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A Combined Method to Improve Image Contrast Using Fuzzy Entropy and Fuzzy Measure

Saeid Iranmanesh
MS.c, Member of Young Researcher Club of Islamic azad university, Bardsir branch, IRAN
E-mail: iranmanesh.s@gmail.com

M.Amin Mahdavi
Ph.D., Lecturer, Department of Computer Engineering, Imam Khomeini International University, Qazvin, IRAN
E-mail: mahdavi@researchattic.ca

***Abstract*__Contrast is perhaps one of the most noticeable aspects of an image. This paper proposes a hybrid method for improving the contrast in an image. It describes the application of fuzzy measure to the maximization of fuzzy entropy in the combined fuzzy contrast (CFC), resulting in a much improved contrast. The proposed method is tested on various fingerprint images. The results have shown a significant improvement on both strong and weak edges compared to common edge detection algorithms.**

***Key words*__fuzzy entropy, fuzzy measure, edge detection, contrast.**

I. INTRODUCTION

Segmentation is the act of dividing an image into regions of varying size. These regions may be interpreted as objects contained within an image, which may have similar intensities or colors[1]. To highlight the demarcation of each object, its neighboring regions must show a significant change in color or intensity. The process of segmenting an image is used in various areas such as image processing, machine vision, processing medical images, digital libraries, image retrieval, and image compression. Essentially, there are five basic techniques for segmentation: 1) using pixels[2], 2) using regions[3], 3) by edge detection[5][4], 4) hybrid method using edge detection and regions[6], 5)using k-mean algorithm [7], FCM[8], DCPSO[11], ISODATA[9][10].

In computer vision and pattern recognition, edge detection is a useful low-level image processing tool for image analysis and interpretation. It is also a segmentation tool for various recognition applications. Edges and contours are often useful features as they represent an image by its object boundaries and separation of dissimilar regions in terms of pixel intensities. Furthermore, edges are considered important elements in a picture, as they present essential information of an object of interest in a picture.

Contrast plays an important role in the process of segmenting an image into sub-regions. As the degree of color separation is increased in an image, the contrast is improved; hence an improved segmentation. The focus of this study is to propose a technique to improve the image contrast so that the segmentation process via contour or edge detection is also improved. This technique relies on the image histogram to compute an improved image level.

A. Histogram

Each pixel in a grey scale image has a brightness value ranging from 0 to 255 for a depth of 8-bits. A histogram results when image pixels are scanned for their brightness values. A histogram is a bar chart of pixel frequencies for each level (0 through 255). A histogram is an indication of the tonal ranges in an image. It marks the distribution for highlight, mid-tone, and shadow pixels in an image.

B. TONES

On a histogram, the region with heaviest concentration of grey values is called the tonal range. Developing an intuition for how histogram distribution translates into image brightness is an art photographers master by experience. However, there is no ideal configuration for a histogram to describe a good quality image. At best, histograms represent tonal range in a photograph. For instance, conditions of even lighting, when combined with a properly exposed subject, would produce a histogram whose peaks are concentrated in the centre. The width of the tonal range depends on the image contrast.

C. CONTRAST

A histogram may also describe the contrast level in an image. Contrast measures the grey level difference between light and dark pixels in an image. Usually, the grey level values for a low contrast image are concentrated in a narrower range than a higher contrast

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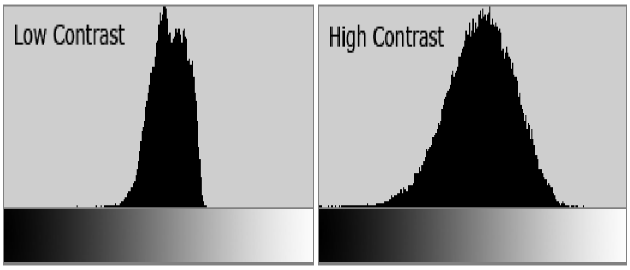
image. In other word, when comparing the broadness of grey level histogram in two different exposures of the same photograph, the one with narrower band of peaks has a lower contrast. This contrast level can be caused by the features in the subject matter or the lighting condition under which the image is produced. In any case, the clarity of image depends on its contrast. Contrast can have a significant impact on an image by emphasizing texture. Thus, improving the contrast in images loaded with data features is a desirable outcome in image processing.



