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# IMAGE ENHANCEMENT BASED ON FUZZY LOGIC AND THRESHOLDING TECHNIQUES



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# ABSTRACT

An automatic histogram threshold approach based on a fuzziness measure is presented in this paper. This work is improvement of an existing method. Using fuzzy logic concepts, the problems involved in finding the minimum of a criterion function are avoided. Similarity between gray levels is the key to find optimal threshold. Two initial regions of gray levels, located at the boundaries of the histogram, are defined. Then, using an index of fuzziness, a similarity process is started to find the threshold point.

**Key words:** Fuzzy logics. Thresholding Technique, Image Segmentation, Image Enhancement.

## **1. INTRODUCTION**

Typical computer vision applications usually require an Image Enhancement is the simplest and most appealing areas of digital image processing. Basically, the idea behind enhancement technique is to bring out detail that is obscured, or simply to highlight certain features of interest in an image [1]. Ex:- to increase the contrast of an image, "so that it looks better'. : Image Enhancement alters an image to makes its meaning clearer to human observers [2]. It is often used to increase the contrast in images that are substantially dark or light. Enhancement algorithms often play attention to humans' sensitivity to contrast. The goal of our project is to segment the given image based on fuzzy measures. This type of segmentation is done automatically without the use of image histogram. This eliminates the need for finding the threshold manually for images with more noise level. Our project is mainly useful in classification and analysis of objects in an image. 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 [3]. 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 [5]. 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, as shown in Fig. 1, 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 possess different levels of computational complexity. Some methods use a probabilistic approach to achieve the pixel separation [7]. 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, as that shown in Fig. 2. To segment images that present multimodal gray-level histograms, we need more elaborate methods, which are normally more expensive computationally [8].



Fig1. (a) Gray-level histograms that can be partitioned by (a) a single threshold, and (b) multiple thresholds

In this paper, we propose a new segmentation method to images that have multimodal gray-level histograms. The main method used is based on the theory of fuzzy sets [10]. The aim method is to determine the threshold location in the image of histogram. Some experimental results are presented to illustrate the effectiveness of the proposed approach these peaks represent the object and background gray levels. Then, by setting a threshold in the valley region, as shown in Fig. 1, 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 N. Janaki Devi et al., International Journal of Advanced Trends in Computer Science and Engineering, 3(6), November-December 2014, 102-106

key to minimize the pixel misclassification rate is to find the correct threshold level to separate these two pixel sets. Several methods for ham thresholding have been proposed in the literature [12].

# 2. FUZZY LOGIC

Fuzzy logic is a powerful problem-solving methodology with a myriad of applications in embedded control and information processing. 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 fuzzy logic and probability theory are the most powerful tools to overcome the imperfection. Fuzzy logic and Fuzzy set theory provide a rich and meaningful addition to standard logic. The mathematics generated by these theories is consistent, and fuzzy logic may be a generalization of classic logic. Fuzzy Logic has been gaining increasing acceptance during the past few years. There are over two thousand commercially available products using Fuzzy Logic, ranging from washing machines to high speed trains. Nearly every application can potentially realize some of the benefits of Fuzzy Logic, such as performance, simplicity, lower cost, and productivity.

#### 2.1. Fuzzy set theory

Fuzzy set theory assigns a membership degree to all elements among the universe of discourse according to their potential to fit in some class. The membership degree can be expressed by a mathematical function  $\mu_A(x_i)$  that assigns, to each element in the set, a membership degree between 0 and 1.Let be the universe (finite and not empty) of discourse and  $\mathcal{I}_i$  an element of .A fuzzy set A in X is defined as

$$A = \{(x_i, \mu_A(x_i)) | x_i \in X\}.$$

The S –function is used for modeling the membership degrees. This type of function is suitable to represent the set of bright pixels and is defined as

$$\begin{split} \mu_{AS}(x) = S(x; a, b, c) \\ &= \begin{cases} 0, & x \leq a \\ 2\left\{\frac{(x-a)}{(c-a)}\right\}^2, & a \leq x \leq b \\ 1 - 2\left\{\frac{(x-c)}{(c-a)}\right\}^2, & b \leq x \leq c \\ 1, & x \geq c \end{cases} \\ \text{where } b \ = \ (1/2)(a + c). \end{split}$$

