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Optic Nerve Head Assessment for Glaucoma Detection

Mr. Prasad N. Maldhure
Department of Electronic & Telecommunication
Sinhgad College of Engineering,
Vadgoan (Bk.), Pune 414041, India

Asso. Prof. V. V. Dixit
Department of Electronic & Telecommunication
Sinhgad College of Engineering,
Vadgoan (Bk.), Pune 414041, India

***Abstract*— Glaucoma is an eye disease which leads to vision loss. Detection of Glaucoma is very important because it cannot be cured. There are several methods which are used to detect glaucoma such as intraocular pressure (IOP) measurement, abnormal visual field and damaged optic nerve head assessment. Out of which optic nerve head assessment is more reliable and sensitive .In this method optic disc & optic cup segmentation is used. To extract optic cup & optic disc boundaries from optic nerve head cross-section, it uses adaptive histogram equalization ,SLIC algorithm & texture feature extraction using Gabor filter.**

Keywords*— *Optic disc segmentation, Optic cup segmentation, CDR, gabor filter, SLIC.

I. Introduction

Glaucoma is an eye disease in which an optic nerve is progressively damaged, which causes the vision loss permanently. There are various methods for detection of glaucoma out of which we are using optic nerve head assessment. For extraction of optic disc & optic cup boundaries superpixel based segmentation is used. After which area of cup to disc ratio is calculated i.e., CDR.CDR value is compared with certain threshold value and it is decided whether it is normal or severe glaucoma.

For optic disc & cup segmentation, first step is to enhance the contrast of an image using adaptive histogram equalization .After that superpixel classification method is used for disc & cup segmentation. For segmentation simple linear iterative clustering [3] SLIC algorithm is used which aggregates nearby pixels into superpixels. To classify superpixel as disc or non disc region, feature extraction method using Gabor filter is used.

The paper is ordered as follows: in section 2, for optic disc segmentation various parameters are evaluated such as adaptive histogram equalization, SLIC algorithm & feature extraction using Gabor filter. Section 3 uses above three methods while doing optic cup segmentation. In section 4, we calculate CDR ratio for detection of Glaucoma. Conclusion is presented in final section.

II. OPTIC DISC SEGMENTATION

A. Adaptive Histogram Equalization

For optic disc segmentation, we enhanced the contrast of an image using adaptive histogram equalization. First we resize the color image to a dimension of 512 * 512 [4]. Then we sepreat the three color components i.e., red, green & blue.

After that on each color component, adaptive histogram equalization is used which gives contrast limited histogram equalization. After which we concatenate all the three colors adaptive histogram equalized image into single image, which is used for superpixel generation algorithm.

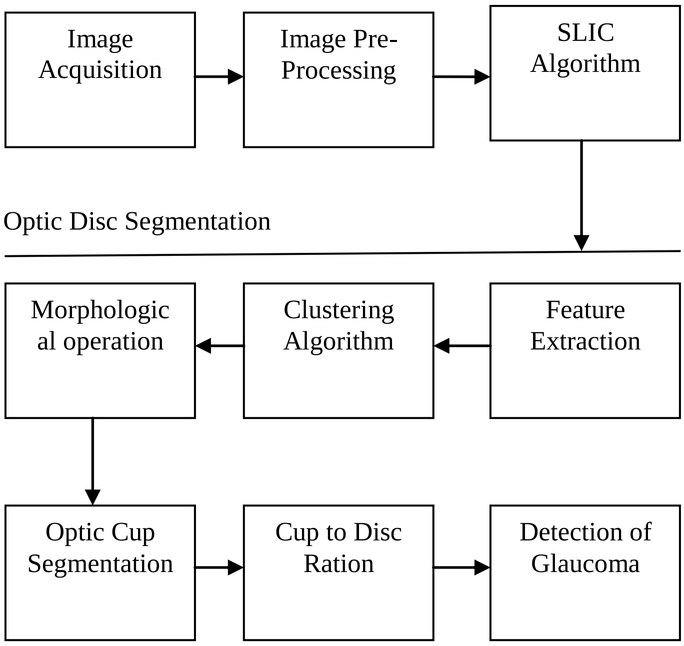
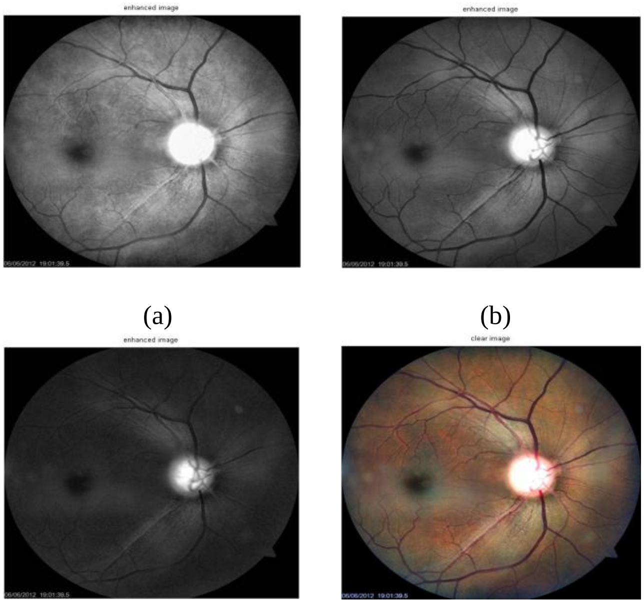


