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Research on Weld Strengthening Based on Machine Vision Technology

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ABSTRACT

Welding, as an important process in industrial manufacturing, is often accompanied by various forms of light, heat, and electromagnetic radiation, which can pose significant harm to the human body. The modern industry has effectively mitigated direct harm to humans from welding by introducing robots and embracing intelligent manufacturing, thereby enhancing the quality of welding. Traditional welding quality inspection relies on human eyes, requiring extensive experience and resulting in low detection efficiency. Due to the complexity of the welding process and the randomness of process interference, false detection and missed detection are inevitable during testing. With the rapid development of machine vision, characterized by precision and high intelligence, it has found wide applications in industrial measurement, product testing, and identification. However, machine vision methods impose high requirements on image quality. Utilizing MATLAB to build the algorithm platform, the methods of gray scale conversion, image filtering, and histogram equalization have been respectively adopted to enhance weld image processing. The experimental results demonstrate that histogram equalization holds practical engineering significance for the research objects selected in this paper, effectively improving the image quality of the inspected weld.

KEYWORDS

Image Enhancement; Grayscale Conversion; Image Filtering; Histogram Equalization

1. INTRODUCTION

The quality of welded joints is largely dependent on the quality of the weld, and various inspection methods have been developed to ensure its integrity and durability. Machine vision, as a non-contact and non-destructive testing method, is particularly suitable for large-scale repetitive industrial production processes. It can improve detection efficiency and automation, enhance real-time and accuracy of detection, and reduce the need for manpower. Additionally, the vision system serves as the core component of third-generation welding robots, effectively improving their reliability and work efficiency. However, in low illumination conditions, the image quality acquired by the vision system may be compromised, leading to reduced detection accuracy. Image enhancement technology can effectively improve detection accuracy through a series of image prepossessing techniques, thereby achieving the goal of controlling welding quality.

2. IMAGE ENHANCEMENT TECHNIQUE

Image enhancement technology typically highlights or enhances certain features of an image, such as edge features, contour information, and contrast, in order to better convey useful information in the image and enhance its utility. The traditional image enhancement method, which directly calculates the gray value in the image, utilizes the spatial domain as the foundation for signal processing, thus emphasizing the characteristics of linear operation processing. These methods include gray transformation, histogram equalization, image smoothing and sharpening, false color processing, etc. Such enhancement methods can enhance image quality. Spatial domain denoising is the most commonly used approach, where the gray value of each image pixel in the spatial region is processed to eliminate noise.

2.1. Graying

The biggest advantage of processing the color weld images collected by the camera into grayscale is to reduce the computational workload and complexity of subsequent image analysis, minimize unnecessary data operations, and shorten the time required for weld image recognition. Grayscale processing involves converting an image from the RGB color space to a single-channel grayscale color space. An RGB color model image comprises three components: red, green, and blue, each with 255 brightness levels, resulting in over 16 million potential color combinations per pixel. Conversely, in a grayscale map, a pixel is represented by only 256 shades, where the R, G, and B component values are identical. Consequently, converting the image to grayscale significantly reduces computational complexity. A color image can be represented as follows:

$$F(x,y)=[f_R(x,y),f_G(x,y),f_B(x,y)] \tag{1}$$

Where (x,y) represents the pixel coordinates of the image; F(x,y) represents the brightness information of the image at (x, y); , and respectively represent the brightness information of the R, G, and B components of the image at (x, y). The commonly used grayscale methods include the average value method, the maximum value method, and the weighted average method. Among these, the weighted average method is most commonly used, where the gray image is obtained by applying different weights and summing them based on the given components.

2.2. Mean filtering

The mean filter, also known as the normalized filter, is the simplest linear filter. It functions as a low-pass filter, effectively removing high-frequency signals. The fundamental principle involves computing the average value of several adjacent pixels to determine the pixel value in the original image. The process entails selecting a mask for each target pixel (x, y) in the original image (convolution computing core - point-by-point convolution computing template), applying the corresponding mask to each pixel for processing. The mask consists of neighboring pixels, with the average value of each pixel within the mask assigned to the current target pixel (x, y). Subsequently, convolution takes place from left to right and top to bottom until every target pixel is reprocessed and analyzed. The pixel value of the resulting image is based on the pixel values within the processed area. The mask required for mean filtering is determined by the operator:

$$b(x,y)=\frac{1}{mn}\sum_{(r,c)\in T_{xy}} a(r,c) \tag{2}$$

Where b(x,y) represents the gray value of image pixels after mean filtering; m and n are the dimensions of the template; is the mean filtering template used; a(r,c) denotes the pixel gray value of the input image; (r,c) signifies the pixel coordinate within the template.

