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Glaucoma Screening Using Superpixel Classification

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Abstract:
Glaucoma is a chronic eye disease that leads to vision loss. As it cannot be cured, detecting the disease in time is important. At present to detect Glaucoma intraocular pressure (IOP) method is used. It is a fluid pressure inside the eye. The intraocular pressure (IOP) measurement uses tonometry, which sometimes may increases the pressure due to which optic nerve is damaged. Optic nerve head assessment in retinal fundus images is both more promising and superior. This method uses 3D fundus images. 3D images are not easily available and of high cost. So to avoid these problems glaucoma screening using superpixel classification is used. This project proposes glaucoma screening using superpixel classification. It uses the 2D fundus images. In optic disc segmentation, histograms and centre surround statistics are used to classify each superpixel as disc or non-disc. For optic cup segmentation, in addition to the histograms and centre surround statistics and the location information is also included in the cup segmentation. The proposed segmentation methods have been evaluated with optic disc and optic cup boundaries manually marked by trained professionals. The segmented optic disc and optic cup are then used to compute the cup to disc ratio for glaucoma screening. The Cup to Disc Ratio (CDR) of the color retinal fundus camera image is the primary identifier to confirm Glaucoma for a given patient.
Keywords: *Optic disc segmentation, K-Means clustering, Gabor filter, Optic cup segmentation, Glaucoma screening.*

I. INTRODUCTION

Glaucoma is a major eye disease in the world. Glaucoma is a diasease of the major nerve of vision, called the optic nerve and it is often associated with elevated intraocular pressure, in which damage to optic nerve can lead to loss of vision. Progression of the disease leads to loss of vision, which occurs gradually over a long period of time. It is second most common cause of blindness worldwide. As the symptoms only occurs when the disease is quite advanced, glaucoma is called the silent thief of sight. However, several glaucoma patients are not known of the disease until it has reached its final stage. Glaucoma cannot be cured, but its progression can be slowed down by treatment. Therefore, detecting glaucoma in time is critical. There are three methods to detect glaucoma: (1) assessment of raised intraocular pressure (iop), (2) assessment of abnormal visual field, (3) assessment of damaged optic nerve head. The iop measurement using non contact tonometry is neither specific nor sensitive enough to be an effective screening tool because glaucoma can be present with or without increased iop. In tonometry normal inner pressure range is 12-22 mmhg. In tonometer the value exceeds the normal pressure range we can confirmed as glaucoma is present. High IOP is the strongest known risk factor for glaucoma but it is neither necessary nor sufficient to induce the neuropathy. A functional test through vision loss requires special equipments only present in territory hospitals and therefore unsuitable for screening. Assessment of the damaged optic nerve head is both more promising, and superior to tonometry or perimetry for glaucoma screening.

Optic nerve head assessment can be done by a trained professional. However, manual assessment is subjective, time consuming and high cost. Therefore, automatic optic nerve head assessment would be very usefull. One strategy for automatic optic nerve head assessment is to use image features for a binary classification between glaucomatous and healthy subjects. There are many glaucoma risk factors such as the vertical cup to disc ratio CDR, disc diameter. Although different ophthalmologists have different opinions on the usefulness of these factors, CDR is well accepted and commonly used. A larger CDR indicates a higher risk of glaucoma. There has been some research into automatic CDR measurement from 3D images in automated segmentation of neural canal opening and Optic cup in 3-d spectral optical coherence tomography volumes of optic nerve head but 3D images are not easily available and the high cost of obtaining 3D images make it inappropriate for a large scale screening program.

II .RELATED WORK

Cheng proposed the optic disc and optic cup segmentationfor glaucoma detection. Optic nerve head assessment in retinal fundus images is both more promising and superior. Using this method the optic disc segmentation, center surround statistics and histograms are used to classify each super pixel as disc region or non disc region. And also segment the optic cup region. Calculating the cup to disc ratio value. However this method had poor visualquality.

Achanta proposed to improve the segmentation performance by using a super pixel algorithm,simple linear iterative clustering (SLIC) method. It empirically compares five state-of-the-art super pixel algorithms for their ability to adhere to image boundaries, speed, memory efficiency, and their impact on segmentation performance. However this method increased the computations.

Joshi proposed an approach for an automatic OD parameterization technique based on segmented OD and cup regions obtained from monocular retinal images. In an active contour model is presented to get robust OD segmentation. This has been achieved by enhancing Chanvese (C-V) model by including image information at the support domain around each contour point. The drawback of this method was that it does not provide better quality.Babu proposed for the measurement of CDR.It is considered as a parameter for the diagnosis of glaucoma and 90% accuracy is obtained The CDR ratio is an important indicator of the risk of the presence of the glaucoma in an individual.