The S-function can be controlled through parameters **a** and **c**. Parameter **b** is called the cross over point where  $\mu_{AS}(b) = 0.5$ . The higher the gray level of a pixel (closer to white), the higher membership value and vice versa. A typical shape of the **S** –function is presented in Fig.1.The **S**-function is used to represent the dark pixels and is defined by an expression obtained from S-function as follows:

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

Both membership functions could be seen, simultaneously, in Fig.3.The S-function in the right side of the histogram and the Z-function in the left.



Figure: 2. Typical shape of the S-function function



Figure: 3. Histogram for the seed subsets

## 2.2. Fuzzy sets and membership functions

If X is a collection of objects denoted generically by x, then a "fuzzy set" A in X is defined as a set of ordered pairs:

$$A = \{ (x, \mu_A(x)) \mid x = X \}. (2.1)$$

Where  $\mu_A(x)$  is called "membership function" (or MF for

short) for the fuzzy set A.

The MF maps each element of X to a membership grade (or membership value) between 0 and 1.

Obviously, the definition of a fuzzy set is a simple extension of the definition of a classical set in which the characteristic function is permitted to have any values between 0 and 1. If the values of the membership function  $\mu_A(x)$  is restricted to either 0 or 1, then A is reduced to a classical set and  $\mu_A(x)$  is the characteristic function is permitted to have any values between 0 and 1. If the values o f the membership function  $\mu_A(x)$  is the characteristic function is permitted to have any values between 0 and 1. If the values o f the membership function  $\mu_A(x)$  is restricted to either 0 or 1, then A is reduced to a classical set and  $\mu_A(x)$  is the characteristic function  $\mu_A(x)$  is restricted to either 0 or 1, then A is reduced to a classical set and  $\mu_A(x)$  is the characteristic function of A

## 2.3. 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 these t or N. Janaki Devi et al., International Journal of Advanced Trends in Computer Science and Engineering, 3(6), November-December 2014, 102-106

not. If  $\mu_A(x) = 0.5, \forall x$ , the set is maximally ambiguous and its fuzziness should be maximum. Degrees of membership near 0 or 1 indicate lower fuzziness, as the ambiguity decreases. Kaufmann in 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:

$$\mu_{A^*}(x) = \begin{cases} 0, & \text{if } \mu_A(x) < 0.5 \\ 1, & \text{if } \mu_A(x) \ge 0.5. \end{cases}$$

This index is calculated by measuring the normalized distance between **A** and **A\*** defined as

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

Where n is the number of elements in A,  $k \in [1, \infty[$ . 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 exist a low ambiguity among elements.

#### 2.4. Introduction to Thresholding:

Suppose that the gray-level histogram shown in Fig.10.26(a) corresponds to an image, f(x,y), composed of light objects on a dark background, in such a way that object 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 an *object point*; otherwise, the point is called a *background point*. Fig.1 shows a slightly more general case of this approach, where three dominant modes characterizes the image histogram (for example, two types of light objects on a dark background). Here, multiple thresholding classifies a point (x,y) as belonging to one object class in  $T_1 < (x,y) \le T_2$ , to the other object class if  $f(x,y) > T_2$ , and to the background if  $f(x,y) \le T_1$  In general, segmentation problems requiring multiple thresholds are best solved using region growing methods, which we are going to see in next section. Based on the preceding discussion, thresholding may be viewed as an operation that involves tests against a function T of the form

## T=T[x,y,p(x,y),f(x,y)]

where f(x,y) is the gray level of point (x,y) and p(x,y) denotes some local property of this point- for example, the average gray level of a neighborhood centered on (x,y). A thresholded image g(x,y) is defined as

$$\begin{split} g(x,y) &= 1 \quad \text{if } f(x,y) > T \\ 0 \text{ if } f(x,y) &\leq T. \end{split}$$

Thus, pixel labeled 1(or any other convenient gray level) corresponds to objects, whereas pixels labeled 0(or any

other gray level not assigned to objects) corresponds to the background.

