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Efficient Implementation of Niblack Thresholding for MRI Brain Image Segmentation

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***Abstract*— Medical images are most complicated to process by human and computer. Brain tissue donated by magnetic resonance imaging (MRI) is very important issue in many applications such as surgery and treatments. Most common and simplest approach to segment an image is using thresholding. In this work we present an efficient implementation for threshoding and give a detailed comparison of some existing local thresholding algorithm. Niblack thresholding algorithm is implemented on preprocessed input MRI image. The output results are processed under Region Nonuniformity quality metrics and the quality of efficient implementation. Our implementation is suitable for processing the MR brain images, making interactive smooth boundaries to the segmented object.**

***Keywords*— Magnetic resonance imaging, thresholding, Niblack, Region Nonuniformity**

I. Introduction

The gray levels of pixels belonging to the object are entirely different from the gray levels of the pixels belonging to the background, in many applications of image processing. Thresholding becomes then a simple but effective tool to separate those foreground objects from the background. We can divide the pixels in the image into two major groups, according to their gray-level. These gray-levels may serve as “detectors” to distinguish between background and objects is considering as foreground in the image [1]. Select a gray-level between those two major gray-level groups, which will serve as a threshold to distinguish the two groups (objects and background).

Image segmentation is performed by such as boundary detection or region dependent techniques. But the thresholding techniques are more perfect, simple and widely used [2]. Different binarization methods have been performed to evaluate for different types of data. The locally adaptive binarization method is used in gray scale images with low contrast, Varity of background intensity and presence of noise. Niblack’s method was found for better thresholding in gray scale image, but still it has been modified for fine and better result [3].

In this work the input data of the Niblock algorithm is under some preprocess for enhanced the output data. The MRI brain images are naturally having low contrast. This low contrast images also enhanced and produce a better result to analysis the object from the background. The Local Histogram Equalization is enhanced the input image [12], [13]. Histogram Equalization generates a gray map. It changes the histogram of an image and rearranges all pixels values to be as close as possible to a user specified desired histogram. Histogram Equalization enriches the areas of lower local contrast to gain a higher contrast.

This paper is organized as follows, section II is for the purpose of presenting information about image thresholding. Local adaptive thresholding technique is explained detailed in section III. Section IV focused the efficient implementation of Niblack algorithm. Visual results and quality metric results of section IV are discussed in section V. Finally section VI contains the conclusion.

II. Thresholding

Simply the basic function [5] for thresholding creates the binary image from gray level ones by turning all pixels below some threshold to zero and all pixels above that threshold to one [1],[5]. If *g(x, y)* is a threshold version of *f(x, y)* at some global threshold *T*. g is equal to 1 if *f(x, y) T* and zero otherwise [1].

$$g(x, y) = \begin{cases} 0 & if\ f(x, y) < T \\ 1 & if\ f(x, y) \geq T \end{cases}$$

Thresholding techniques can be classified generally into two categories like Global thresholding and Local thresholding. Global thresholding methods consider a single intensity threshold value. Local thresholding methods compute a threshold for each pixel in the image on the basis of the content in its neighbourhood [13]. It considers presences of all intensity level in the image. So the local thresholding methods generally perform better for low quality images [3].

We categorize the thresholding methods in groups according to the information they are exploiting. Histogram shape-based methods, this method used the peaks, valleys and curvatures of the smoothed histogram are analyzed. Clustering-based methods perform where the gray-level samples are clustered in two parts as background and foreground (object). Entropy-based methods result in algorithms that use the cross-entropy between the original and binarized image, the entropy of the foreground and background regions [3], [4]. Object attribute-based methods; search a similarity measure between the gray-level and the binarized images, such as edge coincidence, fuzzy shape similarity. The spatial methods use correlation between pixels and/or higher-order probability distribution. Local methods adapt the threshold value on each pixel to the local image characteristics [4].

III. LOCAL ADAPTIVE THERSHOLDING

The local thresholding method is partitioned the original image into smaller subimages and a threshold value is determined for each of the subimages [6], [3], [9]. This yields some discontinuities in gray level due to a different gray level of two different subimage. The threshold of a region can be calculated by the point-dependent method or the region-dependent method. A smoothing technique is then applied to eliminate the discontinuities of gray level between the subimages [6].

