한국산학기술학회논문지
Vol. 7, No. 3, pp. 398-403, 2006

Fuzzy Threshold Inference of a Nonlinear Filter for Color Sketch Feature Extraction

Sung-Mok Cho[1*] and Ok-Lae Cho[2]

컬러 스케치특징 추출을 위한 비선형 필터의 퍼지임계치 추론

조성목[1*], 조옥래[2]

Abstract In this paper, we describe a fuzzy threshold selection technique for feature extraction in digital color images. this is achieved by the formulation a fuzzy inference system that evaluates threshold for feature configurations. The system uses two fuzzy measures. They capture desirable characteristics of features such as dependency of local intensity and continuity in an image.
We give a graphical description of a nonlinear sketch feature extraction filter and design the fuzzy inference system in terms of the characteristics of the feature. Through the design, we provide selection method on the choice of a threshold to achieve certain characteristics of the extracted features.
Experimental results show the usefulness of our fuzzy threshold inference approach which is able to extract features without human intervention.

Key Words : Fuzzy Threshold Inference, Fuzzy Measure, Sketch Feature, Channel Splitting

요 약 본 논문에서는 컬러 디지털 영상에서의 특징점 추출을 위한 퍼지 임계치 설정기법을 제안한다. 이를 위하여 두 가지 종류의 퍼지 측정자를 사용하여 임계치를 계산하는 퍼지추론 시스템을 구성한다. 퍼지추론 시스템에 사용된 측정자들은 디지털 영상에서의 국부영역 밝기를 매우 잘 반영할 뿐만 아니라 특징점 추출 성능이 매우 우수함을 보여준다.
또한, 퍼지측정자로 사용되는 비선형 스케치 특징점 추출 필터의 특성을 도식적으로 해석하였고 특징점들의 특성이 반영된 퍼지추론 시스템을 설계하였다. 이와 같이 설계된 퍼지추론 시스템을 통해 디지털 영상에 포함된 특징점의 특성이 반영된 임계치를 선택하였다.
실험결과를 통해 제안된 퍼지 임계치 추론 방법이 매우 유용성을 증명할 수 있었다.

I. Introduction

In order to successfully analyze and understand images in many applications such as robot vision, medical diagnostic system, and motion video transmission, it is reasonable to assume that the early stages in image analysis and understanding consist of detecting intensity discontinuities However, due to the complexity of the physical objects and of the imaging apparatus, and to multiple sources of noise, the signal to be processed is complex, and the selection of the threshold which we use to extract meaningful intensity discontinuities is non trivial. Until now, various feature extracting operators and thresholding techniques have been developed. Basically, the idea underlying most feature extraction techniques is the computation of a local derivative operator and the selection of a threshold[1]. However, conventional operators are usually not efficient to extract features in images because image feature formation in eyes is more sensitive to dark regions than to bright regions.
And the establishment of a threshold for extracting features may be viewed as an operation that involves

[1]Dept. of Information Security, Tongmyong University
[2]Dept. of Computer Engineering, Tongmyong University
*Corresponding Author : Sung-Mok Cho(smcho@tu.ac.kr)

trials and errors test because an optimal threshold depend on image contents.

In this paper, we introduce a new operator using difference between the arithmetic mean and the harmonic mean in a window for extracting sketch features and use it as a fuzzy measure for extracting features. this operator has some advantages, for example simple computation, dependence on local intensities and less sensitive to small intensity changes in very dark regions. We also present a fuzzy threshold selection technique for feature extraction in images. this is achieved by the formulation a fuzzy inference system that evaluates threshold for feature configurations. This paper is organized as follows. In section Ⅱ, we describe thresholding methods for extracting features. In section Ⅲ, a fuzzy reasoning technique for establishing a threshold is described. we propose a fuzzy inference system and two fuzzy measures in order to use for selecting a threshold which is independent on being processed images. Finally, we provide experimental results and some concluding remarks in Section Ⅳ.

Ⅱ. Feature Extracting and Thresholding Methods

In case of projection of object space with non-uniform reflection, the features called edges occur at points which have abrupt changes in luminance and in case of projection of object space with uniform reflectance, the features occur at points which have local luminance minima called valleys. Since the major portion of the visual information of an image is contained in the edges and valleys, these features extracting process from digital images is very important[2-3]. Despite their fundamental importance in digital image processing and analysis, there is no precise and widely accepted mathematical definition of these features. Several operators have been emerged to improve the performance of the sketch feature extraction in images. These include Van Vliet's nonlinear gradient and nonlinear Laplacian [4], and the entropy operator [5], etc.

