An Adaptive Algorithm for Workpiece Edge Detection Combining Morphology and Canny Operator

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Abstract: Addressing the challenges of limited noise suppression, inaccurate edge detection, and poor adaptability encountered in the detection of workpiece image edges in complex industrial environments, this study introduces an adaptive algorithm for edge detection that integrates morphological processing with the Canny operator. Firstly, a weighted adaptive morphological processing is designed to extract the gradient magnitude and direction. Secondly, this extracted information is weighted fused with the gradient magnitude and direction obtained from the traditional Canny operator. Subsequently, an adaptive dual threshold algorithm is devised for edge detection and connection. Finally, the proposed algorithm is experimentally validated using images collected from industrial robot assembly lines. The results demonstrate that the proposed algorithm outperforms traditional methods, detecting more effective and continuous edges with significant noise reduction.

Keywords: Morphology; Canny Operator; Workpiece Edge Detection; Adaptive; Fusion Algorithm

1. Introduction

With the rapid advancement of "Made in China 2025", replacing manual labor with robots in industrial manufacturing has become an inevitable trend, and the application of machine vision in industrial robot target recognition is becoming more and more widespread [1]. In order to improve the accuracy of edge detection, literature [2-4] combined mathematical morphology with wavelet transform algorithm, adaptive median filtering, and bilateral filtering, and literature [5-7] used Canny operator combined with geometric features, guided filtering, and two-dimensional Cauchy distribution algorithms, which improved the accuracy of defect detection, but the effect of removing the noise from the images in the complex industrial environment is not good. Literature [8-9] proposed deep learning methods, edge extraction effect accuracy is greatly improved, but the neural network training time is too long, and the hardware requirements are high, which greatly increases the cost.

Aiming at the above problems, this paper proposes a fusion algorithm based on weighted adaptive mathematical morphology and adaptive dual threshold for Canny operator edge detection. Experimental results show that the algorithm in this paper improves the edge clarity of the workpiece target, maintains the continuity of the image edges, has better image denoising effect, better adaptive ability, and is more suitable to be applied to the adaptive edge detection of video images.

2. Improved Mathematical Morphological Edge Detection Operator

2.1 Traditional mathematical morphological edge detection operator

The traditional mathematical morphology edge detection operators have four mathematical morphology operations, Erosion, Dilation, Opening and Closing. Let the original image pixel point be $O(x, y)$ and the structural element of morphological operation be $S(x', y')$. Then each pixel point after the operation is $T_C(x, y)$, $T_E(x, y)$, $T_{Open}(x, y)$ and $T_{Close}(x, y)$ respectively.

$$\begin{cases} T_C(x, y) = \min\limits_{x', y' \in S} \{O(x + x', y + y')\} \\ T_E(x, y) = \max\limits_{x', y' \in S} \{O(x + x', y + y')\} \\ T_{Open}(x, y) = T_E(T_C(x, y)) \\ T_{Close}(x, y) = T_C(T_E(x, y)) \end{cases} \tag{1}$$

2.2 Weighted adaptive morphology approach

In order to better remove the influence of discontinuous traces on the surface of the image on edge detection, maintain the continuity of the edges of the artifact and enhance the denoising ability of the image, a weighted adaptive mathematical morphological edge detection method is proposed.

First, we construct the OtC(Opening then Closing) filter. Let the number of times the workpiece image is "OtC" using circular, square, and flat structural elements be N_R, N_S, and N_F, respectively, and the total number of processing $N(N = N_R + N_S + N_F)$ times. The number of processing times is calculated according to the difference between the result of each structural element and the original image, and the smaller the difference is, the more the number of morphological processing times under the structural element will be. Taking the square structural element $s(x', y')$ to "OtC" the image (selecting scale 4) as an example, let f_n be the image function obtained by the nth OTC, i.e.:

First OtC: $f_1 = f \Theta \mathrm{g}$ (2)

Second OtC: $f_2 = f_1 \Theta g$ (3)

Until $\{(x', y') | f_n - f_{n-1} = 0\}$, the number of treatments of structural elements at that scale is obtained.