II. COMBINED FUZZY CONTRAST (CFC)

Fuzzy logic was first introduced by Lotfi Zadeh in 1965. It provides a good description for uncertainty and vagueness [12]. Fuzzy logic is widely used in digital image processing, classification and pattern recognition. In this paper, we will combine Shannon's function and fuzzy entropy function to do the fuzzification on an image. The fuzzy image is then applied to fuzzy measure. Subsequently, edge detection is performed on the image.

The proposed method is comprised of two stages of fuzzification and fuzzy measure. During the fuzzification phase, the emphasis is placed on maximizing the entropy to reach at the S function, based on which a membership function is derived. In the next phase, the emphasis is placed on reducing the fuzzy measure. In other words, the intention is to redistribute grey value so that distribution peaks are pushed closer towards the boundary values of 0 and 1.

A. *Fuzzification*

Given an image A of size M x N, the gray level of pixel (i, j) is represented as g_{ij}. The image can be written as an array of fuzzy set as follows [13]:

$$A = \{\mu x(gij)/gij \mid i= 1,2,\ldots,M, j=1,2,\ldots,N\} \quad (1)$$

Where $\mu x(g_{ij})$ is the membership of the gray level g_{ij}. It gives the degree of brightness of g_{ij}.

In fuzzy logic, the key issue is to arrive at the membership function. There are several membership functions that can be used. The often used membership function for gray level image is the S-function [14, 15]. The S-function is defined as follows:

$$\mu_X(g_{ij}) = S(g_{ij},a,b,c) = \begin{cases} 0 & 0 \le g_{ij} \le a \\ \dfrac{(g_{ij}-a)^2}{(b-a)(c-a)} & a \le g_{ij} \le b \\ 1-\dfrac{(g_{ij}-c)^2}{(c-b)(c-a)} & b \le g_{ij} \le c \\ 1 & g_{ij} \ge c \end{cases} \quad (2)$$

Where g_{ij} is the gray level of pixel (i, j), and a, b, and c are the parameters that determine the shape of the S-function. See Figure 1.

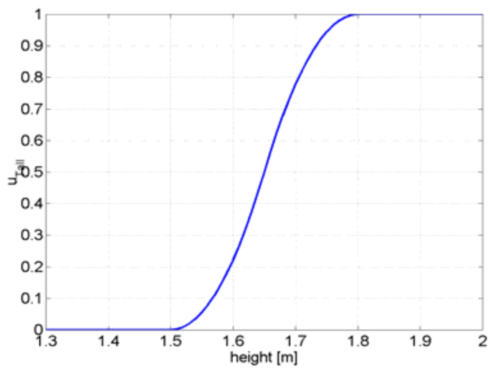


Figure 1: S-Function

The optimal values of a, b, and c may reduce the noise and minimize information loss during fuzzification. There are two different algorithms for finding the optimal parameters a, b, and c. (a) simulated annealing algorithm [16]. (b) Based on image histogram [17]. Both of them use maximum fuzzy entropy principle. Method (a) uses simulated annealing to reach at the optimal values for a, b, and c parameters in the gray level range. The time complexity for method (a) is high. Method (b) is a faster automatic way to determine the optimal values for a, b, and c. This paper chooses method (b) over method (a) to establish the values for a, b, and c parameters. The following is the set of steps to follow for fuzzification:

Step 1: Get the histogram of image I

Step 2: Compute the mean value for all local maxima in the histogram, $His_{max}(g_1)$, $His_{max}(g_2)$,…, $His_{max}(g_n)$, where *g* is the gray level.

$$\overline{His_{\max}(g)} = \frac{\sum_{i=1}^{n} His_{\max}(g_i)}{n} \quad (3)$$

Step 3: Find the peak values greater than $\overline{His_{\max}(g)}$, select the first peak g_{min} and last peak g_{max}.

