

# Image Fusion based Edge Detection Using Mathematical Morphology

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**Abstract:** Edge detection is one of the most commonly used operations in image analysis, and there are probably more algorithms in the literature for enhancing and detecting edges. Edges form the outline of an object. An edge is the boundary between an object and the background, and indicates the boundary between overlapping objects. If the edges in an image can be identified accurately, all of the objects can be located and basic properties such as area, perimeter, and shape can be measured. In this paper, we extract the detailed edge information by the fusion of proposed two edge detection algorithms, Adaptive Multi-Structure Morphological Edge detection algorithm and Adaptive Multi-Scale Morphological Edge detection Algorithm. Finally, the experiment results indicate that the novel algorithm ensures the continuity, integrity, and accurate location of image edge than other edge detection operators using mathematical morphology.

**Keywords:** Mathematical Morphology, Edge Detection, Image Processing.

## 1. INTRODUCTION

Edge detection is a very important area in the field of Computer Vision. Edges define the boundaries between regions in an image, which helps with segmentation and object recognition. They can show where shadows fall in an image or any other distinct change in the intensity of an image. Edge detection is a fundamental of low-level image processing and good edges are necessary for higher level processing [1]. Mathematical morphology [2] is a nonlinear filtering method. In the traditional edge detection algorithm based on morphology, the structure element (SE) is fixed, symmetric, and single, so the extracted edge has the deficiency of discontinuity and blurring.

However, for a real time image processing, the single edge detection method [7] can only reflect the edge information from certain aspect, and it is not effective to extract the edge with only one structure or only one scale [3]. This paper proposes adaptive multi-structure and adaptive multi-scale morphological edge detection algorithm based on image fusion. It fuses the edge extracted by multi-structure elements with the one detected by multi-scale elements to get the final binary edge image with optimal threshold segmentation. The experimental results indicate that the new edge detection algorithm can reasonably consider accurate edge location. The steps of new algorithm are shown in figure 5.

This paper is organized as follows: Section 2 presents Mathematical Morphological operations, Section 3 presents, Adaptive Multi-structure Morphological Edge detection algorithm, Section 4 presents Adaptive Multi-scale Morphological edge detection algorithm, Section 5 presents image fusion using PCA, Section 6 presents

Experimental results, and finally Section 7 reports conclusion.

## 2. MATHEMATICAL MORPHOLOGY

In morphology, basic operations include erosion, dilation, opening and closing [4]. The erosion of an image  $I$  by a flat structuring element  $b$  at any location  $(x,y)$  is defined as the minimum value of the image in the region coincident with  $b$  when the origin of  $b$  is at  $(x,y)$ . In equation form, the erosion at  $(x,y)$  of an image  $I$  by a structuring element  $b$  is given by

$$[I \ominus b](x,y) = \min_{(s,t) \in b} \{I(x+s, y+t)\} \quad (1)$$

The dilation of an image  $I$  by a flat structuring element  $b$  at any location  $(x,y)$  is defined as the maximum value of the image in the window outlined by  $\hat{b}$  when the origin of  $\hat{b}$  is at  $(x,y)$ . In equation form, the erosion at  $(x,y)$  of an image  $I$  by a structuring element  $b$  is given by

$$[I \oplus b](x,y) = \max_{(s,t) \in b} \{I(x-s, y-t)\} \quad (2)$$

The opening of image  $I$  by structuring element  $b$ , denoted  $I \circ b$  is

$$I \circ b = (I \ominus b) \oplus b \quad (3)$$

Similarly, the closing of  $I$  by  $b$ , denoted  $I \bullet b$ , is

$$I \bullet b = (I \oplus b) \ominus b \quad (4)$$

## 3. EDGE DETECTION USING ADAPTIVE MULTISTRUCTURE MORPHOLOGICAL ALGORITHM

Because of the unicity and fixity of SE in traditional edge detection using mathematical morphology, there are two main deficiencies [5]: on the one hand a single SE can only detect the edge of the same direction with the SE, but is not sensitive to different directions; on the other hand large-scale SE has strong ability to restrain noise, but the detected edge image is rough, small-scale SE is good at checking the details of the edge, but weak at noise suppression. In order to effectively restrain noise and preserve image edge information, we use multi-structure morphological adaptive algorithm to get the edge images. We calculate the gray scale distance of original image to adaptively define the weights of SEs. The eight structuring elements of different directions with the size of 5X5 are shown in figure 1.

