line area.

Figure 9 KAZE feature points of the welding pool image under the arc (240A, 33V, 0.6m/min)

5.4 SURF-BRISK-KAZE feature description and matching

In order to match the feature points in SURF, BRISK and KAZE methods, the descriptor was determined for the extracted feature points. The details of descriptor, which is a 64 dimensional vector, has been discussed in reference [24].

The 64 dimensional vector obtained by the above method only included the grayscale information of welding pool images, the color information of images were not considered which might decrease the matching accuracy of welding pool images.

The information of original welding pool images (color) was much richer than the pre-processed the welding pool images(gray) in Section 4. The signal interference was also included in original welding pool images. To utilized the color information of original images effectively,

only the information of feature points in Sections 5.1-5.3 and their eight neighborhoods were used to improve the above 64 dimensional vector. The steps were as follows:

(1) It was assumed that r , g , b were the values of color information for the feature point (x, y) , respectively. n_c was the total number of the feature points (x, y) and their neighborhood pixels. Here, $r, g, b \in [0, 255]$, n_c was 9 in this study.

(2) Calculating the mean values μ_r , μ_g and μ_b of the feature point (x, y) and its eight neighborhoods. E was the 3D vector composed by μ_r , μ_g and μ_b . The details of equations were shown as follows.

$$\begin{cases} \mu_r = \frac{1}{n} \sum_{i=1}^n r_i \\ \mu_g = \frac{1}{n} \sum_{i=1}^n g_i \\ \mu_b = \frac{1}{n} \sum_{i=1}^n b_i \\ E = (\mu_r, \mu_g, \mu_b) \end{cases} \quad (14)$$

(3) Calculating the variances δ_r , δ_g and δ_b of the feature point (x, y) and its eight neighborhoods as follows. F was the 3D vector composed by δ_r , δ_g and δ_b .

$$\begin{cases} \delta_r = \frac{1}{n} \sum_{i=1}^n (r_i - \mu_r)^2 \\ \delta_g = \frac{1}{n} \sum_{i=1}^n (g_i - \mu_g)^2 \\ \delta_b = \frac{1}{n} \sum_{i=1}^n (b_i - \mu_b)^2 \\ F = (\delta_r, \delta_g, \delta_b) \end{cases} \quad (15)$$

(4) Normalizing vector E and F respectively.

$$\begin{cases} E_n = (\frac{\mu_r}{255}, \frac{\mu_g}{255}, \frac{\mu_b}{255}) \\ F_n = (\frac{\delta_r}{255}, \frac{\delta_g}{255}, \frac{\delta_b}{255}) \end{cases} \quad (16)$$

(5) The normalized mean value vector E_n and variance vector F_n were combined to form a six dimensional RGB color classification descriptor vector V_c .

$$V_c = (\frac{\mu_r}{255}, \frac{\mu_g}{255}, \frac{\mu_b}{255}, \frac{\delta_r}{255}, \frac{\delta_g}{255}, \frac{\delta_b}{255}) \quad (17)$$

(6) By substituting Eq (17) into $V_s=(i_1, i_2, \dots, i_{64})$, the descriptor V was expressed as follows:

$$V = (i_1, i_2, \dots, i_{64}, \frac{\mu_r}{255}, \frac{\mu_g}{255}, \frac{\mu_b}{255}, \frac{\delta_r}{255}, \frac{\delta_g}{255}, \frac{\delta_b}{255}) \quad (18)$$

The matching process was carried out as follows. A feature point P_1 (image of camera 1) was compared with a feature point P_2 (image of camera 2) by calculating the Euclidean distance between their descriptor V . The Euclidean distance is:

$$d_E = \sqrt{(i'_1 - i''_1)^2 + (i'_2 - i''_2)^2 + \dots + (\frac{\delta'_r}{255} - \frac{\delta''_r}{255})^2 + (\frac{\delta'_g}{255} - \frac{\delta''_g}{255})^2} \quad (19)$$

Where, $V'=(i'_1, i'_2, \dots, \delta'_g/255, \delta'_b/255)$ is the descriptor of P_1 and $V''=(i''_1, i''_2, \dots, \delta''_g/255, \delta''_b/255)$ is the descriptor of P_2 . A matching pair was detected if the ratio of their distance to the distance of the second nearest neighbor was less than 0.6.