A threshold value is calculated at each pixel, which depends on some local statistics like variance, range, or surface-fitting parameters of the pixel neighbourhood [4]. The threshold value is indicated as a function *T (i, j)* and the coordinates *(i, j)* at each pixel. If this is not possible, the object / background decisions are indicated by the logical variable *B (i, j)* [4]. Niblack and Sauvola methods are used the local image property variance and standard deviation values. The neighbourhood size should be small, it enough to preserve local details, but at the same time large enough to suppress noise [3].

IV. EFFICIENT IMPLEMENTATION OF NIBLACK ALGORITHM

The general description of the efficient implementation local thresholding algorithm procedure is summarized in Fig. 1.

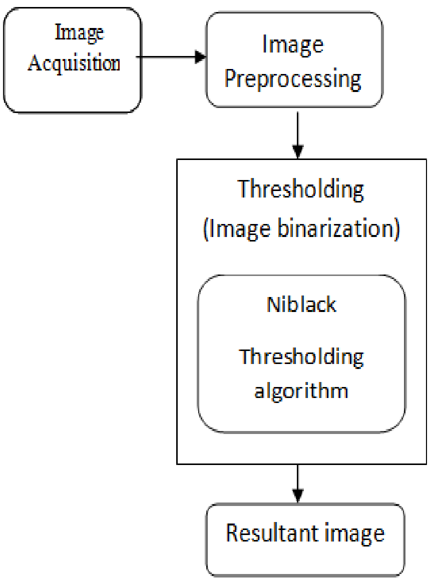


Fig. 1 Block diagram of efficient implementation.

A. Localized Histogram Equalization

An input image stores the pixel values of this image in a buffer. Using these pixel values, various enhancement and modification techniques are to be applied [11]. The input image processed to enhancing its intensity values using histogram algorithm. Histogram equalization is a method to processing the image and adjusts its contrast using the image histogram. Histogram equalization automatically finds a transformation function seeking to produce an output image with a uniform Histogram [12].

Let $X=\{X(i, j)\}$ denotes an image composed of L discrete gray levels denotes as

$$X = \{X_0, X_1, \ldots\ldots, X_K\}$$

Given image, the probability density function $p(X_K)$

$$p(X_K) = \frac{n^K}{n}$$

Where $K=0,1,\ldots\ldots\ldots.L-1$, represents the number of times that $p(X_K)$ the level X_K appear in the input image X, n is the total number of samples in the input image, associated with the histogram of the input image which represents the number of pixels that have a specific intensity X_K.

Based on the probability density function, the cumulative density function is defined as

$$c(x) = \sum_{j=0}^{K} p(x_j)$$

Where $X_K = x$ for $k=0, 1\ldots..L-1$ and $c(X_{L-1})=1$ by definition.

HE is a scheme that maps the input image into the entire dynamic range (X_0, X_{L-1}) by using the cumulative density function as a transform function. A transform function *f(x)* based on the cumulative density function defined as [12].

$$f(x) = X_0 + (X_{L-1} - X_0)c(x)$$

Then the output image of the HE, $Y=\{Y(i, j)\}$can be expressed as

$$Y = f(x)$$

$$= f\{x(i, j) / \forall X(i, j) \in X\}$$

Based on this information the uniform distribution occurred on the input image. This Local Histogram Equalization enhances the contrast of the MRI brain image.

B. Smoothing

The local thresholding method is partition the original image into smaller group of pixels or subimages. A threshold value is determined for each of the subimages [6]. This yields some discontinuities in gray level due to a different gray level of two different subimages [3], [9].

The threshold of a region can be calculated by the point-dependent method or the region-dependent method. A smoothing technique is then applied to eliminate the discontinuities of gray level between the subimages [6].