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**Figure 1. SEs with different directions.**

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a <sub>10</sub>	a <sub>23</sub>	a <sub>24</sub>	a <sub>25</sub>	a <sub>4</sub>
a <sub>11</sub>	a <sub>22</sub>	a <sub>1</sub>	a <sub>2</sub>	a <sub>3</sub>
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**Figure 2. Image Sub-block**

Figure 2 shows the sub-block with the size 5X5, in which  $a_1$  is the gray-scale value of the center pixel, and  $a_2, a_3, a_4, \dots, a_{25}$  stand for its neighborhood gray scale value, then the gray-scale distance of  $a_1$  and its neighborhood can be performed as:

$$d_k = |a_1 - a_k|, k = 2, 3, 4, \dots, 25. \quad (5)$$

The larger the gray-scale distance, the higher extent of salutation, and the bigger possibility that the pixel is an edge point in the image. The Edge Gray-Scale distances of  $a_1$  can be defined as follows.

$$G_1(x,y) = d_4 + d_5 + d_6 + d_7 + d_8 + d_9 + d_{10} + d_{12} + d_{13} + d_{14} + d_{15} + d_{16} + d_{17} + d_{18} + d_{19} + d_{20} + d_{21} + d_{23} + d_{24} + d_{25}; \quad \text{---for direction } 0^0$$

$$G_2(x,y) = d_4 + d_5 + d_6 + d_7 + d_8 + d_9 + d_{10} + d_{11} + d_{13} + d_{14} + d_{15} + d_{16} + d_{17} + d_{18} + d_{19} + d_{20} + d_{21} + d_{22} + d_{23} + d_{24} + d_{25}; \quad \text{---for direction } 22.5^0$$

$$G_3(x,y) = d_2 + d_3 + d_4 + d_6 + d_7 + d_8 + d_9 + d_{10} + d_{11} + d_{12} + d_{14} + d_{15} + d_{16} + d_{17} + d_{18} + d_{19} + d_{20} + d_{22} + d_{23} + d_{24}; \quad \text{---for direction } 45^0$$

$$G_4(x,y) = d_2 + d_3 + d_4 + d_5 + d_6 + d_7 + d_8 + d_9 + d_{10} + d_{11} + d_{12} + d_{13} + d_{14} + d_{15} + d_{16} + d_{17} + d_{18} + d_{19} + d_{21} + d_{22} + d_{23} + d_{24} + d_{25}; \quad \text{---for direction } 67.5^0$$

$$G_5(x,y) = d_2 + d_3 + d_4 + d_5 + d_6 + d_8 + d_9 + d_{10} + d_{11} + d_{12} + d_{13} + d_{14} + d_{16} + d_{17} + d_{18} + d_{19} + d_{20} + d_{21} + d_{23} + d_{25}; \quad \text{---for direction } 90^0$$

$$G_6(x,y) = d_2 + d_3 + d_4 + d_5 + d_6 + d_7 + d_9 + d_{10} + d_{11} + d_{12} + d_{13} + d_{14} + d_{15} + d_{17} + d_{18} + d_{19} + d_{20} + d_{21} + d_{22} + d_{23} + d_{24} + d_{25}; \quad \text{---for direction } 112.5^0$$

$$G_7(x,y) = d_2 + d_3 + d_4 + d_5 + d_6 + d_8 + d_9 + d_{10} + d_{11} + d_{12} + d_{13} + d_{14} + d_{16} + d_{17} + d_{18} + d_{19} + d_{20} + d_{21} + d_{23} + d_{25}; \quad \text{---for direction } 135^0$$

$$G_8(x,y) = d_2 + d_3 + d_4 + d_5 + d_6 + d_7 + d_8 + d_{10} + d_{11} + d_{12} + d_{13} + d_{14} + d_{15} + d_{16} + d_{18} + d_{19} + d_{20} + d_{21} + d_{24} + d_{25}; \quad \text{---for direction } 157.5^0$$

As for the whole image, the gray-scale distances of each edge and adaptive weights of SEs can be calculated as below:

$$ED_k = \sum_{x=2}^{M-1} \sum_{y=2}^{N-1} G_k(x,y), k=1,2,\dots,8 \quad (6)$$

$$w_k = ED_k / \left( \sum_{k=1}^8 ED_k \right), k=1,2,\dots,8 \quad (7)$$

The edge E extracted adaptively by multi-structure morphology is given by

$$E = \sum_{k=1}^8 w_k [ (I \circ b_k) - b_k \cdot (I \bullet b_k) \Theta b_k ] \quad (8)$$

#### 4. EDGE DETECTION USING ADAPTIVE MULTISCALE MORPHOLOGICAL ALGORITHM

Multi-scale morphology overcomes the contradictions of large-scale SEs, and small-scale SEs are good at keeping edge. This operator takes advantages of large-scale SE to identify edge reliably, as well as location property of small-scale SE to track edge from coarse to fine, then uses the approach of adaptively determining weight based on image variance to synthesize the edge image.