The operators presented by Van Vliet *et al.* relate closely to the morphological gradient operators[6] and the implementation of these operator is very easy. The nonlinear gradient operator is relatively insensitive to noise and granularity but it extracts ramp edges often existing in real images as thick lines and does not depend on local intensities. The Laplacian operator produces a zero crossing at an edge location. It detects high frequency details accurately and its implementation is facilitated, but it is generally more sensitive to noise than other convolutional operators. This defect can be overcome to some extent by adopting its nonlinear versions. The shifting effect of the edge locations which occurs in the nonlinear gradient operator does not occur in the nonlinear Laplacian because of its second-order derivatives. However, the nonlinear Laplacian does not depend on local intensities and creates several false edges, especially in the areas where the image variance is small, because small intensity perturbations tend to produce false zero-crossings.

The entropy operator extracts the features of dark regions quite well because of its dependence on local intensities. However, the features are extracted as thick lines since it weights all pixels uniformly within the local region. It is noted that the entropy operator needs a large amount of computation due to the logarithmic operation.

In general, there have been attempted mode methods, P-tile methods and variable thresholding methods to establish a threshold for features extraction[7-8]. However, there are various histogram types according to images and the perception of features by the human visual system is an extremely complex process that is strongly influenced by prior knowledge. So, it is very difficult to select an optimal threshold by mode methods because of a number of histogram types. And in P-tile methods and variable thresholding methods, some prior informations about being processed images are needed for an efficient threshold, Besides, a global threshold method is ineffective to find the features in an image because there exist sketch features over a broad range of intensity distributions in an image and human visual system is more sensitive to features in dark region rather than a bright region. Haralick *et al* proposed a variable threshold in pixel (i,j) as follows:

$$\theta(i,j) = \frac{\sum_{i=-n}^{n} A(i,j)}{n \times n}\left(1 + \frac{p}{100}\right), \qquad (1)$$

where n×n denotes a window size and p is a probability. The variable threshold using equation (1) reflects local characteristics considerably well but it needs a prior image information because probability value p should be set differently according to processed images. Kundu etal classified the intensity range of an input image as Devris-Rose region, Weber region and Saturation region. They proposed local thresholds considered not only local intensities but also intensity variations as follows:

$$\begin{aligned} E(i,j) = 1 \ \text{ if } \frac{\Delta B}{\sqrt{B}} \geq K\sqrt{\alpha_2 B_t} \\ \textit{when } \alpha_1 B_t \leq B \leq \alpha_2 B_t \ \textit{ or} \\ \text{if } \frac{\Delta B}{B} \geq K \\ \textit{when } \alpha_2 B_t \leq B \leq \alpha_3 B_t \ \textit{ or} \\ \text{if } \frac{\Delta B}{B^2} \geq \frac{K}{\alpha_3 B_t} \end{aligned} \quad (2)$$

$$\textit{when } B \geq \alpha_3 B_t$$

$$E(i,j) = 0 \ \ \textit{otherwise}$$

,where

$$\begin{aligned} B = \sum_{i=-n}^{n} \sum_{j=-n}^{n} \frac{I(i,j)}{n \times n} \\ \Delta B = |I(i,j) - B| \\ 0 < \alpha_1, \alpha_2, \alpha_3 < 1 \\ B_t = I(i,j)_{\max} - I(i,j)_{\min} \\ K = \frac{1}{100}\beta\left(\frac{\Delta B}{B}\right)_{\max} \end{aligned} \quad (3)$$

and β is 2 approximately. The above method is very efficient for extracting feature in images but it has 4 parameters which should be set differently according to images.