Arturo proposed to optic disc boundary using morphological, edge Detection, and feature Extraction techniques .It requires a pixel located within the OD as initial information. For this purpose, a location methodology based on a voting-type algorithm is also proposed. The algorithms were evaluated on many images and the results were fairly good. However this method had poor visual quality.

III. PROPOSED SYSTEM

This paper focuses on automatic glaucoma screening using CDR from 2D fundus images. This paper proposes superpixel classification based disc and cup segmentations for glaucoma screening. We compute centre surround statistics from super pixels and unify them with histograms for disc and cup segmentation In this proposed approach, preprocessing such as image filtration, color contrast enhancement are performed which is followed by a combined approach for image segmentation and classification using texture, thresholding and morphological operation. Multimodalities including K-Means clustering, Gabor wavelet transformations are also used to obtain accurate boundary delineation. We incorporate prior knowledge of the cup by including location information for cup segmentation. Based on the segmented disc and cup, CDR is computed for glaucoma screening.

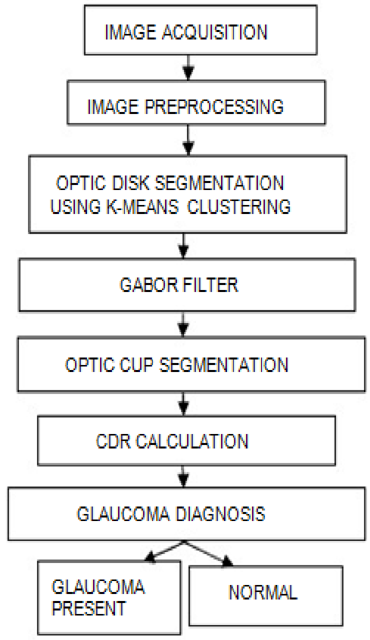


Fig: Proposed system block diagram

IV. OPTIC DISC SEGMENTATION

The optic nerve head or the optic disc (in short, disc) is the location where ganglion cell axons exit the eye to form the optic nerve, through which visual information of the photo receptors is transmitted to the brain. There are no light sensitive rods or cones to respond to a light stimulus at this point. This causes a break in the visual field called "the blind spot" or the "physiological blind spot". The optic disc represents the beginning of the optic nerve. The optic disc is also the entry point for the major blood vessels that supply the retina. Optic disc region has inner white cup called as optic cup. The area between the optic disc and optic cup is the neuroretinal rim region. The optic nerve carries 1 to 1.2 million neurons from the eye towards the brain. Optic disc detection is very use for automated diagnosis of various serious eye diseases. Optic disc segmentation is not an easy matter. Besides the variations in OD shape, size, and color pointed out, there are some additional complications to take into account. Using this technique, Cluster center can be applied. It aggregates the nearby pixel into super pixels. Select the pixel from an image and the centers move towards the lowest gradient position. In this technique searches for its best matching pixel from the neighborhood based on the color and spatial proximity. And then compute the new cluster center based on the found pixel. This iteration will be continue until the distance between the new center and previous one is small enough.

The output of the SLIC technique is given as input to the K-means Clustering algorithm. It classifies the input data into multiple clusters. And also apply the image in gabor filter technique. It is a linear filter used for edge detection. It is used to reduce noise. By applying thresholding technique to the segmented optic disc, optic cup will be segmented. The optic disc and optic cup diameter is measured to calculate the Cup to Disc Ratio (CDR). From the CDR value, the disease condition of the patient can be identified. In addition, we also present a superpixel classification based approach using histogram to improve the initialization of the disc for deformable methods. The segmentation comprises: a superpixel generation step to divide the image into super pixels; a feature extraction step to compute features from each superpixel; aclassification step to determine each superpixel as a disc or non-disc superpixel to estimate the boundary; a deformation step using deformable models to fine tune the disc boundary.

A. Superpixel generation

To generate sperpixels we can use Simple Linear Iterative Clustering Algorithm (SLIC). Which adapts a k-means clustering approach to efficiently generate super pixels. At the same time, it is faster and more memory efficient, improves segmentation performance, and is straightforward to extend to superpixel generation. SLIC is simple to use and understand.

By default, the only parameter of the algorithm is k, the desired number of approximately equally-sized super pixels. For color images in the CIELAB color space, the clustering procedure begins with an initialization step where k initial cluster centers = li,ai,bi,xi,yi T are sampled on a regular grid spaced S pixels apart. To produce roughly equally sized super pixels, the grid interval is S= Nk . The centers are moved to seed. Locations corresponding to the lowest gradient position in a 3 ∗3 neighborhood. This is done to avoid centering a super pixel on an edge, and to reduce the chance of seeding a superpixel with a noisy pixel.

