Effective Histogram Thresholding Techniques for Natural Images Using Segmentation

K. K. Thanammal, R. R. Vijayalakshmi, and S. Arumugaperumal
Department of Computer Science, S. T. Hindu College, Nagercoil
Email: {thanaravindran, vijimphil86, arumugam.visvenk}@gmail.com

J. S. Jayasudha
Sri Chitirai Tirunal College of Engineering, Triuvandrum
Email: jayasudhajs@gmail.com

***Abstract*—Segmentation subdivides an image into its constituent regions or objects. Segmentation should stop when the objects of interest have been isolated. In this paper, histogram based segmentation method is proposed. The fuzzy based segmentation algorithm prefers natural images for experimental purpose. Segmentation based on histogram threshold is a method to divide an image containing two regions namely objects and background. Here the optimal threshold can be obtained by finding the similarity between gray levels. Two initial regions should be located at the boundary of histogram, and then by using the index of the fuzziness the optimal threshold point could be found. Object is assigned to dark and the background is assigned to bright. List of modes is a feature that better describes a 1D histogram, a proper segmentation can be obtained by determining appropriate thresholds separating the modes in thehistogram.**

***Index Terms*—fuzzy set theory, fuzzy logic, index of fuzziness, histogram threshold**

I. Introduction

Image segmentation is awidelyused research area. Segmentation is to distinguish objects from background. Segmentation of image also entails the division or separating of the image into regions of similar attributes. There are many approaches available for segmentation of images

The segmentation technique used here is segmentation based on Histogram Threshold [2]. Histograms are largely used in image analysis and data analysis for reasons that they proved a compact representation of large amount of data. It is also possible to conclude global properties of the data from the behavior of their histogram.

Histogram Thresholding

Suppose that the gray-level histogram corresponds to an image *f(x,y*), composed of dark objects and background pixels have gray levels grouped into two dominant modes. One obvious way to extract the objects from the background is to select a threshold 'T' that separates these modes. Then any point *(x,y)* for which*f (x,y)> T* is called on object point. Otherwise the point is called a background point. If two dominant modes characterize the image histogram, it is called a bimodal histogram. Only one threshold is enough for partitioning the image.

If for example, an image is composed of two types of light object and a dark background, three or more dominant modes characterize the image histogram. In such a case, the histogram has to be partitioned by multiple thresholds. Multilevel thresholding classifies point *(x,y)*as belonging to an object class.

In general, threshold selection can be categorized into two classes, local and global methods. Using global thresholding methods an entire image is binarized with a single threshold, while the local methods divides the given image into a number of sub-images and select a suitable threshold for each sub-image. The global thresholding techniques [10] are easy to implement and less demanding. Therefore they are more suitable then local methods in terms of many real image processing applications.

II. Materials and Methods

A. Fuzzy Set Theory

Fuzzy set [1] theory assigns a membership degree to all elements among the universe of discourse according to their potential. The membership degree can be expressed by a mathematical function μ_A (x_i) that assigns a membership degree between 0 and 1

A fuzzy set A in X is given by

$$\boldsymbol{A} = \{(\boldsymbol{x_i}, \boldsymbol{\mu_A}(\boldsymbol{x_i}))|\boldsymbol{x_i} \in \boldsymbol{X}\} \qquad (1)$$

where X- is the universe of discourse, A is the fuzzy set and x_i element of X

The '**S**' function is used for modeling the membership degrees. The S function is used to represent the set of bright pixels.

The set of bright pixels is given by

$$\boldsymbol{\mu_{AS}}(\boldsymbol{x}) = \boldsymbol{S}(\boldsymbol{x}; \boldsymbol{a}, \boldsymbol{b}, \boldsymbol{c})$$

Manuscript received July 1, 2014; revised December 14, 2014.

doi: 10.12720/joig.2.2.113-116

$$= \begin{cases} \mathbf{0}, & x \le a \\ \mathbf{2}\left\{\frac{(x-a)}{(c-a)}\right\}^{\mathbf{2}} & a \le x \le b \\ \mathbf{1}-\mathbf{2}\left\{\frac{(x-c)}{(c-a)}\right\}^{\mathbf{2}} & b \le x \le c \end{cases} \quad (2)$$

where b= $b = (1/2)(a+c)$ The S function can be controlled through parameters a and c. parameter c is called as the cross over point where $\mu_{AS}(b)=0.5$.

