SEGMENTATION OF CUP AND DISC FOR GLAUCOMA DETECTION

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Abstract - Automatic analysis of retina images is becoming an important screening tool now days. This technique helps to detect various kind of risks and diseases of eyes. One of the most common diseases which cause blindness is Glaucoma. This disease happens due to the increase of Intraocular Pressure (IOP). Early detection of this disease is essential to prevent the permanent blindness. Screenings of glaucoma based on digital images of the retina have been performed in the past few years. Several techniques are there to detect the abnormality of retina due to glaucoma. The key image processing techniques are image registration, image fusion, image segmentation, feature extraction, image enhancement, morphology, pattern matching, image classification, analysis and statistical measurements. The An optic disc and optic cup segmentation is Used to identify the glaucoma disease in time. In this paper optic disc and optic cup segmentation, Super pixel classification for glaucoma screening is proposed. In optic disc segmentation, Histograms and centre surround statistics are used to classify each super pixel as disc or non-Disc. A self assessment reliability score is computed to evaluate the quality of the automated optic disc segmentation .In optic cup segmentation, The location information is also included into the feature space for better performance in addition to The histogram and centre surround statistics. The segmented optic cup and optic disc is then used to compute the cup to disc ratio for glaucoma screening. From the cup to disc ratio, Analysis Is performed to Identify Whether the given image is glaucomatous or not. The segmentation can be analyzed using the matlab .

Keywords – optic disc segmentation , optic cup segmentation ,glaucoma screening ,macula ,bit plane decomposition, mathematical morphology.

INTRODUCTION-One of the second leading causes of blindness is glaucoma, which is a chronic eye disease in which the optic nerve is progressively damaged. Progression of the disease leads to loss of vision, which occurs gradually over a long period of time. As the symptoms only occur when the disease is quite advanced, glaucoma is c a l l e d the silent thief of sight. 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. Assessment of the damaged optic nerve head is both more promising and superior to IOP measurement or visual field testing for glaucoma screening. Optic nerve head assessment can be done by a trained professional. However, manual assessment is subjective, time consuming and expensive. Many glaucoma patients are unaware of the disease until it has reached its advanced stage. In Singapore, more than90% of patients are unaware that they have this condition.

In Australia, about 50% of people with glaucoma are un- diagnosed. Since glaucoma progresses with few signs or symptoms and the vision loss from glaucoma is irreversible, screening of people at high risk for the disease is vital One strategy for automatic optic nerve head assessment is to use image features for a binary classification between glaucomatous and healthy subjects . These features are normally computed at the image-level. In these methods, selection of features and classification strategy is difficult and challenging. Many glaucoma risk factors are considered, such as the vertical cup to disc ratio (CDR) , disc diameter , peripapillary atrophy (PPA) , notching etc. Although different ophthalmologists have different opinions on the usefulness of these factors, CDR is well accepted and commonly used.

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. In 2-D images, the disc can be divided into two distinct zones; namely, a central bright zone called the optic cup (in short ,cup) and a peripheral region called the neuroretinal rim. Fig. 1 shows the major structures of the disc. The CDR is computed as the ratio of the vertical cup diameter (VCD) to vertical disc diameter (VDD) clinically. Accurate segmentations of disc and cup are essential for CDR measurement. Several method have been proposed for automatic CDR measurement from 2-D fundus images This focus on automatic glaucoma screening using CDR from 2-D fundus images. It includes a super pixel classification based disc and cup segmentations for glaucoma screening and also introduce super pixel classification based OD segmentation including the generation of super pixels, the extraction of features from super pixels for the classification and the computation of the self-assessment reliability score and also super pixel classification based cup segmentation, where the procedure is similar to that in disc segmentation