Let W_R, W_S, and W_F denote the weight coefficients of the morphological treatments accounted for by the circular, square, and flat structural elements, respectively, as shown in Equation 4:

$$\begin{cases} W_R = \dfrac{N_R}{N} \\ W_S = \dfrac{N_S}{N} \\ W_F = \dfrac{N_F}{N} \end{cases} \tag{4}$$

Let the image before processing be $f(x, y)$ and the image after morphological processing be $F(x, y)$. The weighted adaptive morphological processing formula is as follows:

$$F_W(x, y) = W_R \times f_R(x, y) + W_S \times f_S(x, y) + W_F \times f_F(x, y) \tag{5}$$

Where, $f_R(x, y)$, $f_S(x, y)$, $f_F(x, y)$ denote the results of one "OtC" morphological processing of the original image with circular, square and flat structural elements, respectively.

3. Improved Canny operator

3.1 Traditional Canny operator

Canny edge detection operator is by far one of the most widely used and classical edge detection algorithms. It includes four basic steps: Gaussian filtering, calculating gradient magnitude and direction, non-extremely large value suppression of gradient magnitude, and dual threshold algorithm to detect and connect edges.

3.2 Adaptive Dual Threshold Algorithm

The traditional Canny algorithm adopts the method of double threshold to discriminate the edge information, the size of the high and low threshold need to be manually selected and set, and need to rely on the a priori experience and repeated trials to determine the algorithm is poorly adaptive, in order to solve these problems, this paper proposes an adaptive double threshold algorithm based on OTSU, automatic determination of threshold using maximum interclass variance.

For an M×N image, the segmentation threshold of foreground and background is denoted as T. The number of pixels in the image whose gray value is less than the threshold is N_p, and the ratio of the number of pixel points in the foreground to the whole image is denoted as p_p, and its average gray scale is AG_p; the number of pixels in the image whose gray value is greater than the threshold is N_b, and the ratio of the number of pixel points in the background to the whole image is p_b, and its average gray scale is AG_b. The total mean gray level of the image is denoted as AG and the inter-class variance is denoted as v,then there are:

$$\begin{cases} p_p = \dfrac{N_p}{M \times N} \\ p_b = \dfrac{N_b}{M \times N} \end{cases} \quad (6)$$

$$N_p + N_b = M \times N \quad (7)$$

$$P_p + P_b = 1 \quad (8)$$

$$AG = AG_p \times P_p + AG_b \times P_b \quad (9)$$

$$v = P_p \times \left(AG - AG_P\right)^2 + P_b \times \left(AG - AG_b\right)^2 \quad (10)$$

Jointly calculating equations (9) and (10), we get:

$$v = P_p \times P_b \times \left(AG_P - AG_b\right)^2 \quad (11)$$

Then use the traversal method to find the threshold T when v is the maximum, then T is the optimal threshold, so that it is the high threshold T_h in the double threshold, then the low threshold can be denoted as T_l :

$$T_l = T_h \times k \quad (12)$$

Where, is the ratio of low threshold and high threshold, in general the value range is [1/3,1/2], here take 1/2.

4. ACMC(Adaptive algorithm for Combining Morphology and Canny operator)

The flowchart of ACMC proposed in this paper is shown in Fig. 1 and is implemented as follows:

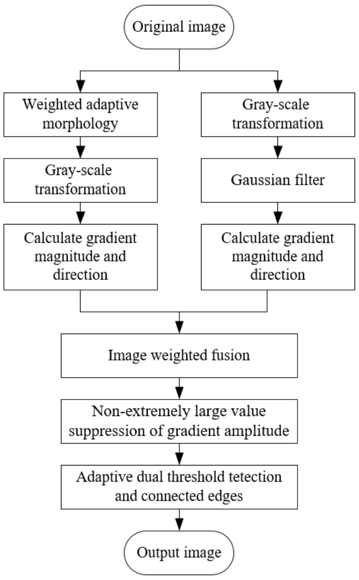
(1) Sub-process 1: The original color image is detected by Improved weighted adaptive morphological approach in 2.2 in HSV color space; then the result is gray-scale transformed, and then its gradient magnitude and direction are calculated to get the gradient image.

