Implementation of object oriented approach to Automatic Histogram Threshold based on Fuzzy Measures

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Abstract— **Image segmentation plays an important role in computer vision and image processing applications. This is one of the most difficult tasks in image processing. Previously various authors proposed different methods, but still there is a problem. To fulfill this, in this paper, we present a new method for image segmentation based on histogram thresholding by means of a fuzzy set theoretical measure. The threshold is calculated by measuring the index of fuzziness of background and object sets. The experimental results say that this method somehow better compared to other methods.**
Index Terms— **Digital Image Processing, Image segmentation, fuzzy logic**

I. INTRODUCTION

Typical computer vision applications usually require image *segmentation* or *object isolation* preprocessing algorithm as a first procedure. Thus, at this stage, each object of the image must be isolated from the rest of the scene into non-overlapping regions. The image segmentation process can be approached from two different ways. The first approach is called *region approach,* in which one assigns pixels to particular objects or regions. In the second one, the *boundary approach,* we seek just to locate the boundaries among the regions.

Next, we search to find closed boundaries and to decide if the inner pixels are object or background pixels. The region approach uses the image gray-level histogram to isolate the objects from the background. Various techniques have been proposed in this regard. In an ideal case, the image histogram has a deep valley between two peaks. These peaks represent the object and background gray levels. Then, by setting a threshold in the valley region, we can separate the objects from the background. By using a segmentation technique, we can find a threshold level. So, we assign the pixels above the gray-level threshold to the object and the pixels below it to the background. The key to minimize the pixel misclassification rate is to find the correct threshold level to separate these two pixel sets.

Several methods for histogram thresholding have been proposed in the literature [1,2]. They possess different levels of computational complexity. Some methods, [1,3], use a probabilistic approach to achieve the pixel separation. Others, [4] and [5], use the theory of fuzzy sets and entropy approaches to determine the threshold level in the image histogram. These techniques work very well when the image gray-level histograms are bimodal or nearly bimodal, but they fail when the image gray-level histograms are multimodal. To segment images that present multimodal gray-level histograms, we need more elaborate methods, which are normally more expensive computationally.

In this paper, we propose a new segmentation method to images. The method used is based on the theory of fuzzy sets.

II. LITERATURE SURVEY

Thresholding the histogram of an image, due to its simplicity and ease of implementation has been a popular technique used in various low-level image processing tasks. A plethora of bilevel histogram thresholding techniques exist in literature for purposes such as separating the foreground from the background in images [6]–[10] and removing the spurious edges during edge detection [11], [12]. Multilevel histogram thresholding finds application in partitioning an image into different regions [6], [13].

Comprehensive reviews of various histogram thresholding techniques are available in [14] and [15]. Most of these histogram thresholding algorithms are based on optimizing certain criteria, searching certain features such as "valleys" and "shoulders," or decomposing the histogram on the basis of modeling. However, as mentioned in [16], such methods would perform satisfactorily only when the histogram is "well-defined" with respect to the technique used, that is, when the histogram meets the prior assumptions made about it. Some examples of histograms being "well-defined" are those which posses specific characteristics such as prominent "valleys" or "peaks," fit a particular model very well, or whose regions can be appropriately described using certain homogeneity measures.

However, in practice, one can not guarantee that images having "well-defined" histograms will be encountered. Hence, it is desirable to have thresholding techniques that do not depend on whether the histogram is "well-defined" or not.

A. Categories and Preliminaries

We categorize the thresholding methods in six groups according to the information they are exploiting. These categories are:

- Histogram shape-based methods, where, for example, the peaks, valleys and curvatures of the smoothed histogram are analyzed
- clustering-based methods, where the gray-level samples are clustered in two parts as background and foreground, or alternately are modeled as a mixture of two Gaussians
- entropy-based methods result in algorithms that use the entropy of the foreground and background regions, the cross-entropy between the original and binarized image, etc.
- object attribute-based methods search a measure of similarity between the gray-level and the binarized images, such as fuzzy shape similarity, edge coincidence, etc.
- the spatial methods use higher-order probability distribution and/or correlation between pixels
- local methods adapt the threshold value on each pixel to the local image characteristics.

III. PROPOSED SYSTEM ARCHITECTURE

A. Introduction to Fuzzy Logics

Fuzzy logic is a powerful problem-solving methodology with a myriad of applications in embedded control and information processing.