III. Fuzzy Inference System for Reasoning Local Thresholds

The simplest of all thresholding techniques is to partition the gradient histogram by using a single threshold. But the task of finding the features that correspond to true edges and valleys in an image remains a difficult problem. Part of the difficulty lies in finding a suitable definition of a feature that is generally applicable. The cause of existing features may be due to a combination of several factors, such as the geometry of the object, surface reflection characteristics, viewpoint, illumination. So, no absolute definition of a feature exists and there is also an ambiguity in the process of selecting a threshold deciding whether a pixel in an image is a feature or not[6-7]. Hence, in this paper we introduce a fuzzy inference system to evaluate local thresholds for extracting color image features. The overall process for a color sketch feature map is show in Figure 1. First, we split a color input image into HSI channels, and use I-channel(Intensity channel) for feature extraction.

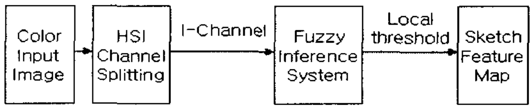


Fig 1. the overall process for color sketch feature map

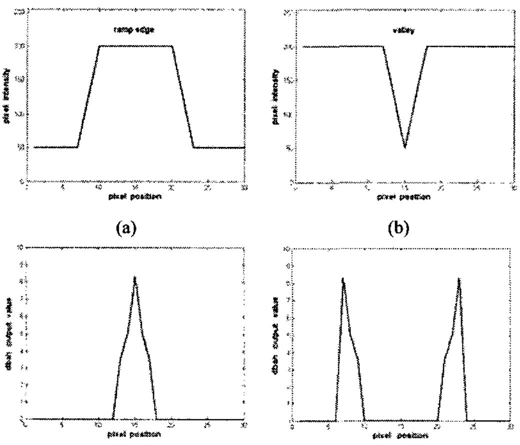
$$I = (R+G+B)/3 \quad (4)$$

,where I, R, G, and B are intensity, red, green and blue component value of a color image, respectively. To accomplish our goal, the DBAH(Difference Between Arithmetic mean and Harmonic mean)[9] and DF(Degree of Fuzziness) are used as fuzzy measures for a local threshold decision to extract features in an image. The DBAH fuzzy measure is defined by the difference between the arithmetic mean and the harmonic mean in a window as follows:

$$DBAH_{\max - cen} = \frac{f_{\max} + f_{cen}}{2} - \frac{2 f_{\max} f_{cen}}{f_{\max} + f_{cen}} \quad (5)$$

The above DBAH measure tends to become larger for the greater intensity change. This tendency is the result that the arithmetic mean increases linearly but the harmonic mean approaches to the center pixel intensity with higher rate as the difference between the maximum and center pixel intensities increases. And the DBAH filters are apt to be larger in the dark region for the same intensity change rate. This tendency is the result that the arithmetic mean decreases linearly but the harmonic mean approaches more rapidly and closely to the center pixel intensity for the lower sum of the selected two pixel intensity values. As a result, the DBAH tends to become larger for the greater difference between these two intensities and are apt to be higher in the dark region where the sum of these two intensity values is lower. Moreover, it is noted that the DBAH filters are extremely small in the very dark region because both of the intensities are quite small. The advantages of the DBAH filters discussed so far are that the DBAH filters can take into account the intensity change rates, the local intensities and the very dark regions as well in images, which make it possible to develope an efficient feature extraction technique akin to the human visual system.

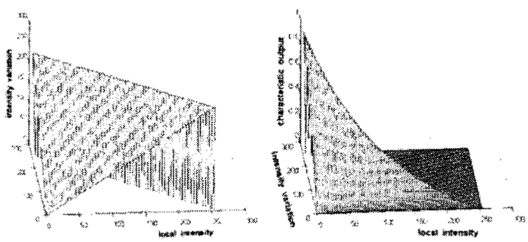
Figure 2 shows the output responses of the DBAH measure to an ideal ramp edge and an ideal valley



(a) (b) (c) (d)

Fig 2. (a) an ideal edge; (b) an ideal valley; (c)-(d) result applying DBAH to (a) and (b), respectively.

Figure 3(b) illustrates the transfer characteristic function of DBAH employing to the input which has all possible combination of local intensities and intensity variations in an image (Figure 3(a)). As it is seen in Figure 3, the output of the DBAH agrees quite closely with the perception of human being especially in very dark regions.



(a) (b)

Fig 3. (a) all possibile combination of local intensities and intensity variations in an image; (b) transfer characteristic function of the DBAH measure.