(2) Sub-process 2: Gray-scale transform the original color image, and then perform Gaussian filtering, and then calculate its gradient magnitude and direction to get the gradient image.

(3) The results of steps (1) and (2) are subjected to image weighted fusion.

(4) Using the gradient magnitude and angle from step (2), the gradient magnitude is suppressed for the fused image of step (3).

(5) Detect and connect the edges using the adaptive dual threshold algorithm in 3.2 to obtain the final fused image.



[Fig. 1] Flowchart of ACMC algorithm

5. Experimental results and analysis

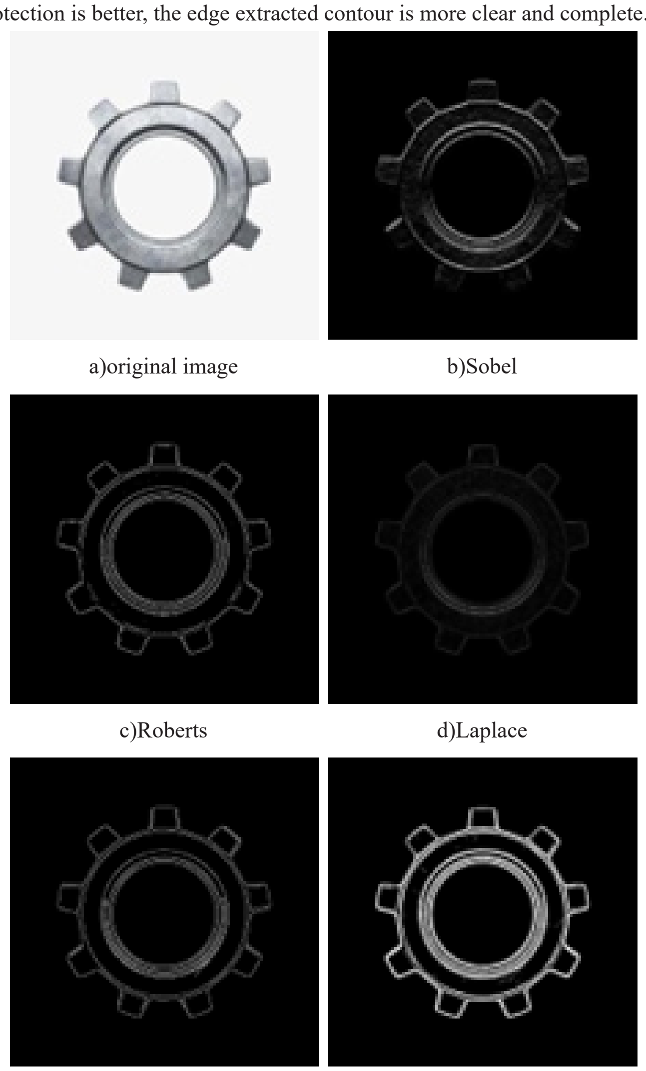
In this paper, the image edge detection algorithm, two evaluation metrics are implemented on MATLAB R2018a version.

5.1 Experimental effects and subjective evaluation

In order to test the feasibility and effectiveness of the proposed algorithm, workpiece images captured by an industrial camera are used for experimental comparison and verification.