Next, in the assignment step, each pixel i is associated with the nearest cluster center whose search region overlaps its location. This is the key to speeding up our algorithm because limiting the size of the search region significantly reduces the number of distance calculations, and results in a significant speed advantage over conventional k- means clustering where each pixel must be compared with all cluster centers. This is only possible through the introduction of a distance measure D, which determines the nearest cluster center for each pixel.

B. K-Means Clustering

K-Means algorithm is an unsupervised clustering algorithm that classifies the input data points into multiple classes based on their inherent distance from each other. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them. The points are clustered around centroids µiAi = 1…k which are obtained by minimizing the objective.

$$\sum_{J=1}^{K}\sum_{I=1}^{X}||X_i^{(j)} - c_j||^2$$

Where $\| X_i^{(j)}-c_j\|^2$ is a chosen distance measure between a data point x_i and cluster centre c_j , is an indicator of the distance of the n data points from their respective cluster centres.

- Compute the intensity distribution(also called the histogram) of the intensities.
- Initialize the centroids with k random intensities.
- Repeat the following steps until the cluster labels of the image do not change anymore.
- Cluster the points based on distance of their intensities from centroid intensities replicated with the mean value within each of the array and then the distance matrix is calculated.

C. Feature Extraction

1. Contrast Enhanced Histogram

Many features such as colour, appearance, gist, location and texture can be extracted from superpixels for classification. Since colour is one of the main differences between disc and non disc region, colour histogram from super pixels would be better choice. Histogram equalization is applied to red r, green g, and blue b channels from RGB colour spaces individually to enhance the contrast for easier analysis. However, histogram equalization on r, g, b may yield dramatic changes in the image’s colour balance. Thus, hue h and saturation s from HSV colour space are also included to form five channel maps The histogram of each superpixel is computed from all the five channels: the histogram equalized r, g, b as well as the original h, s. The histogram computation uses 256 bins and 256 × 5 = 1280 dimensional feature HISTj = [_j(HE(r)) _j(HE(g)) _j(HE(b))_j(h) _j(s)] is computed for the jth superpixel SPj , where HE(・) denotes the function of histogram equalization and _j(・) the function compute histogram from SPj.

2. Centre surround statistics

It is important to include features that reflect the difference between the PPA region and the disc region. The super pixels from the two regions often appear similar except for the texture: the PPA region contains blob-like structures while the disc region is relatively more homogeneous. The histogram of each superpixel does not work well as the texture variation in the PPA region is often from a larger area than the superpixel because the superpixel often consists of a group of pixels with similar colours. Inspired by these observations, we propose centre surround statistics (CSS) from super pixels as a texture feature. To compute CSS,nine spatial scale dyadic Gaussian pyramids are generated with a ratio of 1:1 (level 0) to 1:256 (level 8).

C. Initialization and Deformation

The LIBSVM with linear kernel is used as the classifier in our experiments. The output value for each superpixel is used as the decision values for all pixels in the superpixel. In our implementation, the mean filter is used as a smoothing filter to achieve the smoothed values. The smoothed decision values are then used to obtain the binary decisions for all pixels with a threshold. In our project, we assign +1 and -1 to positive(disc) and negative (non-disc) samples and the threshold is the average of them is 0.Now we have a matrix with binary values with 1 as object and 0 as background. The largest connected object, i.e., the connected component with largest number of pixels, is obtained through morphological operation and its boundary is used as the raw estimation of the disc boundary. The best fitted ellipse using elliptical

Hough transform is computed as the fitted estimation. The active shape model employed in is used to fine tune the disc boundary. Compared with, the proposed method can also be treated as an active shape model based approach with initial contour obtained by superpixel classification.

V. GABOR FILTER

Gabor filter is a linear filter used to detect the edge. It is used to reduce noise. Gabor filter can be tuned for specific frequencies and orientations which are useful edge detection. They act as low level oriented edge discriminators and also filter out the background noise of the image. Since that have directional pattern so 2-D Gabor filter is best option due to its directional selectiveness capability of detecting oriented features and fine tuning to specific frequencies.