Step 4: Find lower limit B1 and higher limit B2. Information loss is allowed in the ranges of [gmin, B1] and [B2, gmax], which is equal to f1, i.e.

$$\sum_{i=g_{\min}}^{B_1} His(i) = f_1 \tag{4}$$

$$\sum_{i=B_2}^{g_{\max}} His(i) = f_1$$

Step 5: Determine parameters a and c as follows:

$$\begin{aligned} & a = (1-f_2)(g_1 - g_{\min}) + g_{\min} \\ & if\ (a > B_1) \quad then \quad a = B_1 \\ & c = f_2(g_{\max} - g_n) + g_n \\ & if\ (c < B_2) \quad then \quad c = B_2 \end{aligned} \tag{5}$$

f1, f2 are used to eliminate the noise for very low and high gray levels. If these two parameters are too large, they will lose some useful information, and if they are too small, it will not remove noise effectively. In this paper, we choose f1 = 0.01 and f2 = 0.01. B1 and B2 are used to avoid important information loss. The gray level less than B1 may be considered as the background, and the gray level larger than B2 may be considered as noise.

Step 6: Determine parameter b based on maximum entropy principal.

The fuzzy entropy represents the degree of ambiguity of an image. Fuzzy entropy is defined by the following formula [18]:

$$H(X) = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} S_n\left(\mu_X(g_{ij})\right) \tag{6}$$

Where, $S_n(\ )$ is the Shannon function. It is computed as follows:

$$S_n\left(\mu_X(g_{ij})\right) = -\mu_X(g_{ij})\log_2 \mu_X(g_{ij}) - \left(1-\mu_X(g_{ij})\right)\log_2\left(1-\mu_X(g_{ij})\right)$$
$$i = 1,2,\cdots,M;\ j = 1,2,\cdots N \tag{7}$$

The maximum fuzzy entropy principle states that for greater values of entropy, there is more information within the system [14, 18-19]. We will try every $b \in [a+1, c-1]$ to get the optimal b, by which it will have the largest H(X).

$$H_{\max}(X, a, b_{opt}, c) = \max\{H[X; a, b, c] \mid g_{\min} \le a < b < c \le g_{\max}\} \tag{8}$$

After the parameters *a*, *b*, *c* are determined, we can map the given image from a space domain (g_{ij}) to a fuzzy domain ($\mu_x(g_{ij})$).

B. *Fuzzy Measure*

Here, as the degree of fuzziness is reduced, the values between 0 and 0.5 are driven nearer to 0. Similarly, values ranging between 0.5 and 1 are moved closer to 1. In other words, as the value of n increases the fuzzy measure is reduced, which translates into a higher contrast for the image.

$$T(\mu_{ij}) = 2 * \mu_{ij}^{\,n} \ ; \quad 0 \le \mu_{ij} \le 0.5$$
$$T(\mu_{ij}) = 1 - 2 * \left(1 - T(\mu_{ij})\right)^n \ ; \ 0.5 \le \mu_{ij} \le 1 \tag{9}$$

III. OBSERVATIONS

In this study, a set of 80 TIF fingerprint images are used to run the experiments on. Here, the proposed CFC method is compared with other edge detection methods. The observations indicate that CFC method performs well on images with clear boundaries. The cell image processed using fuzzy logic displays a high contrast. It is easier for edge detector to make edge detection.

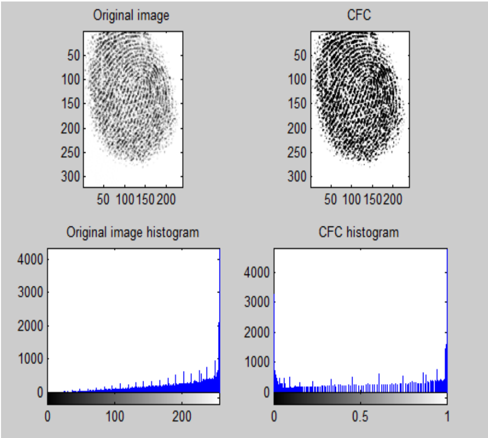
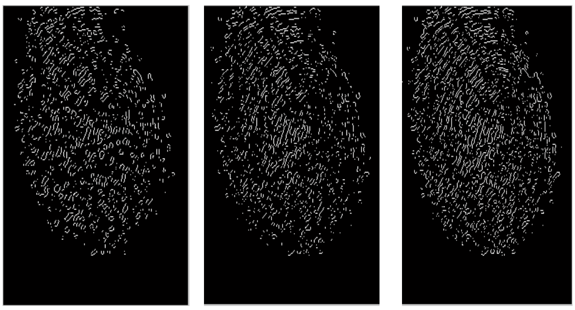


