Welding Groove Detection Based on Hough Transform and Gray-Level Co-Occurrence Matrix

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Abstract. With the development of the intelligent robot industry and the increasing labor costs of production, the demand for the quality identification of welding products using robots is increasing. Position identification and shape judgment of the welding groove are important conditions for measuring welding precision and welding quality. Based on a variety of welding groove images, the mathematical model of groove size and texture is constructed. Hough transform and gray-level co-occurrence matrix are used to identify and extract the welding groove position and shape characteristics in order to judge the quality of welding products. According to the identification and extraction of welding groove position and topography, through the simulation of the welding groove location and terrain identification and extraction of the model were analyzed from various angles and the accuracy of the algorithm.

1. Introduction
The welding robot is a highly automated welding equipment. With the application of the intelligent robot industry, improving welding quality, reducing costs, and improving the working environment are the trends in the development of modern welding manufacturing. Positioning and topographical feature detection of welding bevels is a crucial part in the design and use of welding robots [1-3]. The quality of welding is highly dependent on the detection and identification of the groove, which requires high-precision detection and positioning. Huo Ping [4] used the slope method and the least squares method to extract the feature information of the weld image. Wang Xiuping and Bai Ruilin [5] improved Steger algorithm to extract the laser center line, and extracted the location information of the weld center by Hough transformation, with high extraction accuracy. In this paper, the Hough transform is used to extract the weld information to establish the model for extracting candidate regions from the scene. Then the Gray-level co-occurrence matrix and Radon transform are used to identify the candidate areas, fine tune the parameters of the model and refine the position of the effective candidate box to achieve the desired goal.

2. Position Identification of Welding Groove
After visual recognition, the image of the weld bevel is stored and each image is converted to a gray scale image. In order to obtain a higher quality groove image, global mean filtering is performed on all the pixels to make the welding detection image smoother, which greatly reduces noise interference. Then, the gray average value of each picture is obtained, and the corresponding gray histogram is derived. Since the gray histograms of the pictures are different, we choose the Otsu segmentation
method suitable for processing the dynamic threshold to obtain the basic shape of the welding groove. The Sobel edge detection method is used to process the image after the Otsu method, smoothing the noise, reducing the blurring degree of the image edge, and further enhancing the effect of the image. Finally, Hough transform is used to detect and extract the edge curve of the groove, and record the boundary related information [6]. As shown in the Figure 1.

\[ g(x,y) = \frac{1}{M} \sum_{(x,y) \in S} f(x,y) \] (1)

Suppose that \( M=9 \). We use the template to perform mean filtering on all points in the original gray scale image, so that the groove detection image is smoother, and the obtained image is picture 3.
2.2. Otsu Division
The gray histogram of the image is derived, and the gray histogram presents a bimodal distribution. The pixel gray values at the two peaks and troughs in the figure are obtained, and these values are used as the threshold of the segmentation process, and the groove and the background are segmented. The Otsu segmentation method binarize the segmentation threshold of the image based on the principle of least squares method, and obtains the minimum intra-class variance and the maximum inter-class variance to calculate the threshold.

Figure 4. Weld picture gray histogram

The image can be divided into two parts: the background and the groove by the difference of the gray level. The area with the larger gray value is the background, and the area with the smaller gray value is the welding groove. The larger the variance between the background and the target, the greater the differences between the two parts. We make the segmentation that maximizes the variance between classes. It indicates that the probability of making errors is the smallest.

For image \( f(x, y) \), the segmentation thresholds for the groove and background are recorded as \( T \). The proportion of the pixel points belonging to the groove is \( \omega_0 \), and the average gray level is \( \mu_0 \); the ratio of the pixels belonging to the background to the whole picture is \( \omega_1 \), and the gray level is \( \mu_1 \); the average gray level of the whole picture is \( \mu \), and the variance between the classes is recorded as \( h \). Suppose the image size is \( M \times N \). The number of pixels whose gray level is less than the threshold \( T \) is recorded as \( N_0 \), and the number of pixels whose gray level is greater than the threshold \( T \) is recorded as \( N_1 \).

\[
\omega_0 = \frac{N_0}{M \times N} \tag{2}
\]

\[
\omega_1 = \frac{N_1}{M \times N} \tag{3}
\]

\[
N_0 + N_1 = M \times N \tag{4}
\]

\[
\omega_0 + \omega_1 = 1 \tag{5}
\]

\[
\mu = \omega_0 \times \mu_0 + \omega_1 \times \mu_1 \tag{6}
\]
The equivalent formula is:
\[
h = \omega_0 (\mu_0 - \mu)^2 + \omega_1 (\mu_1 - \mu)^2
\]
(7)

The equivalent formula is:
\[
h = \omega_0 \omega_1 (\mu_0 - \mu_1)^2
\]
(8)

The traversal is used to obtain the threshold, and the optimal segmentation threshold is the gray value corresponding to the maximum variance between classes. The optimal segmentation threshold is used for binarization of the gray scale image. If the pixel is smaller than the assigned value of 0, and the value is greater than 255, the image segmentation is completed, and the output image is as shown in picture 5.