- The higher gray level (closer to white has the higher membership value).
- The lower gray level (closer to black has the lower membership value).
- S function is for modeling the membership value from which higher & lower membership values can be obtained. Z function can be obtained from S function.
- Z- Function is used to represent the dark pixels. And it is defined as

$$\mu_{AZ}(x) = Z(x; a, b, c) = 1 - S(x; a, b, c) \quad (3)$$

B. *Measures of Fuzziness*

A reasonable approach to estimate the average ambiguity in fuzzy sets is measuring its fuzziness. The fuzziness of a crisp set should be zero, as there is no ambiguity about whether an element belongs to the set or not. Kaufmann introduced an index of fuzziness (IF) comparing a fuzzy set with its nearest crisp set

A fuzzy set A* is called crisp set of A if the following conditions are satisfied.

$$\mu_{A*}(x) = \begin{cases} \mathbf{0}, & if\ \mu_A(x) \le \mathbf{0.5} \\ \mathbf{1}, & if\ \mu_A(x) \ge \mathbf{0.5} \end{cases} \quad (4)$$

The Index is calculated by measuring the normalized distance between A and A*defined as

$$\psi_k(A) = \frac{2}{n^{1/k}} \sum_{i=1}^{n} |\mu_A(x_i) - \mu_{A*}(x_i)|^{k}]^{\frac{1}{k}} \quad (5)$$

where n is the number of element in A, kc-[1,ά].depending if k=1 or 2 the index of fuzziness is called linear or quadratic. Such an index reflects the ambiguity in a set of elements. If a fuzzy set shows low index of fuzziness there exists a low ambiguity among elements.

C. *Distribution Hypothesis Testing*

Consider a discrete histogram h=(hi) $_{i=1,2,\ldots L,}$ with N samples on L bins *{1,2,…,L}*. The number h_i is the value of h in the bin *i*. It follows that equation (6)

$$\sum_{i=1}^{L} h_i = N \quad (6)$$

For each discrete interval *[a,b]* of{1,….L}, let *r(a,b)* be the proportion of points in*[a,b]*

$$\text{r (a,b)} = \frac{1}{N}\left(\sum_{i=a}^{b} h_i\right) \quad (7)$$

Assume that an underlying discrete probability *law* $p=(p_i)_{\ i=1\ldots L}$ hypothesized for *h*. For each interval *[a,b]* of*{1…L}* let *p(a,b)* be the probability for a point to fall into the interval*[a,b]* it is as given in the equation (8)

$$\text{P (a,b)} = \sum_{i=a}^{b} P_i \quad (8)$$

D. *Pool Adjacent Violators*

The minimal distance can be obtained by algorithm Pool Adjacent violators Consider the operator $D: P(L) \rightarrow P(L)$ defined by: for $r = (r_i)_{\ i=1\ldots L} \in P(L)$, and for each interval [i,j] on which r is increasing i.e$r_i \le r_{i+1} \le \ldots \le r_j$and r_{i-1} r_i and $r_{j+1}<r_j$, set

$$D(r)_k = \frac{r_i + \cdots r_j}{j-i+1} \textbf{for } \epsilon\textbf{[i,j]} \quad (9)$$

And D(r)k=rk otherwise

This operator D replaces each increasing part of r by a constant value.

$$\mathbf{r} \quad =\mathbf{D^L(r)} \quad (10)$$

E. *Fine to Coarse(FTC) Segmentation Algorithm*

1) Initialize S={ $s_{0\ldots\ldots}\ s_n$}as the finest segmentation of the histogram , i.e, the list of all local minima plus the end points s0=1 and sn=L.
2) Repeat:
   Choose I randomly in *[1, length(S)-1]*. If the pair of segments on both side of si can be merged into a single interval *[s_{i-1},s_{i+1}]* follow the unmoral hypothesis group them. Update S.
3) For j from 3 to l_o repeat step 2 with the unions of j segments.

F. *Performance Evaluation Metrics*

The performance of the algorithm is being evaluated and the results are tabulated in Table1 and Table2.The metrics chosen for evaluation is MSE (Mean Squared Error) and PSNR (Peak Signal to Noise Ration).

Performance Evaluation based on MSE

TABLE I. THE MSE VALUE OBTAINED FOR DIFFERENT IMAGES

Algorithm	Image Chosen	MSE Value
Fuzzy measure	Round.bmp	7093.10
Fuzzy measure	Man.bmp	27894.00
Fuzzy measure	Potato.bmp	23795.00
Fuzzy measure	House.bmp	19957.00
Non parametric approach	Round.bmp	8650.80
Non parametric approach	Man.bmp	28203.00
Non parametric approach	Potato.bmp	26918.00
Non parametric approach	House.bmp	12969.00

The Table I represents the MSE values of various images. Here the Fuzzy measure algorithm shows lower errors when compared to Non Parametric approach. The MSE value can be calculated by (11).

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1} \sum_{j=0}^{n-1}[I(i,j) - K(i,j)] \quad (11)$$

Performance Evaluation based on PSNR

The Table II represents the PSNR values of various images. The Fuzzy measure shows better PSNR values than the non parametric approach. PSNR can be defined by (12)

$$PSNR = 10.log_{10}\left(\frac{MAX_I^2}{MSE}\right) \quad (12)$$

$$=20.log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right)$$

TABLE II. THE PSNR VALUE OBTAINED FOR DIFFERENT IMAGES

Algorithm	Image Chosen	PSNR Value
Fuzzy measure	Round.bmp	8.7602
Fuzzy measure	Man.bmp	3.6278
Fuzzy measure	Potato.bmp	3.8304
Fuzzy measure	House.bmp	7.0017
Non parametric approach	Round.bmp	9.6224
Non parametric approach	Man.bmp	3.6757
Non parametric approach	Potato.bmp	4.3660
Non parametric approach	House.bmp	5.1299

III. EXPERIMENTAL RESULTS

To illustrate the chosen algorithm three images are chosen. A manually generated ground truth images has been defined as a gold standard. The Fig. 1 shows Histogram and segmented image of an original image. Here the Histogram can be obtained by using the Hist function in MATLAB and then by applying the Fuzzy concepts and finding the index of Fuzziness the foreground is assigned to dark and the background is assigned to bright.