In other hand, the difference between the DBAH in center pixel of a window and the DBAHs' mean in all pixels of a window has some relation with the degree of featureness a in local region. The DF is defined as follows.

$$DF(i,j)=\frac{1}{9}\sum_{l=-1}^{1}\sum_{m=-1}^{1}DBAH(i+l,j+m)-DBAH(i,j) \tag{6}$$

,where l and m denote the number of pixel rows and pixel columns in a window. However, the values computed by using Eq. (5) and Eq. (6) for local thresholds are very ambiguous and have imprecise boundary, so we represent them as qualitative and linguistic descriptions and define them as fuzzy set with membership functions. We classified DBAH and DF into three fuzzy classes represented by the three fuzzy set values low, medium and high.

Fuzzy variable : DBAH, DF
Fuzzy labels : low, medium, high

The fuzzy partitions of input and output spaces which represent the probability of being features and the level of thresholds are shown in Figure 4.

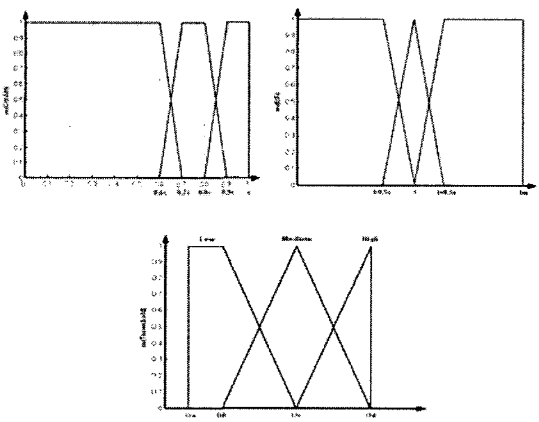


Fig 4. Fuzzy values of fuzzy variables DBAH, DF, and Threshold

In general, a global threshold for feature extraction is found by a heuristic method. In our case, we chose a value corresponding to upper 15% in the feature strength histogram obtaining from applying DBAH to an input image and made a tuning its membership function by a trials and errors method as shown in Figure 4. In Figure, Oa, Ob, Oc and Od should be set differently according to an in image. We normalized a mean value resulting from applying DBAH to an input image by its standard deviation, and assigned them to values of a mean of DBAHs', a mean of DBAHs'+1.5, a mean of DBAHs'+2, a mean of DBAHs'+2.5 divided by a standard deviation of DBAHs', respectively. To achieve our goal for inferencing local thresholds, we established the fuzzy rules for a local threshold evaluation as follows.

R1: if DBAH is Low and DF is Low,
then Threshold is High.
R2: if DBAH is Medium and DF is Low,
then Threshold is High.
R3: if DBAH is High and DF is Low,
then Threshold is Medium.
R4: if DBAH is Low and DF is Medium,
then Threshold is High.
R5: if DBAH is Medium and DF is Medium,
then Threshold is Medium.
R6: if DBAH is High and DF is Medium,
then Threshold is Low.
R7: if DBAH is Low and DF is Low,
then Threshold is High.
R8: if DBAH is Low and DF is High,
then Threshold is Medium.
R9: if DBAH is High and DF is High,
then Threshold is Low.

Finally, we made a defuzzification process by using the center of gravity method.

IV. Performance Results

In this section, we present some experimental results of extracting features based on the fuzzy inference system. Figure 6 shows the thresholded results taken from the edge strength image which was obtained with applying operators on a 3×3 neighborhood for a GIRL image, composed of 256×256 pixels with 8bits by using Eq. (3). The thresholds used for the operators were selected to get the best performance according to the visual quality of the resulting edge map. Cubic nonlinear functions were utilized for the logical Laplacian operator.

The results applying the nonlinear gradient and entropy operators, (a) and (d), revealed the extraction of edges with thick lines and the nonlinear Laplacian and logical Laplacian operators, (b) and (c), with lots of isolated spots. It is also seen that the nonlinear gradient, nonlinear Laplacian and logical Laplacian operators, (a)-(c), can not extract features of dark regions properly. Figure 7 shows the effectiveness of the fuzzy inference system using DBAH and DF as fuzzy variables in order to extract features in digital images. Figure 7(a) and (b) which are the feature maps obtained when applying the above fuzzy inference system to Figure 5(a) and (b), respectively. As reviewed in the preceeding section, the presently existing operators possess their shortcomings for extracting sketch features since they either do not consider local intensities or have some problems such as computational time and sensitivities in dark regions. Figure 7(a) and (b) show that DBAH is well appropriate for the effective extraction of sketch features similar to the human psychovisual phenomena and the fuzzy inference system is well designed.