Multi-scale SE is defined as:  $b^k = b \bullet b \bullet \dots \bullet b$ . (9)

Where b and k are scale parameter and limited SE, respectively. The equation expresses that large-scale element is derived from a series of dilation operations of small-scale SEs. In this paper b is a 5x5 crisscross structuring element.

The algorithm is for edge detection using multi-scale as follows:

Step 1: Obtain the mean value images using open-close morphological filters in different scales:

$$I_k(x,y) = (I \circ b^k \bullet b^k + I \bullet b^k \circ b^k) / 2 \quad (10)$$

Step 2: Use the mean value images got in step 1 to calculate the image variances in different scales:

$$\alpha_k^2 = |I - I_k|^2 \quad (11)$$

Step 3: According to image variances above, the weighting coefficient:

$$w_k = \alpha_k^2 / \sum_{k=1}^n \alpha_k^2 \quad (12)$$

Step 4: Then the edge extracted by multi-scale adaptive morphology is given by following equation:

$$E_2 = \sum_{k=1}^n [w_k (I \circ b^k) - b^k \cdot (I \cdot b^k) \Theta b^k] \quad (13)$$

## 5. EDGE IMAGE FUSION USING PCA

From the two sections above, we get two images of edge detection, in which  $E_1$  is the edge image extracted adaptive multi-structure morphology, and  $E_2$  is detected by adaptive multi-scale morphology. These two edge images are fused into a single image using PCA and calculate final detected binary edge image with optimal threshold segmentation.

The PCA based image fusion is summarized as follows:

The PCA fusion method calculates the output image as a weighted sum of input images, where the weights are the elements of the dominant eigenvector [6]. The set of  $N$  input images is organized into a matrix  $\mathbf{X}$ , where each row is a lexicographically ordered input image. Let vector  $\mu$  be the average of all the rows in  $\mathbf{X}$ , and let  $\mathbf{e}$  be a column vector with all elements equal to 1.

The covariance matrix is given by

$$\mathbf{C} = \frac{1}{M} (\mathbf{X} - \mu \mathbf{e}^T) (\mathbf{X} - \mu \mathbf{e}^T)^T \quad (12)$$

Where  $M$  is the total number of pixels in an image.

The fused image is given by

$$I_P(k, l) = \sum_{j=1}^N v_j I_j(k, l) \quad (13)$$

where  $v_j$  is the  $j^{\text{th}}$  component of the dominant eigenvector, corresponding to the largest eigenvalue of  $\mathbf{C}$ .

## 6. EXPERIMENTAL RESULTS

Proposed Edge detection mechanism is performed on a Lena 256\*256 pixel image that consists of a total of 65536 pixels. The RGB colored image have been converted to grayscale image to specify a single intensity value that varies from the darkest (0) to the brightest (255) for each pixel shown in figure 3.



**Figure 3 a) RGB Color image b) Grayscale Image**

The edge detection result of Lena image of our method is presented in figure 4. The proposed algorithm is compared with existing morphological edge detection operators. Performance can be compared by considering the number of edge pixels detected by various methods using mathematical morphology as shown in table 1. It is evident that proposed edge detection algorithm perform well than other methods.

**Table 1: No. of edge pixels**

Operator	Count
Dilation Type	3066
Erosion Type	3706
Dilation-Erosion Type	3989
Proposed Method	4768

## 7. CONCLUSION

SEs of different shapes have different effects on preserving image details, and SEs of different scales make different impact on de-noising. According to the fact that single edge detection method can only reflect the edge information from certain aspect, this paper proposes a adaptive multi-structure and adaptive multi-scale morphological edge detection algorithm based on image fusion. It fuses the edge extracted by multi-structure elements with the one detected by multi-scale elements to get the final binary edge image with the optimal threshold segmentation. The experimental results show that the novel algorithm is not only more efficient than the morphological edge detection operators but also ensures the continuity, integrity, and accurate location of image edge.