Original Image Histogram Segmented Image

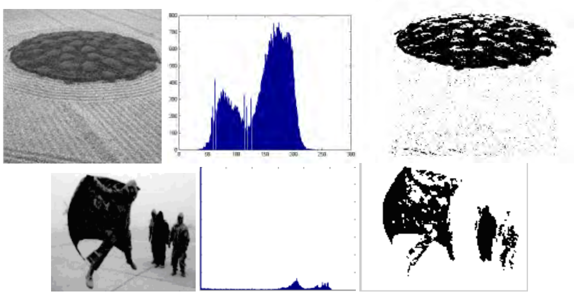
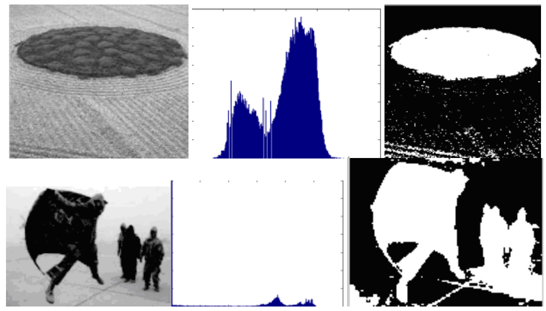


Figure 1. The original image, histogram segmented image.

The Fig. 2 shows the Original Image, Histogram and Segmented Image. The results are obtained by applying the non parametric algorithm. The Histogram Image shows the list of modes available in the image and then by applying the FTC segmentation algorithm the final segmented image can be obtained. Here the foreground is assigned as bright and the background is assigned dark.



Original Image Histogram Segmented Image

Figure 2. The original image, histogram segmented image.

IV. CONCLUSION

In this paper, histogram threshold approach based on Index of Fuzziness is presented. When a histogram does not exhibit a clear separation ordinary algorithm may not perform well. Fuzzy set theory provides a new tool to deal with multimodal histograms. The initial seed is first calculated and then a similarity process is started to find the threshold point. The property of similarity can be obtained by calculating the index of fuzziness. Popular techniques of histogram analysis may over segment the histogram. FTC is an energy minimizing algorithm gives meaningful number of modes even small modes can be easily found by this method. To measure the performance of the method Mean Squared Error and Peak Signal to Noise Ratio is calculated for different images and it is compared with non parametric method. It is concluded that Fuzzy Measures has better performance than non parametric approach.This segmentation process act as preliminary process because any other research work can be carried out after segmenting the desired regions. In future the method used can be extended for Medical Images.

REFERENCES

[1] L. A. ZADEH, "FuzzySets," Departmentof Electrical and Electronics Engineering University of California , Information and Control 8, pp. 338-353, 1965.

[2] R. Kumar and T. C. S. Arumugaperumal, "An adaptive fuzzy-based modeling for contrast stretching," *The IUP Journal of Computer Sciences*, vol. 4, no. 2, pp. 24-29, April. 2010.

[3] S. Mathur and A. Ahlawat, "Application of fuzzy logic in image detection," in *Proc. Intelligent Information and Engineering Systems INFOS 2008*, Varna, Bulgaria, June-July 2008.

[4] Y. Li, B. Q. Liu, and B. Zhou, "The application of image edge detection by using fuzzy technique," in *Proc. Electronic Imaging and Multimedia Technology*, November 2004

[5] Y. Becerikli1 and T. M. Karan, "A new fuzzy approach for edge detection," in *Proc*.Computational Intelligence and Bio inspired Systems, June 2005.

[6] G. Aubert, M. Barlaud, O. Faugeras, and S. Jehan-Basson, "Image segmentation using active contours: Calculus of variations or shape gradients?" *SIAM Applied Math*, vol. 63, no. 6, pp. 2128-2154, 2003.

[7] D. Comaniciu and P. Meer, "Mean shift: A robust approach toward feature space analysis," *IEEE Trans. Pattern Anal. MachIntell.* vol. 24, no. 5, pp. 603-619, May 2002.

[8] A. Desoneux, L. Moisan, and J. M. Morel, "A grouping principle and four applications," *IEEE Trans. .Pattern Anal. Mach. Intell.* vol. 25, no. 4, pp. 508-513, April, 2003.

[9] K. N. Kanpur, P. K. Sahoo, and A. K. C. Wong, "A new method for gray level picture thresholding using the entropy of the histogram," *Graph Models Image Process.* vol. 19, no. 1, 1986.

[10] Y. Solihin and C. G. Leedham, "Integral ratio: A new class of global thresholding techniques for handwriting images," *IEEE Transaction on Pattern Analysis and Machine Intelligence*, vol. 21, no. 8, August, 1999.