Figure 2: image and histogram plot of an original and CFC fingerprint image (with n = 2)

As can be seen in the histograms above, it is clear that the concentration of pixels is redistributed towards the extremities of the range. Comparing the two images in Figure 2, the improvement in contrast too is clearly obvious. In this experiment, the value of n is set at 2. At the next stage of this experiment, three different edge detections are performed; 1) edge detection is applied to the original image, 2) edge detection applied to the image produced by entropy, 3) and finally, edge detection is performed on the hybrid fuzzy CFC image.



a)original edges b)fuzzy entropy edges c) CFC edges(with n = 2)

Figure 3: edge detection on an image with three feature extraction methods

As demonstrated in Figure 3, the application of edge detection on the original image displays a significant loss of edge data. This loss of data can be explained by the low resolution of the original image. In the original image, the low resolution is compounded with the noise introduced by the dirt on the fingertip to produce a weak edge detection result. In the second image, there is a visible improvement in the edge detection results. This is due to fuzzification method described in the previous section (based on the maximization of entropy). However, the histogram distribution does not display a shift towards values 0 and 1. Nonetheless, there are more features in the second image than the original image for edge detection. In the last image however, produced from the application of CFC method, there is a significant amount of data present for improving the edge detection results.

The experiment is repeated for higher values of n. As it can be seen in the following images, produced using different values of n, a trend emerges that shows a correlation between fuzzy measure and edge detection. As the fuzzy measure decreases (due to increase in the value of n), the edge detection algorithm produces better results. Figure 6 demonstrates the edge detection accuracy as fuzzy measure decreases (for increasing values of n).

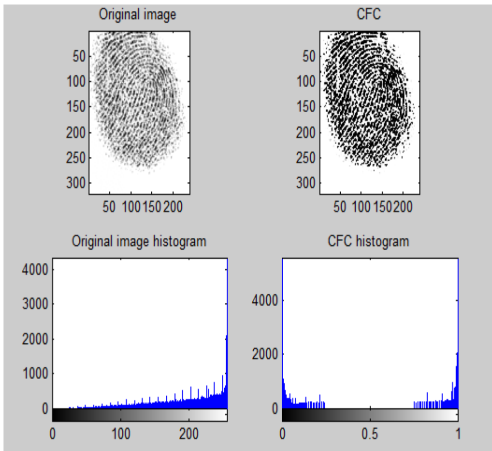
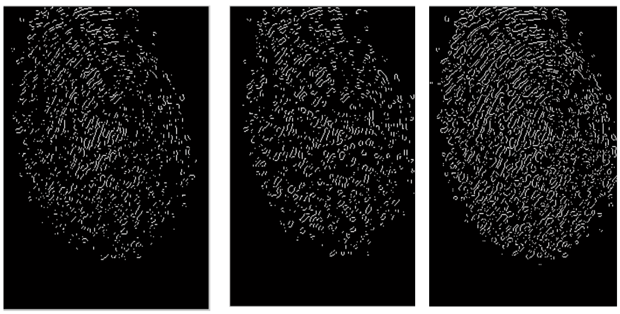


Figure 4: image and histogram plot of an original and CFC fingerprint image (with n = 3)



a)original edges b)fuzzy entropy edges c) CFC edges (with $n = 3$)

Figure 5: edge detection on an image with three feature extraction methods

Original image　　Original edges

CFC image (with n = 1)　CFC image (with n = 2)　CFC image (with n = 3)　CFC image (with n = 4)

CFC edges (with n = 1)　CFC edges (with n = 2)　CFC edges (with n = 3)　CFC edges (with n = 4)

Figure 6: images with related edges

IV. CONTRAST MEASURE

While photographers may have developed an eye for the contrast, it is recommended to avoid subjective measures to determine the proposed contrast improvement. For these purposes, a numerical value is presented here to indicate the contrast improvement.

Since contrast is viewed as the grey level variation in an image, it is proposed to determine the image contrast improvement as an average grey level difference between the original image and the produced image. The higher the contrast measure value (C_m), there is more contrast in the produced image.

$$C_m = \frac{\sum_{i=1}^{n} |po_i - pp_i|}{n} \qquad (10)$$

Where, po_i is the grey value for the i^{th} pixel in the original image and pp_i is the grey value for the ith pixel in the produced image. Here, n is the total number of pixels in an image. Table 1 gives the contrast measure for the produced images using the CFC method and n value ranging from 1 to 4. the table indicates that as the value of n increases, so does the contrast measure for the image.

