An Edge Detection Method by Using Fuzzy 2-Mean Classification and Template Matching

C. C. Kang¹, P. J. Lee² and. W. J. Wang¹

Department of Electrical Engineering, National Central University, Chung-Li, 320, TAIWAN.

(Tel:+886-3-4227151 ext. 4456; Email wjwang@ee.ncu.edu.tw)

Abstract: Based on fuzzy 2-mean classification and template matching method, we propose a new algorithm to detect the edges of an image. In the algorithm, fuzzy 2-mean classification can classify all pixels in the mask into two clusters whatever the mask in the dark or light region; and template matching not only determines the edge's direction, but also thins the detected edge by a set of inference rules and, by the way, reduces the impulse noises.

Keywords: Fuzzy 2-mean; template matching; edge detection; noise reduction; thinning.

1. INTRODUCTION

Edge detection is one of important issues in the image processing. Many tasks in image processing, such as the line detection, segmentation, shape recognition, etc., need an efficient essential pre-process to detect the boundaries. So far, many methods for edge detection have been proposed. For instance, Laplacian operator [1] and Marr-Hildreth operator [2] utilize a mask to do convolution on the gray image for the purpose of detecting the edges which have abrupt change of the gray level. But they have a common problem that the edge direction is depreciated; moreover, the obtained edge is always thick. Both Sobel operator and Prewitt operator [1] employ a couple of masks to detect the edge on the vertical and horizontal directions, but the variation of the gray level in two diagonal directions in the mask is not considered. Canny [3], Petrou and Kittler [4], and Papliński [5] establish the mathematical models for the curve of the gray level variation. These models need heavy complex computation to detect the edges with any direction correctly and require tuning many parameters to optimal the result. Furthermore, Russo [6] utilizes a fuzzy pre-filter to smooth the image and then detect the edge. Law et al. [7] utilizes fuzzy Gaussian filter to sharp the information of the edges and apply the concept of joins to trace the edges and remove the noise. Liang and Looney [8] design a fuzzy classifier and competitive rules to obtain four types of edges. It should be noted that the edges detected by those methods are always thick.

In this paper, based on fuzzy 2-mean classification and template matching method, we propose a new edge detection algorithm such that not only the thin edges of the objects in the image are extracted, but also the noise is reduced.

The organization of this paper is as follows. Section 2 reviews the concept of fuzzy *c*-mean classification. Section 3 is the main algorithm of the edge detection. In section 4, some simulations are shown to illustrate the effectiveness of the proposed algorithm. Finally, a conclusion is addressed in Section 5.

2. REVIEW OF FUZZY C-MEAN CLASSIFICATION

Suppose we have a set of data $X = \{x_1, x_2, ..., x_n\}$, where x_i can be any element belonging to R^p . V_{cn} is a set of real $c \times n$ matrices $M = [m_{ij}]$, and c is an integer with $2 \le c < n$. Then fuzzy c-classification space

for X is the set

$$\hat{M} = \{ M \in V_{cn} \mid m_{ij} \in [0,1], 1 \le i \le c,$$

$$1 \le j \le n, \text{ and } \sum_{i=1}^{c} m_{ij} = 1 \}$$
(1)

where m_{ij} is the fuzzy membership degree of x_j belonging to cluster C_i . For example, suppose $X=\{x_1,x_2,x_3\}$, if we have fuzzy 2-classification as

$$M = \begin{bmatrix} 0.8 & 0.1 & 0.7 \\ 0.2 & 0.9 & 0.3 \end{bmatrix}$$
, that is, all elements of the

set X is classified into two fuzzy clusters C_1 and C_2 , where x_1 belongs to C_1 with membership degree 0.8 and belongs to C_2 with degree 0.2. Similarly, it is easy to see the clustering of x_2 and x_3 . Fuzzy c-mean method is to choose the optimal c classification M from the space \hat{M} and cluster centers ρ_i , i=1,2,...,c, such that the cost function

$$J_h = \sum_{i=1}^{n} \sum_{i=1}^{c} (m_{ij})^h ||x_j - \rho_i||^2$$
 (2)

is minimized, where $h \in (1, \infty)$ is a weighting constant. From Theorem 27.1 of [9], the necessary condition of the above optimal problem is

$$m_{ij} = \left(\sum_{\ell=1}^{c} \left\| \frac{x_{j} - \rho_{i}}{x_{j} - \rho_{\ell}} \right\|^{2/h-1} \right)^{-1}, \quad 1 \le i \le c, 1 \le j \le n, \quad (3)$$

and the centers

$$\rho_{i} = \frac{\sum_{j=1}^{n} (m_{ij})^{h} x_{j}}{\sum_{j=1}^{n} (m_{ij})^{h}}, \ 1 \le i \le c$$
 (4)

Based on the necessary condition (3) and (4), the fuzzy c-mean algorithm can be found in [9].

