A High Performance Edge Detector Based on Fuzzy Logic and Inference Rules

H. D. Cheng and Liming Hu
Department of Computer Science, Utah State University, Logan, UT 84322-4205

Abstract

Edge detection is an important topic in computer vision and image processing. In this paper, we propose a novel fuzzy edge detector based on the fuzzy If-Then rules and edge continuity. We compare it with the popular edge detectors: Sobel and Canny edge detectors. The proposed fuzzy edge detector does not need parameter setting as Canny edge detector does, and it can preserve image details. It is robust to noise and can work well under high level noise situations, while other edge detectors cannot work well. We also discuss the related issues in designing fuzzy edge detectors. The experimental results demonstrate the superiority of the proposed method to existing ones.

Keywords: Edge detector, fuzzy If-Then rule, linguistic variables

1. Introduction

Fuzzy logic theory has been successfully applied to many areas, such as image processing, pattern recognition, etc [1]. Fuzzy logic has been applied to image enhancement [2], image segmentation and threshold value selection [3]. Edge detection is an important topic in computer vision and image processing, and it has many applications in the related areas. The edge pixels are the pixels whose grey levels have big difference with the gray levels of their neighborhood pixels. However, the definition of "big" is quite fuzzy and application-dependant. To deal with the ambiguity and vagueness in the definition of edge pixels, image edge can be defined as a fuzzy set.

A fuzzy If-Then rule approach using fuzzy templates, also called fuzzy operators, to detect specific patterns of neighboring pixels was discussed in [4, 5]. Each neighboring pixel is defined as a linguistic variable [6], "bright" or "dark" pixel, based on the corresponding membership functions. Then a fuzzy aggregator operator is applied to these linguistic variables according to the defined fuzzy templates. Finally, the defuzzification is applied, and all the pixels in the image are classified as edge pixels or non-edge pixels. Different fuzzy template sets for the aggregator operations result different fuzzy edge detectors suitable for different applications. [5] used 8 templates shown in Fig. 1(a), which are similar to Sobel templates. [4] used a different set of 16 templates. [7] applied the fuzzy approach in [5] to detect white line markings. People also tried to use the combinations of aggregator operators to smooth the noise, however these approaches are still quite sensitive to different kind of noise. [5] used arithmetic average aggregator to replace the minimum aggregator, and it claimed that the algorithm was robust to the noise, however, the algorithm was still quite sensitive to noise. [4, 5] used fuzzy inference rules without considering the continuity of the edges. [8] used fuzzy approach for road extraction. A road membership value is assigned to each pixel, and a set of 12 fuzzy templates representing basic 2D road structures is defined. The algorithm can only detect the bright road with one pixel width in low density aerial images.

In this paper, we propose a novel fuzzy If-Then rule edge detector using the continuity characteristics of edges, and it can overcome the shortcomings of the above fuzzy edge detector algorithms. The improvements are: a) it is more robust to noise, even high level noise, b) it can preserve the image details, c) it outperforms other edge detectors.

The paper is organized as follows: Section 2 introduces some existing algorithms, Section 3 discuss newly proposed algorithm, Section 4 shows and explains the experimental results, and finally, Section 5 gives conclusions.

2. The fuzzy inference rules without using edge continuity

For comparison, we first discuss the fuzzy inference rules without considering the edge continuity. In order to decide if a pixel is an edge pixel, the gray level differences between the pixel and its 8-neighbor pixels (3*3 windows, as shown in Fig. 1(c)) are computed. The 4-neighbor pixels (pixel 2,4,6,8, that have a distance 1 with the central pixel Q) have more impact than other pixels (pixel 1, 3, 5, 7) on the decision. The gray level differences are fuzzified using the fuzzy membership function shown in Fig. 1(b). The Gray_dif (Q, i) is defined in Eq. (1). The fuzzy memberships, NEG and POS in Fig. 1(b) are calculated by using the fuzzy templates in Fig. 1(a) [5]. Then they are processed by fuzzy reasoning to determine the fuzzy edge degree value of the pixel Q. First, rule 1 in Fig. 1(a) is calculated using Eq. (4), similarly for rule 2 to 7, and the MAX aggregator operator was used to find the fuzzy value of the pixel Q. After all the pixels have been fuzzified and processed, we defuzzify them using the global centroid method in Eq. (5), and combine it with the local 3*3 template arithmetic average value as the threshold value to classify the pixels as edge pixels or non-edge pixels.