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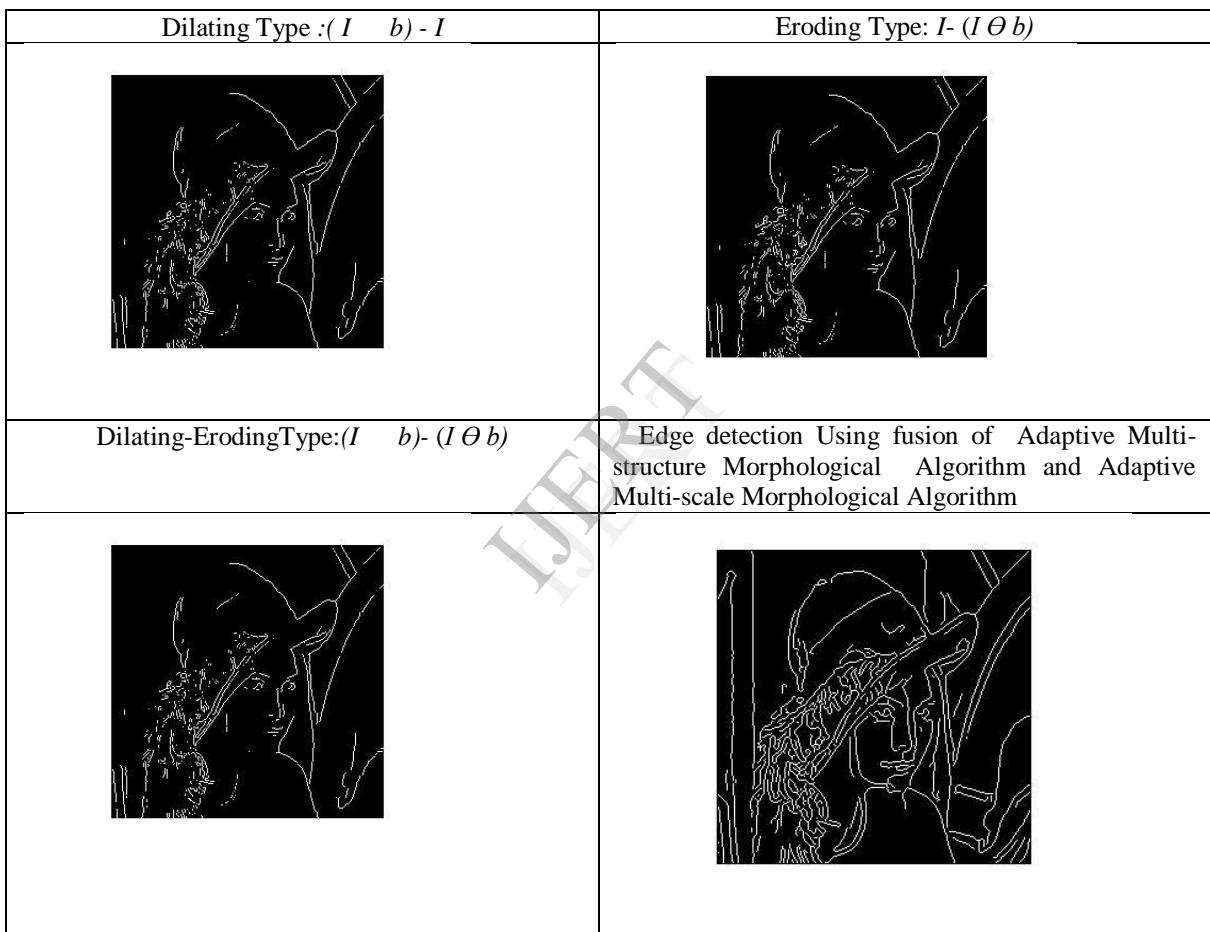


Figure 4: Experimental Result

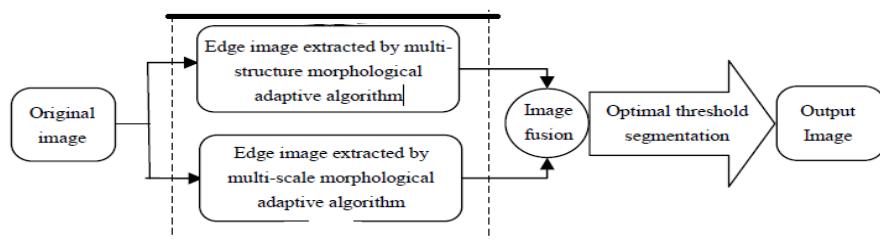


Figure 5: Block diagram of proposed algorithm