Fig. 1.Optic nerve head assessment

Figure 2 shows the adaptive histogram equalization for red, green and blue image plane, while last one gives combined result.

B. Superpixel Generation

There are various algorithm used for superpixel generation, out of which SLIC algorithm is used in our work. SLIC is more advantageous than other methods, because it is memory efficient, fast and has excellent boundary adherence. SLIC algorithm is very simple. Initially in this method RGB color space is transformed to Lab color space, which is shown in figure 3. The single parameter used in this algorithm is desired number of super pixels i.e., k. For SLIC, k initial cluster centers Ck are sampled on a standard grid which is spaced by S = (N/k) ^1/2 pixels away from each other from the image with N pixels [4]. Corresponding to the lowest gradient position, the centers are moved to seed location in a 3*3 neighborhood. This is done to avoid centering of superpixel on an edge.



(a) (b) (c) (d)

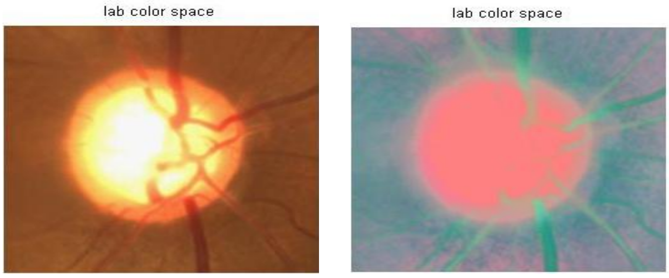
Fig. 2. Figure (a), (b) and (c) shows adaptive histogram equalized images with red, green & blue respectively. Fourth image (d) is addition of all three color components.

For each center Ck, SLIC iteratively looks for its best similar pixel from the 2S*2S neighborhood around center Ck based on color and spatial proximity. After which it computes the new cluster center based on the found pixels. [4] Original image and adaptive histogram equalized image with cluster centers is shown in figure 4, while Lab color space image with cluster centers is shown in figure 5. Finally, post processing is applied to implement connectivity.

C. Feature Extraction Using Gabor Filter

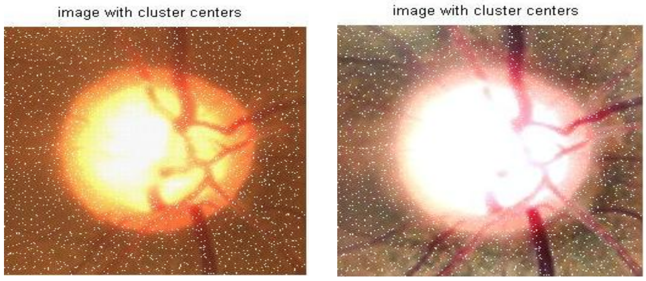
Gabor functions provide the optimal resolution for various wavelet bases in both the frequency and time (spatial) domains. While Gabor wavelet transform looks to be the optimal basis which is used to extract local features for several reasons. Fundamentally the problem with disc and cup segmentation is that bad or irregular visibility of boundary, because of blood vessels entering into the disc region.

Gabor wavelets can be used for specific orientations and frequencies which is useful for difficulties with the blood vessels. Gabor wavelets act as low level oriented edge discriminator which also filters out the background noise of the source image. 2-D Gabor wavelet is the best option because of its directional selectiveness capability which is used for detecting oriented features and fine tuning to specific frequencies [5].