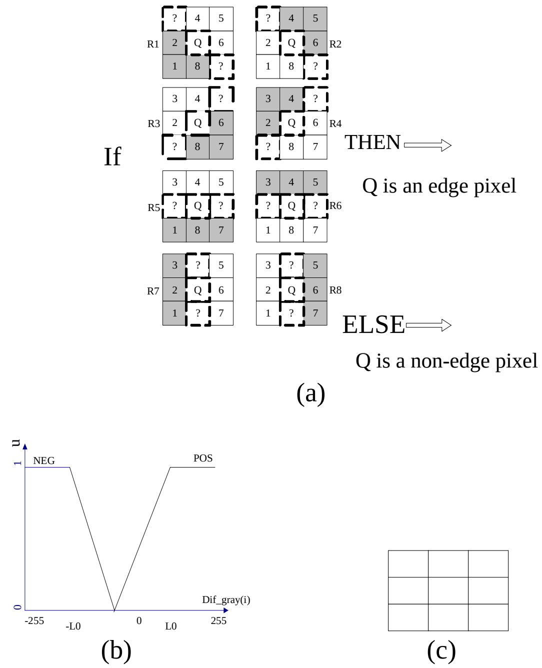


Figure 1 (a) Basic If-Then Rule, (b) Gray Level difference membership function, (c) A 3*3 window neighborhood

In Fig. 1(b), L_0 is $1/2$ of the standard deviation of the gray levels of all the pixels.

In order to discuss the algorithms in detail, the following formulas are defined:

Gray level difference:

$\text{Gray\_Dif}(Q, i) = \text{Gray}(i) - \text{Gray}(Q)$ and $i \in \{1, 2, ..., 8\}$, as shown in Fig. 1(c). (1)

Average gray level:

$$\overline{G} = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} G_{ij} \quad (2)$$

Half of the standard deviation of the pixel gray levels:

$$L_0 = \frac{1}{2} \varepsilon_{STD} = \frac{1}{2} \sqrt{\frac{\sum_{i=0}^{M-1} \sum_{j=0}^{N-1} (G_{ij} - \overline{G})^2}{M*N}} \quad (3)$$

M and N are the dimensions of the image.

We also define the following operators and functions:

- "$\cup$" is the MAX operator.
- "$\cap$" is the weighted arithmetic average operator. For the $\cap$ aggregator operator, we will not use the MIN operator, because it is the strongest aggregator operator [1], and it is quite sensitive to noise. We will use the weighted arithmetic average operator, and the weight is decided as follows: if it is a 4-neighboring pixel, then the weight is 2, if it is an 8-neighboring pixel, then the weight is 1, since the 4-neighboring pixels have more impact on the central pixel than the diagonal neighbors.
- "$\cap_1$" is the strongest MIN aggregator. Here we need a strong constraint on the edge continuity direction (only the minimum value will be reflected in the rule), and we want to get rid of the influence of the noise.
- "$\bar{\ }$" is the ordinary complement operator.
- Defuzzification operator: we use the centroid operator in Eq. (5) and combine it with the local 3*3 template arithmetic average to classify a pixel as an edge pixel or non-edge pixel.
- NEG and POS are the fuzzy membership functions defined in Fig. 1(b).

$R_i(Q)$, (i = 1, 2,…, 8) are the fuzzy rules associated with Fig. 1(a).