Figure 10 shows the matching pairs obtained by the SURF-BRISK-KAZE algorithms whose descriptor was 64 dimensional. Figure 11 shows the matching pairs obtained by the improved 70 dimensional descriptor V . Though the number of mismatching pairs were decreased because of the use of V , some mismatching pairs were still remained and the mismatch elimination was needed.

Camera 1

Camera 2

Figure 10 Traditional SURF-BRISK-KAZE matching pairs and mismatching area (240A, 33V, 0.6m/min)

Camera 1

Camera 2

Figure 11 Improved SURF-BRISK-KAZE matching pairs and mismatching area (240A, 33V, 0.6m/min)

6 Improved RANSAC algorithm

There were some mismatching pairs (gross errors) in the above matching pairs. Random sample consensus algorithm was used to eliminate the mismatches in this paper. The traditional RANSAC algorithm can complete the estimation for the model parameters through data iteration and result validation. It can also reduce the number of gross errors to increase the matching accuracy [27]. However, the traditional RANSAC algorithm also has shortcomings. For example, the iteration time of the traditional RANSAC algorithm depends on the experimental data and the valid data rate. When the number of the valid data is small, the number of iterations of the algorithm will increase exponentially because of large number of mismatching pairs, which greatly increases the running time of the algorithm. Meanwhile, the initial model parameters are calculated based on a subset of the experimental data. When the valid data rate of the subset is not high, the initial model will be extremely unreasonable, and the verification of this unreasonable model will consume a lot of time, which seriously affects the overall efficiency of the algorithm. The traditional RANSAC algorithm was improved as follows.

6.1 Data preprocessing

The data pre-processing model was defined as $M(P, C)$. P was the matching pairs (P_1, P_2) obtained by Section 5.4, which was written as

$$P = \{P_1[i], P_2[j] | i = j = 0, 1, \dots, n-1\} \quad (20)$$

C was the criterion for eliminating mismatching point pairs of P , and it was expressed as

$$C = (|k_i - k| \leq \Delta k) \&\& (|d_i - d| \leq \Delta d) \quad (i = 0, 1, \dots, n-1) \quad (21)$$

Where, k_i is the ratio calculated by pixel coordinates, k is the median of k_i . Δk is the threshold value which was 0.9 in this study. If d_i^* is the square root calculated by pixel coordinates, d_i is top 80% of d_i^* value from small to large. d is the median of d_i , Δd is the threshold value which was 13 in this study. The k_i and d_i were expressed as

$$k_i = \frac{y_j - y_i}{x_j - x_i} \quad (22)$$

$$d_i = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2} \quad (23)$$

Here, x_i and y_i are the pixel coordinates of $P_1[i]$ captured by camera 1, and x_j and y_j are the pixel coordinates of $P_2[j]$ captured by camera 2.

To increase the proportion of valid data in the data set of P , all the matching pairs were calculated first based on Eqs (22) and (23). Any matching pair which did not satisfy Eq (21) was deleted from the data set of P , others were selected as new data set of Q . The Q contains enough matching pairs, which can be used to estimate the truest homography matrix parameter model as much as possible. Proportion of valid data in the Q became larger, which greatly reduces the number of iterations to calculate the maximum valid data. As a result, the efficiency of algorithm was improved. The above work completed the pre-purification of the raw data for the RANSAC algorithm. Figure 12 shows the matching pairs pre-processed by the data pre-processing model. Compared with Figure 11, the mismatching pairs was decreased.

Figure 12 The matching pairs preprocessed by the data preprocessing model (240A, 33V, 0.6m/min)

6.2 Pre-test model

In the traditional RANSAC algorithm, the subset(S) is randomly extracted from experimental data (P) of Section 5.4, and the corresponding initial model is estimated by the subset. The initialization model is tested by all the remaining matching points($\mathbb{L}_P S$), which are not belong to the above subset. This circulative progress needs much verification time because many initialization models are not reasonable, especially when the proportion of mismatching pairs is high.