(a) (b)

Fig 5. (a) Girl image; (b) Lena image

(a) threshold=20 (b) threshold=15

(c) threshold=17500 (d) threshold=0.9917

Fig 6. Conventional operators' feature maps; (a)-(d) obtained when applying nonlinear gradient, nonlinear laplacian, logical laplacian and entropy operator to Fig. 5(a) respectively.

(a) (b)

Fig 7. (a) and (b) feature maps obtained when applying the proposed fuzzy inference system to Fig. 5(a) and Fig. 5(b), respectively.

V. Conclusion

Local thresholds for making a decision of whether a pixel is on a feature may be obatained by the fuzzy inference system using DBAH and DF as fuzzy variables. a fuzzy variables which is named DBAH shows excellent capability for valley feature extraction. Also, the transfer characteristic functions of the variable agree quite closely with the perception of the human being especially in dark regions and its computation process is also very simple. Therefore, the proposed fuzzy variables possess many advantages over the other convolutional filters for extracting sketch features. The excellence in performance make the proposed fuzzy inference system attractive for some automatic thresholding applications.

References

[1] Rafeal C. Gonzalez and Richard E. Woods, Digital Image Processing, Addition Wesley, pp. 414-419, 1992.

[2] D.H. Lim, "Comparison of Edge Detection using Linear Rank Tests in Images," Journal of The Korea Society of Computer and Information, vol. 10, no. 6, pp. 17-25, 2005.

[3] M.K. Kundu and S.K. Pal, "Thresholding for edge detection using human psychovisual phenomena," *Pattern Recogn. Lett.*, vol. 4, pp. 433-441, 1986.

[4] L.J. Van Vliet and I.T. Young, "A nonlinear Laplace convolutional filters as edge detector in noisy images," *CVGIP*, vol. 45, pp. 167-195, 1989.

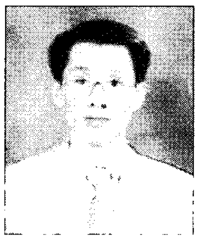
[5] A. Shiojaki, "Edge extraction using entropy convolutional filter," *CVGIP*, vol.36, pp. 1-9, 1986.

[6] J. S. J. Lee, R. M. Haralick, and L. G. Shapiro, "Morphologic edge detection," *IEEE Trans. Robotics and Automation*, vol. RA-3, no. 2, pp. 142-155, Apr. 1987.

[7] R. P. Johnson, "contrast based edge detection", Pattern Recog., vol. 23, No. 3, pp. 311-318, 1990.

[8] S.M. Cho, and O.L. Cho, "Effective Nonlinear Filters with Visual Perception Characteristics for Extracting Sketch Features," Journal of KSCI, vol. 11, no. 1, Mar. 2006.

Sung-Mok Cho [Regular Member]



- 1988. 2. Kyungbook Nat'l Univ. Dept. of Electronics (B.S.)
- 1990. 2. Kyungbook Nat'l Univ. Dept. of Electronics (M.S.)
- 1995년 Kyungbook Nat'l Univ. Dept. of Electronics (Ph.D..)
- 1992. 3. - 2006. 2. : Tongmyong College Full time Lecturer-Associate Processor
- 2006. 3. - : Tongmyong Univ. Dept. of Information Security Assistant Professor

<Area of interest>
Image Processing, Fuzzy Theory, Neural Network

Ok-Lae Cho [Regular Member]

- 1980. 2. Kyungbook Nat'l Univ. Dept. of Statistics (B.S.)
- 1983. 2. Kyungbook Nat'l Univ. Dept. of Statistics (M.S.)
- 2006년 Kyungbook Nat'l Univ. Dept. of Statistics (Ph.D..)
- 1992. 3. - 2006. 2. : Tongmyong College F.T. Lecturer - Processor
- 2006. 3. - : Tongmyong Univ. Dept. of Computer Eng. Associate Professor

<Area of interest>
Baysian Theory, Mobile Computing