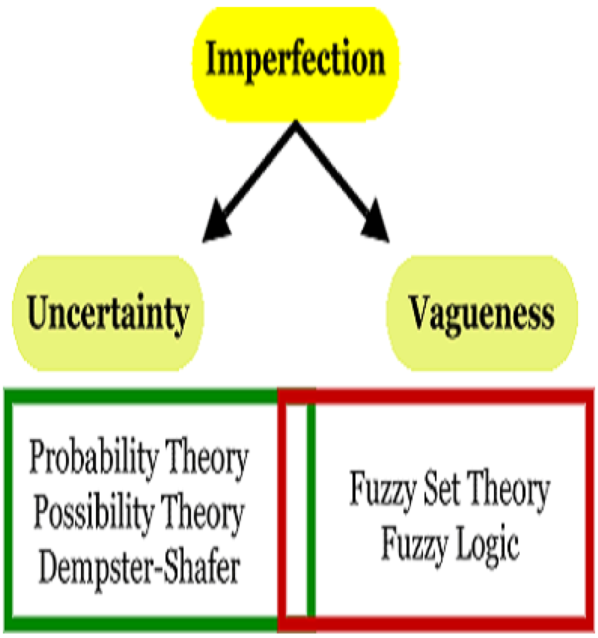

Fig 1: Imperfection and theories to handle it.

Fuzzy provides a remarkably simple way to draw definite conclusions from vague, ambiguous or imprecise information. In a sense, fuzzy logic resembles human decision making with its ability to work from approximate data and find precise solutions. As shown in Figure 1 fuzzy logic and probability theory are the most powerful tools to overcome the imperfection. Unlike classical logic which requires a deep understanding of a system, exact equations, and precise numeric values, fuzzy logic incorporates an alternative way of thinking, which allows modeling complex systems using a higher level of abstraction originating from our knowledge and experience. Fuzzy logic allows expressing the knowledge with subjective concepts such as very hot, bright red and very small height, which are mapped into exact numeric ranges.

B. Structure of Fuzzy Image Processing

Fuzzy image processing is not a unique theory. Fuzzy image processing is the collection of all approaches that understand, represent and process the images, their segments and features as fuzzy sets.

Fig 2: The general structure of fuzzy image processing

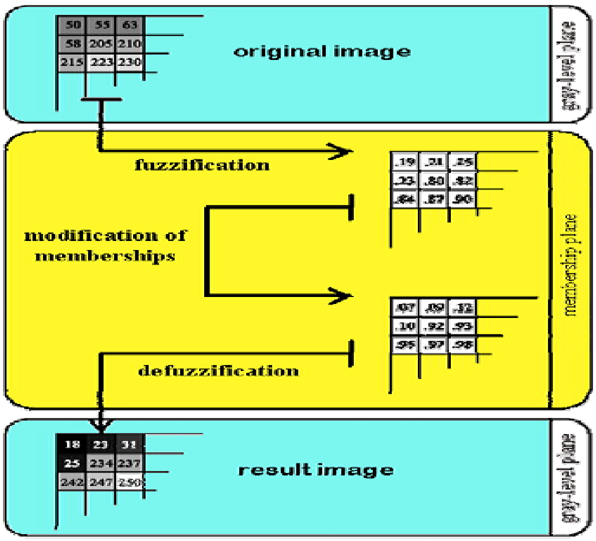

Fig 3: Steps of Fuzzy Image Processing

The representation and processing depend on the selected fuzzy technique and on the problem to be solved. Fuzzy image processing has three main stages: image fuzzification, modification of membership values, and, if necessary, image defuzzification. The fuzzification and defuzzification steps are due to non availability fuzzy hardware. Therefore, the coding of image data (fuzzification) and decoding of the results (defuzzification) are steps that make possible to process images with fuzzy techniques. The main power of fuzzy image processing is in the middle step i.e. modification of membership values, Figure.4.3. After the image data are transformed from gray-level plane to the membership plane (fuzzification), appropriate fuzzy techniques modify the membership values.

C. Proposed Method

The concept presented above sounds attractive but has some limitations concerning the initialization of the seed subsets. In these subsets should contain enough information about the regions and its boundaries are defined manually. The proposed method in this paper aims to overcome some of the limitations of the existing method.