² Department of Electronic Engineering, St. John's & St. Mary's Institute of Technology, Tamsui, TAIWAN

3. EDGE DETECTION ALGORITHM

In this section, we will propose an algorithm to detect the edges in an image. Fuzzy 2-mean classification and templates matching are utilized in the algorithm such that the directions of the edges are found, the impulse noise is reduced, and the detected edges are thin. In the beginning, a 3×3 mask with pixels

$$I(x-1, y-1), I(x, y-1),...,I(x, y+1), I(x+1, y+1)$$

is shown in Fig. 1, in which I(x, y) is the intensity of the center pixel of the mask. Let the values of

$$I(x-1, y-1), I(x, y-1),..., I(x, y+1), I(x+1, y+1)$$

be denoted by $p_1, p_2, \dots, p_8, p_9$, respectively, and let the vector

$$P = [p_1 \quad p_2 \quad p_3 \quad p_4 \quad p_5 \quad p_6 \quad p_7 \quad p_8 \quad p_9]$$

be set. After we have the above notations, the edge detection algorithm is summarized in the following procedure.

Main Algorithm:

Stage 1: Determine the variation of the gray level in the mask. The variance σ is defined as (1)

$$\sigma = \frac{\sum_{i=1}^{9} p_i^2}{9} - \left(\frac{\sum_{i=1}^{9} p_i}{9}\right)^2, \tag{5}$$

If $\sigma \leq T_{v}$, where $T_{v} \in [40,100]$, the variation of the gray level in this mask is regarded as smooth and then the center pixel is classified into the background and set I(x,y)=255. Then check the next mask. Otherwise, $\sigma > T_{v}$, it means the variation of the gray level in this mask is violent, then go to Stage 2.

Stage 2: Fuzzy 2-mean classification method is used to classify these nine pixels in the mask into two classes, such as class-1 (black or white) and class-2 (white or black), and expresses the result as a 2×9 matrix M as follows

$$M = \begin{bmatrix} \mu_1 & \mu_2 & \mu_3 & \dots & \mu_9 \\ 1 - \mu_1 & 1 - \mu_2 & 1 - \mu_3 & \dots & 1 - \mu_9 \end{bmatrix}$$
 (6)

where μ_i , i = 1, 2,..., 9, is the membership degree of p_i belonging to class-1, and $1 - \mu_i$ is that belonging to class-2.

Stage 3: Let four templates be shown in Fig. 2, which represents the edges in four directions, they are, direction-1, direction-2, direction-3, and direction-4, respectively. In fact, we have to mention that the opposite template of direction-j, j=1, 2, 3, 4, should be seen as the same directional edge as the original template-j. The opposite template-j means the black

and white pixels of the template-j are exchanged. Compare the matrix M with four templates one by one. Let us illustrate the comparison between T and M. In Fig. 2(a), the membership function of template-1 is

$$T_1 = \begin{bmatrix} 1 & 1 & 1 & 0 & 1 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 \end{bmatrix},$$

we calculate the error \mathcal{E}_1 as the following form,

$$\mathcal{E}_1 = \sum_{i} \sum_{i} \mid m_{ij} - t_{1ij} \mid, \tag{7}$$

where m_{ij} and t_{1ij} are the ij-th elements of the matrices M and T_1 respectively. On the other hand, we should consider the case template-1 has the corresponding opposite template, which has $\overline{T}_1 = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 \\ 1 & 1 & 1 & 0 & 1 & 1 & 0 & 0 & 1 \end{bmatrix}$. We should also compare M with \overline{T}_1 to get $\overline{\mathcal{E}}_1 = \sum_j \sum_i \mid m_{ij} - \overline{t}_{1ij} \mid$.

Stage 4: Find the minimum error

$$\begin{split} & \mathcal{E}_{\min} = \min(\mathcal{E}_1, \overline{\mathcal{E}}_1, \mathcal{E}_2, \overline{\mathcal{E}}_2, \mathcal{E}_3, \overline{\mathcal{E}}_3, \mathcal{E}_4, \overline{\mathcal{E}}_4) \quad \text{and record} \\ & \text{the number } j = Arg(\min(\mathcal{E}_1, \overline{\mathcal{E}}_1, \mathcal{E}_2, \overline{\mathcal{E}}_2, \mathcal{E}_3, \overline{\mathcal{E}}_3, \mathcal{E}_4, \overline{\mathcal{E}}_4)). \\ & \text{If } \quad \mathcal{E}_{\min} > T_d \quad \text{where} \quad T_d \quad \text{is a threshold set based on experiment, we set } I(x,y) = 255 \quad \text{and the center pixel of the mask is classified into as one pixel of the background.} \\ & \text{If } \quad \mathcal{E}_{\min} \leq T_d \quad \text{, the central pixel is on the edge with the} \end{split}$$

If $\mathcal{E}_{\min} \leq I_d$, the central pixel is on the edge with the direction-j, thus, the following four rules are helpful to reduce noise and thin the line of the edge.