C. Niblack Thresholding algorithm

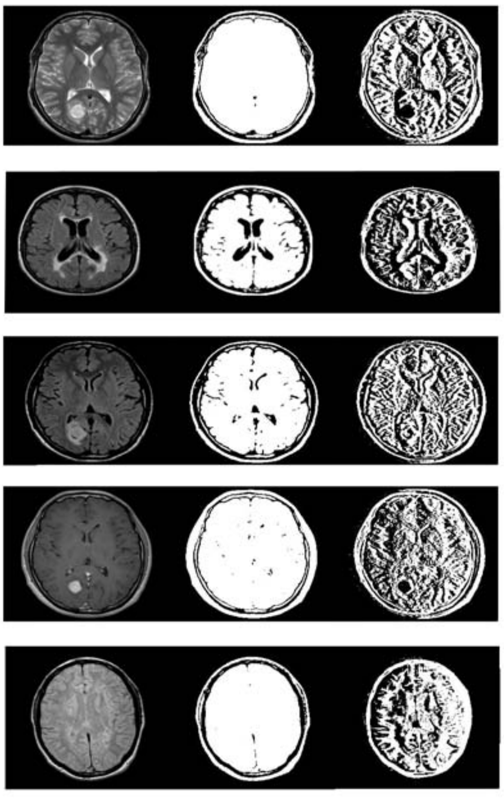
Niblack's algorithm determines a threshold value to each pixel-wise by sliding a rectangular window over the gray level image [7]. The size of the rectangle window may differ. The threshold is calculated based on the local mean m and the standard deviation S of all the pixels in the window and is given by the following derivation [7], [8].

$$T_{niblack} = m + K * S$$
$$= m + K\sqrt{\frac{1}{NP}\sum(p_i - m)^2}$$
$$= m + K\sqrt{\frac{\sum P_i^2}{NP} - m^2}$$

Where NP is the total number of pixels presents in the gray image [7], [8], [9], T represent the threshold value, m is the average value of the pixels p_i, and k is fixed depends upon the noise still live on the background it may be -0.1 or -0.2 [9].

V. RESULTS AND ANALYSIS

A number of images have been binarizcd to evaluate the performance of our efficient implementation algorithm. We have shown a few of them in this paper.



(a) (b) (c)

Fig. 2. (a) Original Image (b) Binary Image produces by Niblack's thresholding algorithm (c) Efficient Implementation of Niblack's algorithm.

We have also binarized the same images Niblack's threshokding algorithm in order to provide comparison. Only low contrasted MRI brain images were taken for experimentation.

Our efficient implementation has recovered as much sharp and accurate foreground object area. This is again an improvement from the Niblack's results. In this experiment there are two normal MRI brain image and three abnormal MRI brain images are taken. From the resultant image the abnormality has been pointed sharply in this work.

D. Quality Metrics

Image thresholding rectify problem when the foreground object constitutes a disproportionately small or large area of the scene, or when the foreground and background gray levels overlapping each other distributions, even resulting in an unmoral distribution [10]. Consequently, misclassified pixels and shape deformations of the object may defiantly affect the quality analysis task. The differing performance features of given thresholding methods, we have used the following five performance criteria: misclassification error, edge mismatch, relative foreground area error, modified Hausdorff distance, and region nonuniformity. Obviously, these five criteria are not all independent. In this criteria there are four methods are using the ground truth image. The region nonuniformity quality measure does not consider the ground truth image to analysis [4].

1. Region nonuniformity: This method does not dependent upon the ground truth image.

$$NU = \frac{|F_T|}{|F_T + B_T|}\frac{\sigma_f^{\ 2}}{\sigma^2}$$

Where σ^2 represents the variance of the whole input image and $\sigma_f^{\ 2}$ represents the foreground variance. F_T is number of pixels present in fore-ground and B_T is number of pixels present in the back ground. It is expected that a well-segmented image will have a nonuniformity measure close to 0, while the worst case of $NU=1$ corresponds to an image for which background and foreground are indistinguishable up to second order moments [4].

The obtained image result from Niblack algorithm and efficient implementation, we got the Region Nonuniformity have been calculated. The values are tabulated in Tabel 1.

TABLE 1.
REGION NONUNIFORMITY VALUES

Sample image	Niblack Algorithm	Efficient implementation of Niblack algorithm
Image 1	0.00058	0.00041
Image 2	0.00099	0.00032
Image 3	0.00074	0.00033
Image 4	0.00015	0.00062
Image 5	0.00671	0.00354

VI. CONCLUSION

This paper has presented comparison of existing Niblack algorithm and the efficient implementation the same algorithm. The results are not only analysis by the visualization. Region nonuniformity is used to analysis the quality of this work. From this work the efficient implementation of Niblack algorithm is suitable for MRI brain images to analysis the abnormality of the image. The thresholding process produces a fine sharp binary image.

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