![Weld picture Otsu segmentation](image)

**Figure 5.** Weld picture Otsu segmentation

### 2.3. Sobel edge detection

Despite the global mean filtering, the grooved area is segmented, but the resulting boundary is rough and the information such as the location of the breach is not reflected. The gray level is discontinuously changed at the edge of the groove, and the gray level change of each pixel point can be obtained by calculating the first derivative. The segmented groove boundary is a step boundary, and the position direction information is obtained by calculating the first derivative.

The Sobel operator uses a weighted operation convolved with the $3 \times 3$ model of the pixel domain to calculate the partial derivatives in the eight directions, and uses the extreme values of the first derivative to achieve edge detection. We multiply the influence of the pixel position factor by its coefficient, and we use differential approximation to find the first derivative in edge detection. Then we reduce the edge ambiguity by convolving the differential operator template in the spatial domain. Traversing the pixels of the entire image, using the Sobel convolution factors and in the horizontal and vertical directions, we calculate the convolution on each pixel point to obtain the convolution values in the horizontal direction and in the vertical direction. We obtain the convolution values in the horizontal direction and in the vertical direction, and they are called partial derivative values. The convolution factor is [8]:

\[
G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} \quad G_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}
\]
(9)

If the original image $A$ is at a gray value at the point $(x, y)$, the specific calculation process is:

\[
G(x) = G_x \times A = \begin{bmatrix} f(x+1,y-1) + 2f(x+1,y) + f(x+1,y+1) \\ f(x-1,y-1) + 2f(x-1,y) + f(x-1,y+1) \end{bmatrix}
\]
(10)
The horizontal and vertical gray values of each pixel of the image are combined to represent the gray level of the point for the direction of the gradient. The edge of the groove is extracted by the Sobel inspection process as shown in picture 6.

2.4. Hough transform extraction weld
The Hough transform line extraction method is used to detect the edge curve, and the curve is shortened and the interference is less. The edge of the image to be pre-processed has reached a clear and smooth degree. Based on this, the Hough change line extraction is performed to determine the specific information of the groove boundary and is marked in the picture.

In the image space (original space) of $x$-$y$, the equation $y_i = a x_i + b$ representing the point line $(x, y)$, as shown in picture 7. We transform the equation into a straight line equation $b = -a x_i + y_i$ of $(a, b)$ in the $a$-$b$ space (parameter space), as shown in the picture 8. In the original space, the point that crosses the same line corresponds to the line in the parameter space that intersects the point $(a, b)$ as the slope $-x_i$ and the intercept $y_i$. 
First we quantify the values of \( a \) and \( b \), and their values are \( \{ a_0, a_1, \cdots, a_{m-1} \} \), \( \{ b_0, b_1, \cdots, b_{n-1} \} \). Traversing all possible values of \( a \), we calculate all the values of \( a \) in terms of all the points \( (x_i, y_i) \) in the source space. Then we take the closest value of \( b \) to \( b \). After traversing the pixels in the graph, the convergence points of the straight lines in the parameter space are determined. These gather points correspond to the straight lines in the original space, and the straight lines are marked in red on the original sheet.

The results obtained through the above steps are shown in picture 9, in which the red straight line is the identified groove position.

![Figure 9. Groove position recognition result map](image)

The two boundaries of the slot groove bottom and the right edge of the groove are better, and the recognition effect of the left boundary of the groove is fuzzy, but overall, the boundary recognition effect is better.

3. Topographic Analysis model Based on Gray Level Co-occurrence Matrix

In order to extract the topographical features of the welding groove, the gray-level co-occurrence matrix is first used to extract the texture features of the image. Then the Radon variation is used to linearly integrate the energy value matrix of the gray level co-occurrence matrix in one direction, and the image is drawn according to the distribution of the data after linear integration. The moving average filtering method is used to represent the texture features of the groove.

3.1. Gray level co-occurrence matrix

The texture is formed by the repeated occurrence of the gray scale distribution in the spatial position, and thus there is a certain gray scale relationship between two pixels separated by a certain distance in the image space. The gray level co-occurrence matrix GLCM is obtained by calculating the number of times the two gray values are adjacent in the image. Each element \( (i, j) \) in the gray-scale common matrix represents the number of times gray scale \( i \) and gray scale \( j \) are adjacent in the image.

Suppose the gray level of the image is \( N \), and its gray level co-occurrence matrix is:

\[
P_{ij} = \#((x_1, y_1), (x_2, y_2) | f(x_1, y_1) = i, f(x_2, y_2) = j)
\]

The number of elements in the set \( x \) is recorded as \( \#(x) \), and \( P \) is an \( N \times N \) matrix. If the distance between \( (x_1, y_1) \) and \( (x_2, y_2) \) is \( d \) and the angle between the two is \( \theta \), then a gray level co-occurrence matrix \( P_{ij, d, \theta} \) can be obtained. In the coarse-grained area, the value of \( P \) is concentrated in the vicinity of the main diagonal; in the fine-grained area, the \( P \) value in the gray-scale co-occurrence matrix is scattered everywhere.