When T depends only on f(x,y) (i.e. only on gray level values) the threshold is called **global threshold**. If T depends on both f(x,y) and p(x,y), the threshold is called **local threshold**. If, in addition, T depends on the spatial coordinates x and y, the threshold is called **adaptive or dynamic**.

#### **3. PROPOSED METHOD**

IMAGE segmentation plays an important role in computer vision and image processing applications. Segmentation of nontrivial images is one of the most difficult tasks in image processing. Segmentation accuracy determines the eventual success or failure of computerized analysis procedures. Segmentation of an image entails the division or separation of the image into regions of similar attribute. For a monochrome image, the most basic attribute for segmentation is image luminance amplitude. Segmentation based on gray level histogram thresholding is a method to divide an image containing two regions of interest: object and background. In fact, applying this threshold to the whole image, pixels whose gray level is under this value are assigned to a region and the remainder to the other. Histograms of images with two distinct regions are formed by two peaks separated by a deep valley called bimodal histograms. In such cases, the threshold value must be located on the valley region. When the image histogram does not exhibit a clear separation, ordinary thresholding techniques might perform poorly. Fuzzy set theory provides a new tool to deal with multi modal histograms. It can incorporate human perception and linguistic concepts such as similarity, and has been successfully applied to image thresholding. 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 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:

MinPix<sub>Bseed(Wseed)</sub> = 
$$P_1 \sum_{i=0(128)}^{127(255)} h(x_i)$$

Where and denotes the number of occurrences at gray level. It 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 contains 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 N. Janaki Devi et al., International Journal of Advanced Trends in Computer Science and Engineering, 3(6), November-December 2014, 102-106

by, where and, is the dimensions of the image, the image histogram is equalized. Equalization is carried out using the concept of cumulative distribution function. 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

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

Thus, a processed image is obtained by mapping each pixel with level  $\mathcal{X}_i$  in the input image into a corresponding pixel with level  $s_i = T(x_i)$  in the output image using above equation.

# 4. EXPERIMENTAL RESULTS

The comparative results of image segmentation performed by existing techniques and by that proposed in this work. From these figures, we can see the superior performance of the proposed method. The proposed method allows the segmentation of an image based on its gray-level histogram, while escaping from the use of more complex methods for images with multimodal histogram. This is especially attractive for real-time applications because histogram-segmentation-based methods are simpler and therefore faster than the other ones. Then see the outputs the fig(a) is the original image and the fig(b) is the Noise image and the Fig(c) is the output image. Mainly the concept of the paper is to give the clarity of the image by using the fuzzy thresholding techniques. In the existing system the pixels of the object and the background are separated by Histogram thresholding in that to change the white and gray Values will assign manually and the proposed system to separate the pixels and back ground of the image. In that the values will be assigning automatically.

Existing	proposed
0.5353	0.986
0.536	0.986
0.5394	0.986
0.5472	0.986
0.5528	0.986
0.5592	0.986



Figure: 4. Results & Graph corresponding to Existing & Propoed Methods



Figure: 5(a).Input Image



Figure: 5(b).Noise Image



Figure: 5(c).output Image for the Proposed method

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# 5. CONCLUSIONS

In this paper, an automatic histogram threshold approach based on index of fuzziness measure is presented. This work overcomes some limitations of an existing method concerning the definition of the initial seed intervals. Method convergence depends on the correct initialization of these initial intervals. After calculating the initial seeds a similarity process is started to find the threshold point. This property of similarity is obtained calculating an index of fuzziness. To measure the performance of the proposed method the misclassification error parameter is calculated. For performance evaluation purposes, results are compared with two well established methods: the Otsu's technique and the Fuzzy C-means clustering algorithm. After results analysis we can conclude that the proposed approach presents a higher performance for a large number of tested images.

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