Infact, the initial subsets are defined automatically and they are large enough to accommodate a minimum number of pixels defined at the beginning of the process. This minimum depends on the image histograms hape and it is a function of the number of pixels in the gray level intervals [0,127] and[128,255]. It is calculated as follows:

$$\mathrm{MinPix}_{\mathrm{Bseed(Wseed)}} = P_1 \sum_{i=0(128)}^{127(255)} h(x_i)$$

where and denotes the number of occurrences at graylevel . Equation(7) can be seen as a special case of a cumulative histogram. However, in images with low contrast, the method performs poorly due to the fact that one of the initial regions contain a low number of pixels. So, previous histogram equalization is carried out in images with low contrast aiming to provide an image with significant contrast. If the number of pixels belonging to the gray level intervals or is smaller than a value defined by, where and, are the dimensions of the image, the image histogram is equalized. Equalization is carried out using the concept of cumulative distribution function[21]. The probability of occurrence of gray level in an image is approximated by

$$p(x_i) = \frac{h(x_i)}{MN}.$$

For discrete values the cumulative distribution function is given by

$$T(x_i) = \sum_{k=0}^{i} p(x_k) = \sum_{k=0}^{i} \frac{h(x_k)}{MN}. \qquad (9)$$

Thus, a processed image is obtained by mapping each pixel with level x_i in the input image into a corresponding pixel with level $s_i = T(x_i)$ in the output image.

D. Experimental Results

Fig 4(a) Inputs of Proposed System

Fig 4(b) outputs of Proposed System

Fig 4(c) Inputs of Proposed System

Fig 4(d) outputs of Proposed System

IV. CONCLUSIONS

We have introduced in this paper a new procedure for image segmentation based on the fuzzy set theory. The pixels of the objects and of the background are separated by histogram thresholding. The threshold level is obtained by means of the measurement of the linear index of fuzziness on the image gray-level histogram using a very simple algorithm. Comparisons to other thresholding techniques showed that the proposed method is a good alternative to deal with multimodal histograms. It is particularly attractive for real-time applications because histogram-segmentation based methods are simpler and therefore faster than the other ones.

References

[1]. N. Otsu, "A threshold selection method from gray-level histograms," IEEE Trans. on Syst., Man, and Cybem., vol. 9, no.1, pp. 62-66, 1979.
[2]. N. R. Pal and S K. Pal, "Entropy: A new defition and its applications," IEEE Trans. on Syst., Man, and Cybem., vol. 21, no.5, pp. 1260-1270,1991.
[3]. D. E. Lloyd, "Automatic target classification using moment invariants of image shapes," Farnborough, UK. Rep. RAE IDN AW126, Dec. 1985.
[4]. T. W. Ridler and S. Calvard," Picture thresholding using an iterative selection method," IEEE Trans. on Syst., Man, and Cybem., vol. 8, pp. 630-632, 1978.
[5]. S. K. Pal, R. A King and A A Hashim "Automatic gray level thresholdma through index offuzziness and entropy," Pattern Recogni%on Letters, vol. 1, p;141-146, 1983.
[6]. N. Otsu, "A threshold selection method from gray-level histogram," IEEE Trans. Syst., Man, Cybern., vol. SMC-9, no. 1, pp. 62–66, Jan.1979.
[7]. J. N. Kapur, P. K. Sahoo, A. K. C.Wong, and C.Wong, "A new method for gray-level picture thresholding using the entropy of the histogram," Comput. Vis., Graph., Image Process., vol. 29, pp. 273–285, 1985.
[8]. J. Kittler and J. Illingworth, "Minimum error thresholding," Pattern Recognit., vol. 19, no. 1, pp. 41–47, 1986.
[9]. S. K. Pal, R. A. King, and A. A. Hashim, "Automatic grey level thresholding through index of fuzziness and entropy," Pattern Recognit. Lett., vol. 1, no. 3, pp. 141–146, 1983.
[10]. W.-H. Tsai, "Moment-preserving thresholding: A new approach," Comput. Vis., Graph., Image Process., vol. 29, pp. 377–393, 1985.
[11]. P. L. Rosin, "Unimodal thresholding," Pattern Recognit., vol. 34, no. 11, pp. 2083–2096, 2001.
[12]. P. V. Henstock and D. M. Chelberg, "Automatic gradient threshold determination for edge detection," IEEE Trans. Image Process., vol. 5, no. 5, pp. 784–787, May 1996.
[13]. J.-S. Lee, M. C. K. Yang, and K. Yang, "Threshold selection using estimates from truncated normal distribution," IEEE Trans. Syst., Man, Cybern., vol. 19, no. 2, pp. 422–429, Feb. 1989.

[14]. M. Sezgin and B. Sankur, "Survey over image thresholding techniques and quantitative performance evaluation," J. Electron. Imag., vol. 13, no. 1, pp. 146–168, 2004.
[15]. P. K. Sahoo, S. Soltani, A. K. C. Wong, and Y. C. Chen, "A survey of thresholding techniques," Comput. Vis. Graph. Image Process., vol. 41, no. 2, pp. 233–260, 1988.
[16]. O. J. Tobias and R. Seara, "Image segmentation by histogram thresholding using fuzzy sets," IEEE Trans. Image Process., vol. 11, no. 12, pp. 1457–1465, Dec. 2002.