VI. OPTIC CUP SEGMENTATION

The optic cup is the white cup, area in the center of the optic disc. During embryonic development of the eye, the outer wall of the bulb of the optic vesicles becomes thickened and invaginated, and the bulb is thus converted into a cup, the optic cup consisting of two strata of cells. These two strata are continuous with each other at the cup margin, which ultimately overlaps the front of the lens and reaches as far forward as the future aperture of the pupil. In cup segmentation, when the pallor is weak or non visible it is difficult to estimate the cup boundary. In cup segmentation, use thresholding or binarization for optic cup segmentation process. This process will convert the image into a B/W (Black & White) image where it can easily segment the optic cup from disc region. We present a superpixel classification based method for cup segmentation. The procedure for the cup segmentation is similar to that for disc segmentation with some minor modifications.

A. Feature Extraction

After obtaining the disc, the minimum bounding box of the disc is used for the cup segmentation. The histogram feature is computed similarly to that for disc segmentation, except that the histogram from red channel is no longer is used. We denote it as HISTc j to be differentiated from that for disc segmentation. Similarly, the centre surround statistics CSSc j can be computed.

B. Superpixel Classification for Optic Cup Estimation

We randomly obtain the same number of super pixels from the cup and non cup regions from a set of images with manual cup boundary. The LIBSVM with linear kernel is used again in our experiment for classification. The output value for each superpixel is used as the decision values for all pixels in the superpixel. A mean filter is applied on the decision values to get the smoothed decision values. Then the smoothed decision values are used to obtain the binary decisions for all pixels. The largest connected object is obtained and its boundary is used as the raw estimation. The best fitted ellipse is used as the cup boundary.

C. Binarization and Thresholding

We can use thresholding or binarization for Optic Cup segmentation Process. This process will convert the given image into a thresholded or binarized image where we can easily get our Optic Cup. Binary images are coming from the color images by applying segmentation process. Segmentation is the process of assigning each pixel in the source image to two or more classes. If there are more than two classes then the usual result is several binary images. The simplest form of segmentation is probably thresholding which assigns pixels to foreground or background based on grayscale intensity. Another method is the watershed algorithm. Edge detection also often creates a binary image with some pixels assigned to edge pixels, and is also a first step in further segmentation.

1. Binarization

In a binary image, each pixel assumes one of only two discrete values: 1 or 0. A binary image is stored as a logical array. By convention, this documentation uses the variable name BW to refer to binary images.

2. Thresholding

Thresholding is very simple technique for image segmentation. From a grayscale image, thresholding can be used to create binary images. During the thresholding process, individual pixels in an image are marked as "object" pixels otherwise mark as the "background" pixels. This convention is known as threshold above. Variants include threshold below, which is opposite of threshold above; threshold inside, where a pixel is labeled "object" if its value is between two thresholds; and threshold outside, which is the opposite of threshold inside .Typically, an object pixel is given a value of “1” while a background pixel is given a value of “0.” Finally, a binary image is created by coloring each pixel white or black, depending on a pixel's labels.

VII. CDR CALCULATION AND DIAGNOSIS

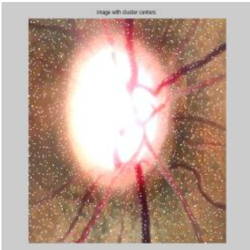
The cup to disc ratio (CDR) compares the diameter of the cup portion of the optic disc with the total diameter of the optic disc. The hole represents the cup and the surrounding area the disc. Based on the segmented disc and cup boundary, we can calculate the disc area diameter (VDD) and cup area diameter (VCD). Then the cup to disc ratio (CDR) is computed as

CDR=VCD/VDD

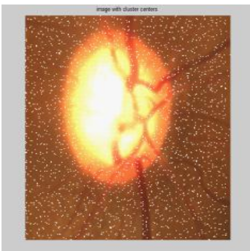
The computed CDR is used for glaucoma screening. Generally, the normal cup to disc ratio (CDR) is 0.3. The cup to disc ratio is above 0.3, then it suggests glaucomatous, otherwise normal.