To increase efficiency of the RANSAC algorithm, a pre-testing model was proposed to estimate the initial models before the traditional testing of RANSAC algorithm. The steps of pre-testing model were:

(1) n pairs of matching points were randomly selected from the new data set(Q) of Section 6.1.

(2) The improved initial model T was estimated by m pairs of matching points which was written as follows. Here, $m \subseteq n$.

$$T = \begin{bmatrix} t_{11} & t_{12} & t_{13} \\ t_{21} & t_{22} & t_{23} \\ t_{31} & t_{32} & t_{33} \end{bmatrix} \quad (24)$$

$$\beta \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix} = \begin{bmatrix} t_{11} & t_{12} & t_{13} \\ t_{21} & t_{22} & t_{23} \\ t_{31} & t_{32} & t_{33} \end{bmatrix} \begin{bmatrix} x_2 \\ y_2 \\ 1 \end{bmatrix} \quad (25)$$

Where, $t_{11}, t_{12}, \dots, t_{33}$ are the parameters of T , respectively. (x_1, y_1) is the pixel coordinate of $P_1[i]$ and (x_2, y_2) is the pixel coordinate of $P_2[j]$. m is the number of matching pairs needed to solve the Eq (25), which was 4 in this study.

(3) The remaining $n-m$ pairs were used to verify the reasonability of T by following equation.

$$E_s = \sum_{i=1}^{n-m} [(x_{1i} \frac{t_{11}x_{2i} + t_{12}y_{2i} + t_{13}}{t_{31}x_{2i} + t_{32}y_{2i} + t_{33}})^2 + (y_{1i} \frac{t_{21}x_{2i} + t_{22}y_{2i} + t_{23}}{t_{31}x_{2i} + t_{32}y_{2i} + t_{33}})^2] \quad (26)$$

Where, E_s is test error calculated by the matching pairs of $\mathbb{L}_m m$. The threshold t_p was 0.6 in this study.

(4) If the E_s of all $n-m$ pairs were less than the t_p , the initial model T was started to be tested by the remaining matching points($\mathbb{L}_{Qn}$) of Section 6.1 as the traditional RANSAC algorithm; otherwise, the initialization model T was discarded directly, and n pairs of matching points were re-selected for the next cycle of iterative estimation.

The unreasonable initial models were discarded quickly by above calculation, which reduced the detection time to verify the initial model. The flow chat of the improved RANSAC algorithm is shown in Figure 13. The real detection time of traditional and improved RANSAC algorithms were discussed in Section 6.3. Figure 14 is the matching point pairs of the welding pool under the arc processed by the improved RANSAC algorithm.

6.3 Estimation of commutating time

To obtain at least one subset that could pass through the verification of traditional RANSAC algorithm under a certain confidence $p(0.95 \sim 0.99)$, the minimum sampling times k must meet the following requirement

$$1 - (1 - (1 - \omega)^{m_i})^k = P \quad (27)$$

Figure 13 The flow chat of the improved RANSAC algorithm

Figure 14 Matching pairs of the improved RANSAC algorithm (240A, 33V, 0.6m/min)

Where ω is the proportion of the mismatching pairs in P , m_i is the minimum sample number for all subsets to calculate the initial model parameters of verification which was 4 in this study.

Supposing that the number of P is n_p . It takes t_s seconds to conduct a random sampling from the data set, and it takes t_c seconds to calculate the initial model. t_j is the time to test the initial model by one couple of remaining matching pairs. The total time to test the initial model is $(n_p-4)t_j$. Therefore, the calculation time T_i of traditional RANSAC algorithm with k random sampling times is:

$$T_i = k(t_s + t_c) + k(n_p - m_i)t_j \quad (28)$$

In this study, the average k was 500, t_s was 2.21×10^{-4} seconds, t_c was 5.45×10^{-5} seconds and t_j was 3.67×10^{-5}

seconds. The processor of computer was Intel(R) Core(TM) i7-9750H CPU @ 2.60GHz and the memory was 8G.