2.3. Histogram equalization

Histogram equalization: By non-linearly stretching the image, the gray histogram of the image is transformed from uneven to uniform, enhancing the image's contrast and brightness. The gray levels of the input image and output image are established within a value range of [0,1]. The corresponding probability density function is summed, and the mapping function is constructed as follows:

$$s = T(r) = \int_0^r p_r(\omega)d\omega \tag{3}$$

Where is a monotone increasing function, and the value range is [0,1]. Taking the derivative of equation (4.1) r, we get:

$$\frac{ds}{dr} = \frac{dT(r)}{dr} = \frac{d\int_0^r p_r(\omega)d\omega}{dr} = p_r(r) \tag{4}$$

Then take the derivative of s on both sides, and we get:

$$p_s(s) = p_r(r) = 1 \tag{5}$$

From this, we can build:

$$p_s(s) = T^{-1}(s) = 1 \tag{6}$$

When the output image probability density function is 1, the image is enhanced.

3. EXPERIMENTAL ANALYSIS

MATLAB software is utilized to establish the algorithm platform, and programming code is developed to implement image enhancement. Three image processing methods including image filtering, histogram equalization, and image grayscale transformation are applied individually in this paper for image enhancement. The data results are analyzed, and the strengths and weaknesses of each algorithm are discussed in conjunction with the analysis findings.

FIG. 1 Original image of weld

The original image is not processed with the Canny operator to highlight the welding effect.

FIG. 2 The original image does not do any processing to mark the weld effect

Effect of marking weld after noise reduction:

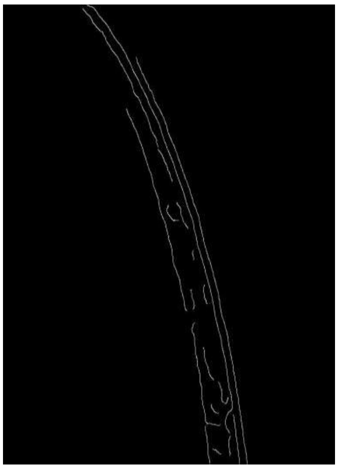

FIG. 3 Effect of marked welds after noise reduction

The effect of highlighting the weld after histogram equalization:

FIG. 5 Effect of marked welds after histogram equalization

After image gray transform processing, mark weld effect:

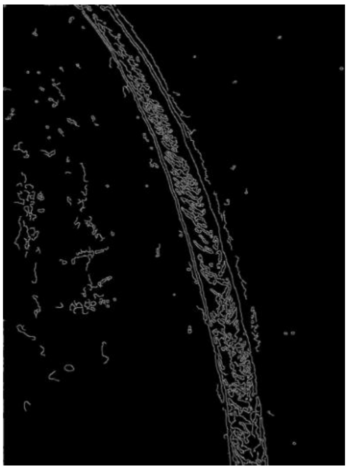

FIG. 6 Effect of marking weld after gray transform processing

As shown in the comparison in the above figure, for the selected research object, the enhanced processing of histogram-equalized images has significantly improved the weld marking effect and enriched the weld texture, which holds practical engineering significance for welding quality detection. After grayscale transformation processing, there is minimal enhancement in weld detection. Noise reduction processing can noticeably refine the weld appearance. In meeting the requirements of welding quality detection, a richer weld texture is preferred. Hence, for the subject of this study, this method lacks practical engineering significance.

4. CONCLUSION

The application of machine vision technology in welding inspection can significantly enhance the efficiency and accuracy of weld inspection. Nonetheless, the quality of images captured of welds may face challenges in specific scenarios like low-light backgrounds, shielded gas interference, or uneven surfaces. To address this issue, it is necessary to utilize image enhancement algorithms to process the images. After thoroughly reviewing relevant data and considering the features of machine vision technology and weld image enhancement techniques, the experimental results indicate that histogram equalization holds practical engineering significance for the selected research object.

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