In order to visually describe the texture features, the feature quantities such as contrast, energy, and entropy of the gray level co-occurrence matrix are used to represent the texture features [9].
1) Contrast: The sharpness of the reflected image and the depth of the texture. The deeper the groove of the texture, the greater the contrast and the clearer the effect. The formula is:

\[
Con = \sum_{i} \sum_{j} (i - j)^2 P(i, j)
\]  

(15)

2) Energy: The degree of gray distribution of the reaction image and the texture thickness. A large energy value indicates that the current texture is a texture with a relatively stable variation. The formula is:

\[
Asm = \sum_{i} \sum_{j} P(i, j)^2
\]  

(16)

3) Entropy: The response image contains a measure of the randomness of the amount of information. When all the mean values in the symbiotic matrix are equal or the pixels exhibit only the greatest randomness, the entropy is maximum. Its formula is:

\[
Ent = - \sum_{i} \sum_{j} P(i, j) \log P(i, j)
\]  

(17)

3.2. Radon transform

The mathematical theory of Radon transformation is: Assume that there is an image \(f(x, y)\), as shown in picture 10, the integral of the function over the straight line \(L\) region is:

\[
\int_{L} \int f(x, y) dx
\]  

(18)

Ds is the differentiation of the line. Rewrite the above points with the Delta function as:

\[
\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \delta \left( x \cos \theta + y \sin \theta - p \right) dx dy
\]  

(19)

Given a set of angles with the coordinate axes, you can get an integral value distributed along a straight line. Therefore, the Radon transform is the line integral of the function \(f(x, y)\).

3.3. Moving average filtering

The moving average filtering is based on the statistical law. The continuous sampling data is regarded as a queue with a fixed length of \(N\). After a new measurement, the first data of the queue is removed,
and the remaining \(N-1\) data are advanced in turn, and the new one is the sampled data is inserted as the
tail of the new queue; then the queue is arithmetically used as the result of this measurement.

We use the moving average filter to reduce noise obtained by Radon transform. Suppose the Radeon
transform result is set to \(x\), and filter result is set to \(y\), then the formula is:

\[
y(n) = \frac{x(n)+x(n-1)+x(n-2)+\ldots+x(n-N+1)}{N}
\]

(20)

3.4. Correlation coefficient analysis

Covariance \(\text{Cov}(X,Y)\) is a feature number that describes the degree of correlation of a random variable
and is defined as:

\[
\text{Corr}(X,Y) = \frac{\text{Cov}(X,Y)}{(\text{Var}(X))^{\frac{1}{2}}(\text{Var}(Y))^{\frac{1}{2}}} = \frac{\text{Cov}(X,Y)}{\sigma_X\sigma_Y}
\]

(21)

\(E(X)\) is the expectation of component \(X\), and \(E(Y)\) is the expectation of component \(Y\). The formula of
the correlation coefficient is:

\[
\text{Corr}(X,Y) = \frac{\text{Cov}(X,Y)}{(\text{Var}(X))^{\frac{1}{2}}(\text{Var}(Y))^{\frac{1}{2}}} = \frac{\text{Cov}(X,Y)}{\sigma_X\sigma_Y}
\]

(22)

\(\text{Var}(X)\) is the variance of \(X\), \(\text{Var}(Y)\) is the variance of \(Y\).

3.5. Model is constructed as follows

1) Step1: We convert a color image to a gray scale image and divide the original image into rows
and columns into multiple images of the same size, and compress the grayscale values into 8 levels.

2) Step2: We calculate the co-occurrence matrix of each small picture and its energy value, and
the obtained energy values are combined again in the original symbiotic matrix order to construct a
new energy value matrix.

3) Step3: The Radon transform is performed on the energy value matrix. We calculate the sum the
energy values of each column and plot an image of the energy value as a function of the number of
columns.

4) Step4: The moving average filter processes the energy value image to obtain an image in
which the final energy value changes with the number of columns.

3.6. Model solving

The MATLAB is used to calculate the gray level co-occurrence matrix, the eigenvalues of the co-
occurrence matrix are Radon transformed, and the image after Radon transform is subjected to moving
average filtering. The result is shown in picture 11.
As we can see through the picture 12, the weld is a V-shaped groove with fish scale features, characterized by low sides and middle heights on both sides, and the overall appearance of the middle and high sides of the fish scale shape [10]. We observe the filtered results. And some parts of the protuberances in the welding slope are relatively downward, which show a downward trend from the middle to the two sides and match the welding slope of the scale features. The edge of the entire welding slope shows the tendency declining at the beginning and rising up in late, and the tendency is consistent with the topography of the V-shaped groove. Our model has good morphology analysis results under the fuzzy picture of the weld.

4. Results Analysis
In this paper, the weld pictures are mostly selected under poor welding conditions, and the welds are not obvious due to poor light interference or poor weld conditions. Under the harsh identification conditions, we can still better identify the bevel and the topographical features of the weld. The identification is more accurate and the method is more practical.

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