(1) Comparison of the effect of edge detection algorithms for noisy images

Sobel operator, Roberts operator, Laplace operator, Canny operator and the algorithm of this paper are used to detect the edges of the original image of the "Gear workpiece" respectively, and the results are shown in Fig. 2(b)~(f). The experimental results show that this paper's algorithm image detail protection is better, the edge extracted contour is more clear and complete.



a)original image b)Sobel

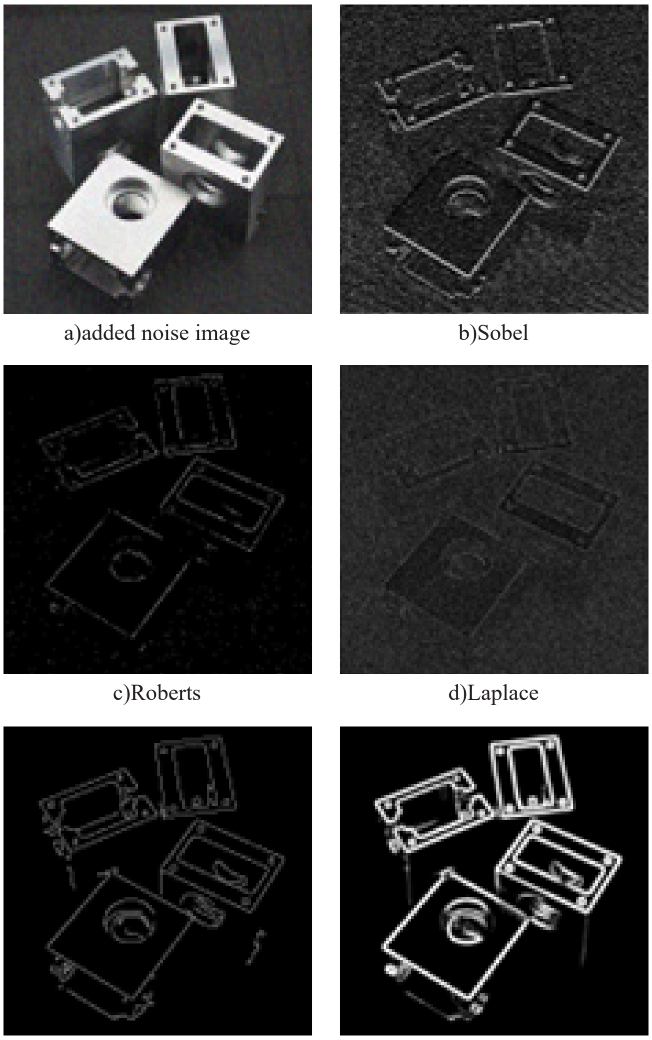
c)Roberts d)Laplace

e)Canny f)Our(ACMC)

[Fig. 2] Comparison of image edge detection algorithms without noise

(2) Comparison of the effect of image edge detection algorithms with Gaussian noise added

Add Gaussian noise with standard deviation $\sigma = 0.01$ to the original image of "Lathe workpiece", such as Fig. 3 a), and then repeat the processing of (2), the results are shown in Fig. 3 b)~f), the experiments show that the algorithm in this paper is able to detect a clearer and more complete edge of the target than other algorithms, and has stronger noise immunity, and has better processing effect on complex background.



a)added noise image b)Sobel

c)Roberts d)Laplace

e)Canny f)Our(ACMC)