The arithmetic representations of the fuzzy rules in Fig. 1(a) are:

$$\begin{aligned} R_1(Q) = {} & \text{NEG}(\text{Dif\_gray}(Q,1)) \cap \text{NEG}(\text{Dif\_gray}(Q,2)) \cap \\ & \text{NEG}(\text{Dif\_gray}(Q,8)) \cap \text{POS}(\text{Dif\_gray}(Q,4)) \cap \\ & \text{POS}(\text{Dif\_gray}(Q,5)) \cap \text{POS}(\text{Dif\_gray}(Q,6)) \end{aligned} \quad (4)$$

The centroid defuzzification is:

$$z^* = \frac{\int \mu(z) z dz}{\int \mu(z) dz} = \frac{\sum_{i=0}^{255} \text{hist}(i) i}{\sum_{i=0}^{255} \text{hist}(i)} \quad (5)$$

3. Fuzzy reasoning using edge continuity

The following issues are important in designing fuzzy If-Then rule edge detectors:

- Selecting the fuzzy template is the key in the design of fuzzy If-Then rule-based edge detectors. The fuzzy template size can decide the width of the edges. Bigger fuzzy template means bigger edge width, and can preserve more detail information of the image.
- Choosing suitable aggregators in the fuzzy If-Then rule sets is also very important.
- Considering the differences between the edge pixels and the noise pixels can make fuzzy edge detectors more robust to noises, if the edge continuity is employed.
- Selecting fuzzy membership function and making fuzzy membership function adaptive to the images is also very important. The fuzzy membership functions in [4, 5, 7, 8] are not adaptive to the images, therefore, it limits their performance.
- Determining defuzzification method. There are many defuzzification approaches: Max-membership principle, Centroid principle, weighted-average method, Mean-max membership method, etc. [6]. Many of them use only global information. However, the thresholding value selection should base on both the global and local information [9].

By considering the above issues, we propose a novel fuzzy edge algorithm which is based on the fuzzy inference rules and uses the edge continuity: If a pixel is an edge pixel, then at least two of its neighboring pixels are also edge pixels due to the continuity. For the ending edge pixel, at least one of its neighboring pixels is an edge pixel. For simplicity, we do not distinguish the ending pixels from other edge pixels. However, it will not affect the detection of the entire edge curve.

The following 8 new fuzzy rules are defined.

Rule 1 in Eq. (4) does not take into account of the two corner pixels: pixel 3 and pixel 7. The new Rule 1 is: if Q is an edge pixel, then pixel 3 and pixel 7 should also be edge pixels, and the constraint of Rule 1 makes pixel 3 and pixel 7 match Rule 1, Rule 5, or Rule 7, if they are edge pixels. As shown in Fig. 2, the central pixel is Q, pixels 1-8 are its neighboring pixels, "?"s represent the pixels that are not considered in Section 2. Rule 1, Rule 5, or Rule 7 is applied to Q's left-above neighboring pixel 3. And pixel 3's 8 neighboring pixels are pixels 3i{i=1,2,…,8}, , if pixel 3 matches Rule 1, and pixel 7 which is the down-right neighboring pixel of Q, also matches Rule 1, then the template becomes the one shown in the right part of Fig. 2. Pixel 7's 8 neighboring pixels are pixels7i {i=1, 2,…,8}.
The above rule can be represented as Eq. (6).
Similarly, we can get all the other new Rules 2 to 8.

$$\begin{aligned} New\_R_1(Q) = \; & \underline{R_1(Q) \cap ((R_1(3) \cup R_5(3) \cup R_7(3)) \cap_1} \\ & (R_2(3) \cup R_3(3) \cup R_4(3) \cup R_6(3) \cup R_8(3))) \cap \\ & \underline{((R_1(7) \cup R_5(7) \cup R_7(7)) \cap_1} \\ & (R_2(7) \cup R_3(7) \cup R_4(7) \cup R_6(7) \cup R_8(7)\,)) \end{aligned} \quad (6)$$