	Contrast Measure
n = 1	0.2492
n = 2	0.2654
n = 3	0.3036
n = 4	0.3327

Table 1: distance measure for a sample picture

V. CONCLUSION

In this paper, we have proposed a hybrid fuzzy-based parameterized edge detector. In other words, this paper endeavors to map an image onto a fuzzy space. In an experiment performed on 80 fingerprint images, it has been shown that the proposed edge detection method is adequate for applications sensitive to edge detection and contour detection such as face and fingerprint recognition. The proposed method does not distort the shape of objects in an image. Furthermore, it is able to retain much of the important edge information. For future directions, we intend to conduct a quantitative evaluation using known performance evaluation measures to make further comparisons with other popular techniques.

References:

1. Amine A¨IT YOUNES, Isis Truck , Herman AKDAG *Color Image Profiling Using Fuzzy Sets* , Turk J Elec Engin, VOL.13, NO.3 2005
2. Ruz GA, Estévez PA, Perez CA. *A neurofuzzy color image segmentation method for wood surface defect detection*. Forest Prod. J. 55 (4) (2005) 52- 58.
3. A. Moghaddamzadeh and N. Bourbakis. *A fuzzy region growing approach for segmentation of color images*. Pattern Recognition, 30(6):867–881, 1997.
4. G.S. Robinson, "*Color edge detection*", Opt. Eng, 16(5): 479-484, 1977.
5. J. Canny, "*A computational approach to edge detection"*, IEEE Trans. Pattern Anal. Mach. Intell, 8(6): 679-698, 1986.
6. A. Shiji and N. Hamada. *Color image segmentation method using watershed algorithm and contour information*. Proc Inter. Conf. on Image Processing, 4:305 – 309, 1999.
7. Zhang B (2000) Generalized K-harmonic *means–boosting in unsupervised learning*. Technical report HPL-2000–137), Hewlett-Packard Labs

8. Bezdek J (1980) *A convergence theorem for the fuzzy ISODATA clustering algorithms*. IEEE Trans Pattern Anal Mach Intell 2:1–8

9. Ball G, Hall D (1967) *A clustering technique for summarizing multivariate data*. Behav Sci 12:153–155

10. Huang K (2002) *A* synergistic *automatic clustering technique (Syneract) for multispectral image analysis*. Photogrammetric Eng Remote Sens 1(1):33–40

11. Mahamed G. H. Omran Ayed Salman Andries P. Engelbrecht *Dynamic clustering using particle swarm optimization with application in image segmentation* Pattern Anal Applic (2006) 8: 332– 344 DOI 10.1007/s10044-005-0015-5, 2005

12. Timothy J. Ross, Fuzzy Logic with Engineering Application, 2nd Edition, Wiley, 2004.

13. T. J. Ross, Fuzzy Logic with Engineering Applications, McGraw-Hill, New York, 1995.

14. H. D. Cheng and J. G. Li, "Fuzzy Homogeneity and Scale Space Approach to Color Image Segmentation," Pattern Recognition. Vol. 35, 373-393, 2002.

15. Zadeh, et al., Eds., "Fuzzy Sets and Their Application to Cognitive and Decision Processes," Academic Press, London, 1-39, 1975.

16. H. D. Cheng, J. R. Chen, "Automatically Determine the Membership function Based on the Maximum Entropy Principle", Intelligent Systems, Vol. 96, 163-182, 1997.

17. H. D. Cheng, J. L. Wang, X. J. Shi, "Microcalcification Detection using Fuzzy Logic and Scale Space Approaches", Pattern Recognition. Vol. 37, 363-375, 2004.

18. S. K. Pal, D. K. D. Majumder, Fuzzy Mathematical Approach to Pattern Recognition, John Wiley & Sons, 1986.

19. H. D. Cheng and Huijuan Xu, "A novel Fuzzy Logic Approach to Contrast Enhancement", Pattern Recognition, Vol 33, 809-919, 2000.

20. Fingerprint dataset http://bias.csr.unibo.it/fvc2000/default.asp