For the improved RANSAC algorithm, the minimum sampling times k' must meet Eq (27) as well, where m_i is mentioned in Section 6.2. The Eq (28) is modified as:

$$T' = k'(t_s + t_c) + k'(n - m)t_j + k'(n_Q - n)(1 - \omega_Q)^n t_j \quad (29)$$

Where, T' is the calculation time of improved RANSAC algorithm, n_Q is the number of Q and ω_Q is the proportion of the mismatching pairs in Q .

The time reduced by the improved RANSAC algorithm is as follows:

$$\Delta T = T_i - T' = (k - k')(t_s + t_c) + [k(n_p - m_i) - k'(n - m) - k'(n_Q - n)(1 - \omega_Q)^n] t_j \quad (30)$$

In this study, k' was 1500. Though the total time of t_s and t_c was increased if k' was larger than k , it was an order of magnitude smaller than the time of testing the initial model. Therefore, the improved RANSAC algorithm reduces a series of unnecessary operations and improves the efficiency of the algorithm. While its calculation accuracy was not smaller than that of traditional RANSAC algorithm. The values of k' , n and m were not optimal yet and can be optimized in the future.

Comparing with the traditional RANSAC algorithm, the calculating efficiency in improved RANSAC algorithm was increased by at least 160% in this study, as shown in Table 3, which showed a large potential to reduce the calculating time.

7 Reconstruction results and validation

The GMAW experiments were carried out to capture the couples of the welding pool images under the arc. The parameters of the welding process were shown in table 2. The feature matching points on each couple of weld pool images were extracted according to Sections 5 and 6. The world coordinates of welding pool surface was reconstructed according to Section 3. The results for 240A-33V are shown in Figure15.

Table 3 The comparison between the improved RANSAC algorithm and the traditional RANSAC algorithm.

Image group	Total feature points	Traditional RANSAC			Improved RANSAC			Time difference $\Delta t/s$	Increasing Efficiency %
		Interior points	rate%	Algorithm time /s	Interior points	rate%	Algorithm time /s		
1	5900	638	10.81	43.77	858	14.54	12.54	31.23	249.04
2	6501	640	9.84	55.55	790	12.15	18.78	36.77	195.79
3	5817	616	10.59	54.05	764	13.13	19.87	34.18	172.02
4	6434	650	10.10	53.69	771	11.98	19.32	34.37	177.90
5	4698	549	11.69	52.13	701	14.92	19.82	32.31	163.02
6	5454	613	11.24	52.71	744	13.64	19.37	33.34	172.12
7	5472	648	11.84	54.64	973	17.78	20.40	34.24	167.84
8	5650	600	10.62	54.30	943	16.69	19.88	34.42	173.14

Figure 15 Point cloud of the welding pool under the arc

7.1 Surface reconstruction

The way to transfer the point cloud into the 3D reconstructed surface was LOWESS regression smoothing filtering algorithm, which was a local scatter weighted estimation algorithm depending on the adjacent points [28]. The algorithm added a sliding window on the basis of the least square method. If the sliding window width was large, there would be more scattered points in the covered window, resulting in smooth surface of welding pool and loss of large original data information. On the contrary, if the sliding window width was small, the welding pool surface was rough, which also increased the accuracy of reconstructed surface.

In this experiment, the window width was selected as 6 pixels based on the comparative tests, which provided high accuracy of the 3D reconstructed data, and produced a smoothly reconstructed surface without trimming. The

point with the smallest z value in the point cloud was selected as the center of the welding pool. It is assumed that the world coordinate of the point was (x_0, y_0, z_0) , the final surface reconstruction was the symmetric treatment of the smoothly reconstructed surface in the plane where $y = y_0$. The final surface reconstruction of Figure 15 is shown in Figure 16. It can be seen that the reconstructed welding pool surface was consistent with the actual welding pool surface in GMAW.