[Fig. 3] Comparison of image edge detection algorithms with added noise

5.2 Objective evaluation of experimental effects

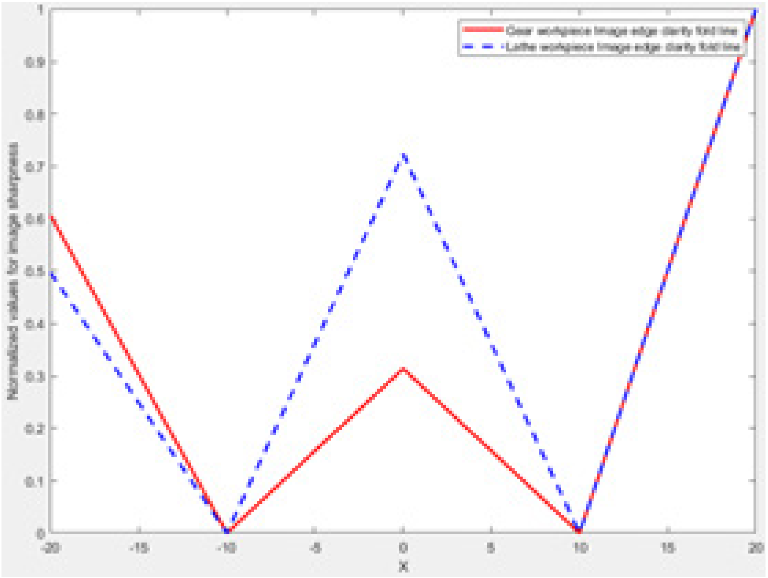
(1) Image edge sharpness evaluation based on image gradient

The clearer the image, the more drastic the change of gray value of pixels at the edge, and the gradient value will be larger. In this paper, the energy gradient function EOG (Energy of Gradient) is used as the image clarity evaluation index: the sum of the squares of the difference between the gray values of the neighboring pixels in the x direction and the y direction is used as the gradient value of each pixel, and the gradient values of all the pixels are added up as the value of the clarity evaluation function, as shown in equation (13).

$$D_f = \sum_x \sum_y \left\{ \left[f(x+1,y) - f(x,y) \right]^2 + \left[f(x,y+1) - f(x,y) \right]^2 \right\} \quad (13)$$

In Fig. 4, the red line is the result of comparing the effect of the edge detection algorithm without noise image. The images detected at points (-20, 0), (-10, 0), (0, 0), (10, 0), (20, 0) are Fig. 3 a), b), c), d) and the algorithm in this paper, respectively. The closer the normalized line graph is to 1, the clearer the image is. From the line graph, it can be seen that the edge of the image after edge detection of this paper's algorithm is the clearest.

In Fig. 4, the blue line is the result of comparing the effect of edge detection algorithms for noisy images. The images detected at points (-20, 0), (-10, 0), (0, 0), (10, 0), (20, 0) are Fig. 4 b), c), d), e) and this paper's algorithm respectively. As can be seen from the normalized line graph, the image edges after edge detection of this paper's algorithm are the clearest and the denoising effect is the best.



[Fig. 4] Image clarity indicators

(2) Image denoising effect evaluation index PSNR

PSNR (Peak Signal-to-Noise Ratio) is the most widely used objective evaluation index for images, the method is to calculate the similarity between the denoised image and the original image, and the larger the value indicates the smaller the image distortion.

The comparison of PSNR values of images without added noise is shown in Table 1 and the comparison of PSNR values of images with added noise is shown in Table 2. From the data in Table 1 and Table 2, it can be seen that the PSNR values of this paper's algorithm are maximized when the target image is processed, indicating that the proposed algorithm in this paper effectively removes the noise and also ensures the image quality well.

<Table 1>Comparison of PSNR values of images without added noise

Image after edge detection	PSNR
Sobel [Fig. 2] b)	24.5447
Roberts [Fig. 2] c)	24.4987
Laplace [Fig. 2] d)	24.5086
Canny [Fig. 2] e)	24.5059
Ours [Fig. 2] f)	28.5584

<Table 2>Comparison of PSNR values of added noise images

Image after edge detection	PSNR
Sobel [Fig. 3] b)	27.9154
Roberts [Fig. 3] c)	27.6798
Laplace [Fig. 3] d)	27.8862
Canny [Fig. 3] e)	27.6838
Ours [Fig. 3] f)	32.0303

6. Conclusion

Based on traditional mathematical morphology theory and Canny operator theory, this paper proposes a fusion algorithm for workpiece edge detection based on morphology and Canny operator, establishes a weighted adaptive morphological processing model and an adaptive dual threshold processing model, and weighted fusion of traditional morphology and Canny operator gradient. Experiments show that the edge detection of this paper's algorithm is more effective and continuous, and the removal of noise is effective.

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