Rule 1: If j=1 and I(x+1, y-1) belongs to the edge in direction-1, the gray level value of the center pixel is set I(x, y) = 255; otherwise it is set 0.

Rule 2: If j=2 and I(x-1, y-1) belongs to the edge in direction-2, the gray level value of the center pixel is set I(x, y) = 255; otherwise it is set 0.

Rule 3: If j=3 and I(x-1, y) belongs to the edge in direction-3, the gray level value of the center pixel is set I(x, y) = 255; otherwise it is set 0.

Rule 4: If j=4 and I(x, y-1) belongs to the edge in direction-4, the gray level value of the center pixel is set I(x, y) = 255; otherwise it is set 0.

Stage 5: Let the single-point, which is isolated with its neighborhood, be regarded as a noise and discard it.

The algorithm is finished.

Remark 1: In Stage 2, the reason to use fuzzy 2-mean classification is as follows. Some regions in an image may be dark or light. Whatever the object in the dark or light region, the edge of the object should be detected. Fuzzy 2-mean classification can classify all pixels in the mask into two

clusters whatever the mask in the dark or light region.

Remark 2: In Rule 1, j=1 means the center pixel I(x, y) belongs to the direction-1. But I(x+1, y-1) has been detected belonging to the edge in direction-1 by the prior mask too, In order to avoid the edge of the direction-1 being thick, I(x, y) should not be one of pixels of edge, then, we set I(x, y) = 255. The same reason can be applied to other three rules.

The above procedure is summarized as a flowchart as shown in Fig. 3

I(x-1,y-1)	<i>I(x,y-1)</i>	I(x+1,y-1)
I(x-1,y)	I(x,y)	<i>I(x+1,y)</i>
I(x-1,y+1)	I(x,y+1)	<i>I(x+1,y+1)</i>

Fig. 1. A 3×3 mask

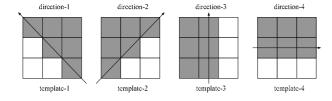


Fig. 2. Four templates with four directions respectively.

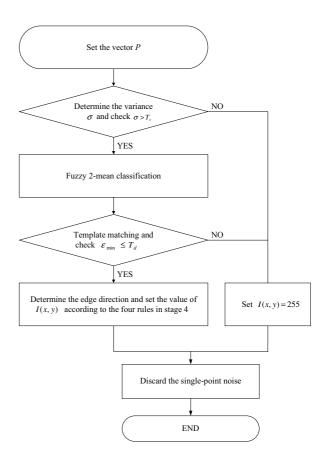
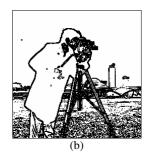


Fig. 3. The flowchart of the proposed method

4. EXPERMENTS

Fig. 4(a) shows the original image of the "camera-man", and Fig. 4(b) shows the result by applying Sobel operator with T=80. The result by using the edge detection method proposed by [8] with lo=8, hi=50, and w=240 shown in Fig. 4(c). The result of the proposed method with $T_{\nu}=100$ and $T_{d}=1.2$ shown in Fig. 4(d). It is seen that Fig. 4(d) has much thinner edges and the face of the camera-man is not as muddy as that in Fig. 4(b). Furthermore, Fig. 4(e) is the "camera-man" corrupted by 5% impulse noise. The Sobel operator and the method proposed in [8] are used to process it and obtain the results shown in Fig. 4(f) and Fig. 4(g) respectively. Fig. 4(h) is the result of the proposed method. By using Stage 5, all isolated pixels are reduced.





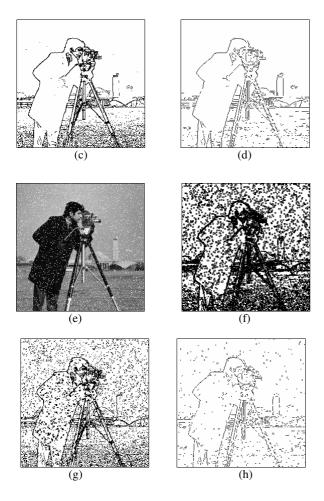


Fig. 4. Comparison of images with different methods.

5. CONCLUSION

Based on fuzzy 2-mean classification and template matching, this paper has provided a new edge detection method. There are two important advantages in the proposed method, one is the thinning of the edge and the other is the reduction of the impulse noise. The former make the textures of the images to be more delicate, the latter make the edge detection to tolerate more disturbances.

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