(a) (b)

Fig .3. (a) Croped original image (b) Transformed RGB to Lab color space image



(a) (b)

Fig .4. (a)Original image with cluster centers (b)Adaptive histogram equalized image with cluster centers

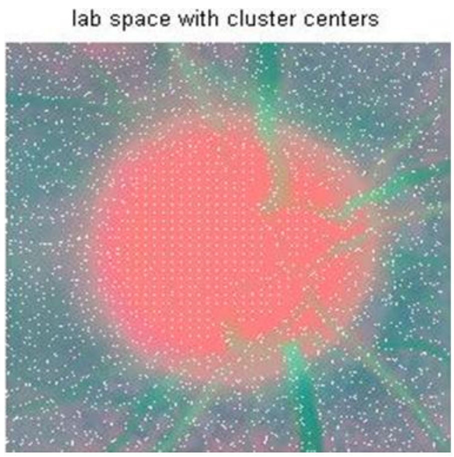


Fig .5. Superpixel generation using SLIC on Lab color space image.

III. OPTIC CUP SEGMENTATION

In this algorithm, for optic cup segmentation thresholding and binarization is used. These processes are used to convert the respective image into a binaries or threshold image, so that we can easily extract our optic cup boundary. Basically segmentation is the process in which each pixel in the source image is assigned to two or more groups. Therefore this process is used to get binary image from color image. In case, if there are more than two groups then the outcome will be more than two binary images. There are various methods used for segmentation such as 1) Watershed algorithm 2) Edge detection and 3) Otsu thresholding in which it assigns the respective values to background or foreground based on grayscale intensity.

A. Binarization

Basically in binarization, it converts the source image into binary image. This process converts each pixel into one bit and it assigns the value binary ‘0’ or ‘1’ depending upon the average value of all the pixels [2]. In this process, each pixel value is compared with the mean value and if it is greater than the overall mean value then binary '1' is assigned otherwise it will be assigned as '0' [2].

B. Thresholding

For image segmentation the simplest method and the basic step is thresholding. This method is used to create binary image from a grayscale image. In this process, individually each pixels in a source image is considered as "object" or “background" pixel, if their pixel value is more than some threshold value it will be assigned as object pixel (assuming a background is darker than the object) [2] otherwise as “background" pixel.

Generally there are two thresholds which are used for detection of object pixel. If the pixel value is in between these two thresholds, then the given pixel is classified as object pixel otherwise it will be considered as background pixel. Typically, an object pixel is assigned with a value of binary “1” while a background pixel is assigned a value of binary “0”. Hence depending on a pixel's labels, a binary image is created and colored, each pixel with white or black color [8].

C. Threshold Selection

In thresholding Process, selection of a threshold value or value as mentioned earlier plays an important role. There are various methods used for choosing a threshold value such as users can manually select a threshold value, another one is thresholding algorithm, in which algorithm is used to compute a value automatically, known as automatic thresholding [4].

For selection of threshold value one way is to choose the mean or median value, but it should satisfy the condition that, the object pixels which are brighter than the background pixel, they ought to also be brighter than the average pixel value [2]. Another more promising way is to create a histogram of the source image pixel intensities and select valley point as the threshold value.

D. Morphological Operation

Because of blood vessels entering the disc, segmented disc and cup boundaries, may not form the actual shape of the cup and disc. Therefore, morphological operations are used to reshape the obtained cup and disc boundary. Finally, by obtaining the ratio of the area of cup to area of disc, CDR ratio is calculated.

IV. CDR MEASUREMENT

As we know CDR is an important factor which is used for Glaucoma detection. We compute CDR i.e., the ratio of area of cup to area of disc.

$$CDR = CA/DA \quad (1)$$

If calculated CDR value is greater than threshold value, then it will be glaucomatous, otherwise healthy.

(a) (b)

Fig .6. (a) Extracted optic disc (b) Extracted optic cup

V. CONCLUSION

We have presented superpixel classification based methods for cup and disc segmentation. It has been demonstrated that feature extraction using Gabor filter is beneficial for both cup and disc segmentation. In disc segmentation, adaptive histogram equalization and feature extraction using Gabor filter complement each other. Feature extraction responds to blobs, which provides better differentiation between Peri-papillary atrophy PPA and disc compared with histograms. Adaptive histograms equalization with the contrast enhancement overcomes the limitation of Gabor filter due to contrast variation.

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