(a) 240A, 33V, 0.6m/min

(b) 240A, 33V, 0.6m/min

Figure 16 3D reconstruction of the welding pool under the arc

7.2 Validation

In order to verify the validity of the above feature point extracting and matching algorithms for couples of welding pool images during GMAW, the verification experiment was carried out. Silicon nitride tracer particles were embedded in the workpiece before welding as shown in the Figure 17. These tracer particles would float on the surface of welding pool when the solid metal near the blind hole was melted. This phenomenon was captured by the above binocular vision system, as shown in the Figure 18. The feature points at the junction of the tracer particle and the welding pool can be selected manually, as shown in Figure 18 (yellow dots). It was clear that the yellow dots were the correct feature matching points. Their world coordinate values calculated directly by Section 3 can be used to verify the accuracy of their neighbor feature matching points (red dots in Figure 18) extracted by above improved algorithms. Here, the heights of yellow dots and red dots were assumed to be similar as they were closed to each other on the smooth surface of welding pool, though their world coordinates in x and y directions were different. Table 4 is the comparison between the heights of yellow dots and red dots. The maximum absolute error in the z

direction was less than 0.07mm and the maximum relative error was smaller than 6.0%. All the results are indicated that the proposed algorithms mentioned above can reconstruct the 3D surface of welding pool for GMAW with high efficiency.

Figure 17 Tracer particles embedded in workpiece

Figure 18 Tracer particle verification (240A, 33V, 0.6m/min)

Table 4 The comparison between the tracer particle and the matching point pairs.

Image group	Tracer particles (z/mm)	Matching point pair 1 (z/mm)	Matching point pair 2 (z/mm)	Matching point pair 3 (z/mm)	Maximum abs(error) (z/mm)	Maximum relative error(%)
1	-1.31727	-1.36893	-1.33676	-1.33862	0.05136	3.92
2	-1.32219	-1.29371	-1.33483	-1.37148	0.05199	3.78
3	-1.19575	-1.23198	-1.23604	-1.12156	0.06419	5.37
4	-1.26499	-1.28316	-1.32741	-1.25829	0.06243	4.93
5	-1.17624	-1.16843	-1.21358	-1.16923	0.03736	3.17
6	-1.42836	-1.47268	-1.43864	-1.43269	0.04432	3.10
7	-1.27823	-1.29906	-1.24084	-1.24821	0.03748	2.93
8	-1.36529	-1.32842	-1.31868	-1.35937	0.04863	3.59

8 CONCLUSION

(1) A new method was proposed to determine the feature matching of the welding pool captured by binocular stereo vision system. It included improved SURF-BRISK-KAZE algorithms, improved RANSAC algorithms and surface reconstruction algorithms, which realized the 3D

reconstruction of the welding pool surface under the GMAW arc.

(2) The feature points descriptor was improved by considering the color information of images which increased the matching accuracy of welding pool images. The data preprocessing and pre-test model was added to the RANSAC algorithm to improve the calculating efficiency of the algorithm.

(3) The experimental results exhibited high accuracy and efficiency of the new method in reconstruction of welding pool surface. For the reconstructed data, the maximum relative error was smaller than 6.0%.

(4) The quantitative relationship between welding pool surface and weld quality should be established based on the experience of skilled welder, and the parallel computing method should be improved by the CUDA to realize the real-time 3D reconstruction of welding pool surface in the future.

9 Declaration

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Availability of data and materials

The datasets supporting the conclusions of this article are included within the article.

Authors' contributions

The author's contributions are as follows: Ji Chen was in charge of the whole trial; Zu-Nan Gu and Ji Chen wrote the manuscript; Chuan-song Wu assisted with sampling and laboratory analyses.

Competing interests

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Appendix

Appendix and supplement both mean material added at the end of a book. An appendix gives useful additional information, but even without it the rest of the book is complete: In the appendix are forty detailed charts. A supplement, bound in the book or published separately, is given for comparison, as an enhancement, to provide corrections, to present later information, and the like: A yearly supplement is issue.

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