The following algorithm is proposed:
For each pixel Q:
1) Compute the gray differences, Gray_Dif(i) = Gray(i)-Gray(Q), (i = 1… 8), i is the index of the neighboring pixels.
2) Based on the membership functions NEG and POS (Fig. 1(b)), fuzzify the grey level differences Gray_Dif(i) (i=1…8), and compute $New\_R_1(Q)$, $New\_R_2(Q)$, $New\_R_3(Q)$, $New\_R_4(Q)$, $New\_R_5(Q)$, $New\_R_6(Q)$, $New\_R_7(Q)$, $New\_R_8(Q)$, respectively.
3) Calculate:

$$\mu(Q)=\max\{New\_R_1(Q),New\_R_2(Q),New\_R_3(Q),New\_R_4(Q),$$
$$New\_R_5(Q),New\_R_6(Q),New\_R_7(Q),New\_R_8(Q)\}$$

4) Defuzzify the result using Eq. (7).

$$Q \text{ is } \begin{cases} \text{edge pixel} & \text{if } \mu(Q) \ge T \\ \text{non-edge pixel} & \text{otherwise} \end{cases} \quad (7)$$

Where $T = \max((0.8 * Z^* + 0.2 * \mu_{\max}), \mu_{local})$, $\mu_{\max}$ is the global maximum membership of the image, and μ_{local} is the mean membership of the local 3*3 window.

4. Experimental results

In order to demonstrate the performance of the proposed approach, we have conducted a lot of experiments on various images. Fig. 3(a) is the original image Lena with dimensions of 512*512 and 256 gray levels. Fig. 3(b) is the result of Canny edge detector [10] with the default parameter of the MATLAB™ software and Fig. 3(c) is the result of Sobel edge detector [9] using the default parameter of the MATLAB™ software. Fig. 3(d) is the result applying the fuzzy If-Then rule without considering the edge continuity. Fig. 3(e) is the result applying the fuzzy If-Then rule using the edge continuity. Compared with the Sobel edge detector, the fuzzy detector can detect more edges and keep more details, and compared with the Canny edge detector, the Canny edge detector can make the edge thinner, but the fuzzy edge detector can keep the details of Lena's eyes. Compared with the fuzzy edge detector without using the edge continuity, the fuzzy edge detector using the edge continuity is more robust to the noise, especially it can remove the small speckles on Lena's face and head.

Fig. 3(f) is the Lena image corrupted by 5% salt and pepper noise. With more noise, the results of Sobel in Fig. 3(g) and Canny edge detectors in Fig. 3(h) become worse, but the fuzzy edge detector using edge continuity still works quite well, even with 5% salt and pepper noise, as shown in Fig. 3(i) and 3(j), respectively.

As discussed before, fuzzy template selection is a key step in designing of a fuzzy If-Then rule based edge detectors. The fuzzy template size can decide the width of the edge. Bigger fuzzy template causes wider edge width and preserves more details of the image.
There are many different defuzzification approaches, some methods only consider global information, and some only consider local information, and some consider both global and local information. We use centroid method here.

5. Conclusions

Edge detection is an important topic in computer vision and image processing. Many edge detectors were developed. However, some of them have difficulty in the selection of parameters such as Canny edge detector, and most of them are very sensitive to the noise. Experimental results demonstrate that the newly proposed fuzzy If-Then rule based edge detector using edge continuity can overcome the above problems, especially, it works well with noisy images that cannot be done by other edge detectors.

6. References:

[1] W. Pedrycz, and F. Gomide, *An introduction to fuzzy sets: analysis and design*. MIT Press, 1998.

[2] H.D. Cheng, and H. Xu, "A novel fuzzy logic approach to mammogram contrast enhancement", *Information Sciences*, Vol. 148, No.1-4, pp. 167-184, 2002.

[3] H. D. Cheng, Liming Hu, "A High Performance Edge Detector Based on Fuzzy Logic and Inference Rules", *Technical Report, TR-USU-CS-2003-12*, 2003

[4] C.W. Tao, W.E. Thompson, and J.S. Taur. "Fuzzy if-then approach to edge detection", *Second IEEE International Conference on Fuzzy Systems*, 1993.