VIII. SIMULATION RESULTS

Fig (a). Original image



Fig(b): SLIC Technique



Fig(c). K-Means clustering

Fig (d). Gray scale image

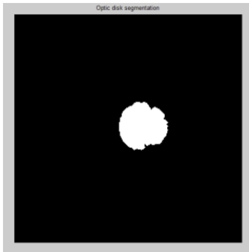


Fig (e). Segmented optic disc

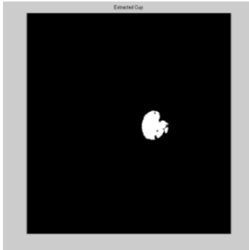


Fig (f). Segmented optic cup

The input image was actually acquired using canon CR5 non mydriatic camera with a 45 degree field of view. In this proposed approach, pre processing such as, image filtaration, contrast enhancement and histogram equalization are performed. In optic disc segmentation, the superpixel generation is carried out as pre processing image. It aggregates the nearby pixel in to superpixels. In this technique, the search is often its best matching pixel from the neighbourhood based on the color and spatial proximity. The output of the SLIC technique is given as input to the K-Means clustering algorithm. It classifies the input data in to multiple clusters and also apply the image in gabor filter technique. It is a linear filter used for edge detection. By applying thresholding or binarization technique the segmented optic disc is determined. Then apply the binarization technique to segmented optic disc image, optic cup will be segmented. The binarization will convert the image in to a gray scale image, where it can easily segment the optic cup from the disc region. The optic disc and optic cup diameter is measured to calculate the cup to disc ratio (CDR). Hence CDR value is useful to explain the conclusion of the eye of the patient.

IX. CONCLUSION

In this paper presented Glaucoma screening using superpixel classification. This paper is presented and evaluated for Glaucoma detection in patients using multimodalities including simple linear iterative clustering (SLIC) algorithm, K-Means clustering and Gabor filter of the color fundus camera image to obtain accurate boundary delineation. Using structural features like CDR (Cut to Disc Ratio), the ratio value exceeds 0.3, we can classify as the glaucoma is present. This shall help in patients worldwide by protecting further vision deterioration through timely medical intervention. We can increase the number of patients and analyze the performance.

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REFFERENCES

[1] J. Lowell, A. Hunter, D. Steel, A. Basu, R. Ryder, E. Fletcher, and L. Kennedy, "Optic nerve head segmentation.," IEEE Trans. Med. Imag., vol. 23, no. 2, pp. 256–264, 2004.

[2] Z. Zhang, J. Liu, N. S. Cherian, Y. Sun, J. H. Lim, W. K. Wong, N. M. Tan, S. Lu, H. Li, and T. Y. Wong, "Convex hull based neuro retinal optic cup ellipse optimization in glaucoma diagnosis," Int. Conf. of IEEE Eng. in Med. and Bio. Soc., pp. 1441–1444, 2009.

[3] L.Tang, M. K. Garvin, Y. H. Kwon, and M. D. Abr` moff, "Segmentation a of optic nerve head rim in color fundus photographs by probability based active shape model," ARVO, 2012.

[4] W. K. Wong, J. Liu, N. M. Tan, F. Yin, B. H. Lee, and T. Y. Wong, "Learning-based approach for the automatic detection of the optic disc in digital retinal fundus photographs," Int. Conf. of IEEE Eng. in Med. and Bio. Soc., pp. 5355–5358, 2010.

[5] J. B. Jonas, W. M. Budde, and S. Panda-Jonas, "Ophthalmoscopic evaulation of the optic nerve head," Surv. Ophthalmol., pp. 293–320, 1999.

[6] J. Cheng, J. Liu, Y. Xu, D. W. K. Wong, B. H. Lee, C. Cheung, T. Aung, and T. Y. Wong, "Superpixel classification for initialization in model based optic disc segmentation," Int. Conf. of IEEE Eng. in Med. And Bio. Soc., pp. 1450–1453, 2012.

[7] J. A. Giaconi, S. K. Law, A. L. Coleman, and J. Caprioli, Pearls of Glaucoma Management, Springer Heidelberg Dordrecht London New York, 2010.

[8] Muramatsu, T. Nakagawa, A. Sawada, Y. Hatanaka, T. Hara, T. Yamamoto, and H. Fujita, "Automated segmentation of optic disc region on retinal fundus photographs: Comparison of contour modeling and pixel classification methods," Computer Methods and Programs in Biomedicine, vol. 101, pp. 23–32, 2011.

[9] T. H. Hildebrandt, "A local neural implementation of histogram equalization," IEEE Int. Conf. on Neural Networks, vol. 3, pp. 1678–1683, 1993.

[10] H. Adelson, C. H. Anderson, J. R. Bergen, P. J. Burt, and J. M. Ogden, "Pyramid methods in image processing," RCA Engineer, vol. 29(6), pp. 33–41.

[11] L. Itti, C. Koch, and E. Niebur, "A model of saliency-based visual attention for rapid scene analysis," IEEE Trans. Pattern Anal. and Mach. Intell., vol. 20, no. 11, pp. 1254–1259, 1998.

[12] Song and D. Tao, "Biologically inspired feature manifold for scence classification," IEEE Trans. Image Processing., vol. 19, no. 1, pp. 174–184, 2010.

[13] MESSIDOR TECHNO-VISION Project France Download Images Section, MESSIDOR: Digital Retinal Images. [Online].Available: http://messidor.crihan.fr/download-en.php.

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