[5] F. Russo, G. Ramponi, “Edge extraction by FIRE operators”, *Proc. 3rd IEEE International conference on Fuzzy Systems*, 1994.

[6] T.J. Ross, Fuzzy Logic with Engineering Applications, McGraw-Hill, 1995

[7] W. Li, G. Lu, and Y. Wang, “Recognizing White line markings for vision-guided vehicle navigation by fuzzy reasoning”, *Pattern Recognition Letters*, Vol. 18, pp. 771-780, 1997.

[8] B. Solaiman, R. Fiset, and F. Cavayas. “Automatic road extraction using fuzzy mask concepts”, *IGARSS'99*, 1999.

[9] R. C. Gonzalez, and R.E. Woods, Digital Image Processing. 2nd ed. Prentice Hall,2002

[10] J. Canny, “A computational Approach to Edge Detection”, *IEEE Trans.Pattern Anal. Machine Intell.* Vol. 8, No. 6, pp. 679-698, 1986.

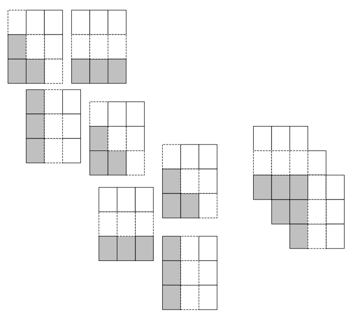
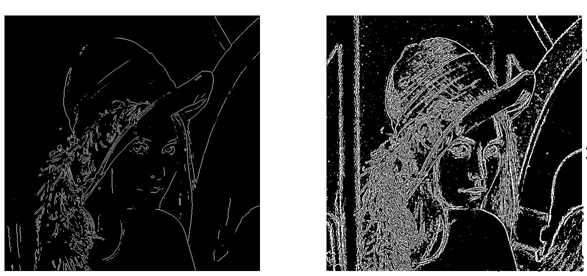


Figure 2 New rule 1

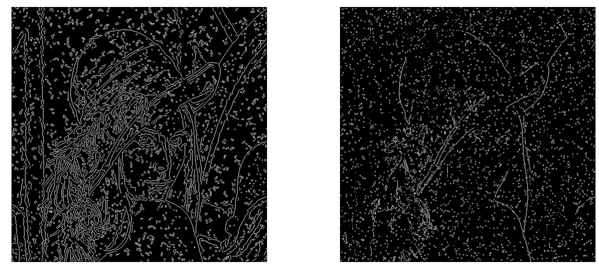
(a) (b)



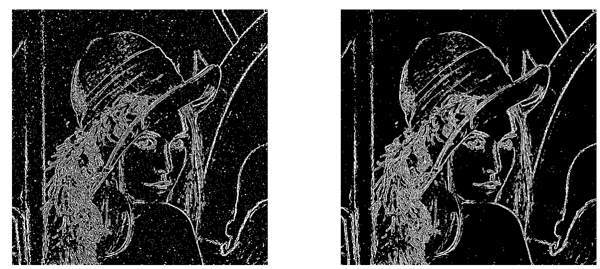
(c) (d)

33 34 35
? 3 ? R5
3´ 38 37
? 4 5 R´
2 Q 6
3´ ? 37
´ 8 ?
R7
? 74 75
72 7 76 R1
7´ 78 ?
33 34 35
? 3 4 5
3´ 38 ? 6 75
´ 72 7 76
7´ ? 77
73 74 75
? 7 ?
7´ 78 77
R5
73 ? 75
72 7 76 R7
7´ ? 77

(e) (f)



(g) (h)



(i) (j)

Figure 3 (a) Original Lena image. (b) the result using Canny operator. (c) the result using Sobel operator. (d) the result applying fuzzy operator without using edge continuity. (e) the result applying fuzzy edge detector using edge continuity. (f) Original Lena image with 5% Salt and Pepper noise. (g) the result using Canny operator. (h) the result using Sobel operator. (i) the result applying fuzzy operator without using edge continuity. (j) the result applying fuzzy edge detector using edge continuity