II. OPTIC DISC SEGMENTATION

A. INTRODUCTION

Localization and segmentation of disc are very important in many computer aided diagnosis systems, including glaucoma screening. The localization focuses on finding a disc pixel, very often the centre. Our work focuses on the segmentation problem and the disc is located by our earlier method ,which works well in our data set for glaucoma screening .The segmentation estimates the disc boundary, which is a challenging task due to blood vessel occlusions, pathological changes around disc, variable imaging conditions, etc. Some approaches have been proposed for disc segmentation, which can be generally classified as template based methods ,deformable model based methods and pixel classification based methods. Both the template and deformable model based methods are based on the edge characteristics. The performance of these methods very much depends on the differentiation of edges from the disc and other structures ,especially the PPA. The PPA region is often confused as part of disc for two reasons:1) it looks similar to the disc2) Its crescent shape makes it t o form another ellipse (often stronger) together with the disc. Deformable models are sensitive to poor initialization. To overcome the problem, a template based approach with PPA elimination is proposed. This method reduces the chance of mistaking PPA as part of the disc. However, the approach does not work well when the PPA area is small, or when the texture is not significantly predominant .Pixel classification based methods use various features such as intensity, texture, etc. from each pixel and its surroundings to find the disc. The number of pixels is high even at moderate resolutions, which makes the optimization on the level of pixels intractable. To overcome the limitations of pixel classification based methods and deformable model based methods, a super pixel classification based method and combine it with the deformable model based methods is used.In the proposed method, super pixel classification is used for an initialization of disc boundary and the deformable model is used to fine tune the disc boundary, i.e., a super pixel classification based disc initialization for deformable models.. The segmentation comprises: a super pixel generation step to divide the image into super pixels; a feature extraction step to compute features from each super pixel; a classification step to determine each super pixel as a disc or non-disc super pixel to estimate the boundary; a deformation step using deformable models to fine tune the disc boundary.

B SUPERPIXEL GENERATION

Super pixels are local, coherent and provide a convenient primitive to compute local image features. They capture redundancy in the image and reduce the complexity of subsequent processing. A super pixel generation step is used to divide the image into super pixels. Many algorithms have been proposed for super pixel classification .The simple linear iterative clustering algorithm (SLIC) is used to aggregate nearby pixels into super pixels in retinal fundus images. SLIC is fast, memory efficient and has excellent boundary adherence. SLIC is also simple to use with only one parameter, i.e., the number of desired super pixels SLIC ALGORITHM SLIC is a simple and efficient method to decompose an image in visually homogeneous regions. It is based on a spatially localized version of k-means clustering. Similar to mean shift or quick shift, each pixel is associated to a feature vector SLIC takes two parameters: the nominal size of the regions (super pixels) region Size and the strength of the spatial regularization regularizer. The image is first divided into a grid with step region Size. The centre of each grid tile is then used to initialize a corresponding k-means (up to a small shift to avoid image edges). Finally, the k-means centres and clusters are refined, yielding the segmented image. As a further restriction and simplification, during the k-means iterations each pixel can be assigned to only the *2 x 2* centres corresponding to grid tiles adjacent to the pixel. After the k-means step, SLIC optionally removes any segment whose area is smaller than a threshold min Region Size by merging them into larger ones. In SLIC, k initial cluster centres Ck are sampled on a regular grid spaced by pixels apart from the image with N pixels. The centres are first moved towards the lowest gradient position in a 3 × 3 neighbourhood. Clustering is then applied. For each Ck, SLIC iteratively searches for its best matching pixel from the neighborhood around Ck based on colour and spatial proximity and then compute the new cluster centre based on the found pixel. The iteration continues until the distance between the new centres and previous ones is small enough.

C. FEATURE EXTRACTION

This is used to compute features from each super pixel .Many features such as colour, appearance, location and texture can be extracted from super pixels for classification using contrast enhanced histogram, centre surround statistics and texture as the features.

CONTRAST ENHANCED HISTOGRAM**:**

Many features such as colour, appearance, gist, location and texture can be extracted from super pixels for classification. Since colour is one of the main differences between disc and non-disc region, colour histogram from super pixels is an intuitive choice .Motivated by the large contrast variation between images and the use of histogram equalization in biological neural networks, histogram equalization is applied to red , green , and blue channels from RGB colour spaces individually to enhance the contrast for easier analysis. Thus, hue and saturation from HSV colour space are also included to form five channel maps. This is computed for the jth super pixel SPj, where HE (.) denotes the function of histogram equalization and hj (.)denotes the function to compute histogram from SPj.

CENTER 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 super pixel does not work well as the texture variation in the PPA region is often from a larger area than the super pixel . This is because the super- pixel often consists of a group of pixels with similar colors. Inspired by these observations, centre surround statistics (CSS) from super pixels as a texture feature can be included. To compute CSS, nine spatial scale dyadic pyramids are generated. The dyadic Gaussian pyramid is a hierarchy of low-pass filtered versions of an image channel, so that successive levels correspond to lower frequencies. It is accomplished by convolution with a linearly separable Gaussian filter and decimation by a factor of two. Then centre surround operation between centre (finer) levels and surround levels (coarser) is performed. Denote the feature map in centre level c as I(c) and the feature map in surround level s as I(s) and the interpolated map is denoted as I(c) , where, fs-c(I(s) denotes the interpolation from the surround level to the centre level . The centre surround difference is then computed as /I(c)-fs-c(I(s)/ .All the difference maps are resized to be the same size as the original.

FINAL FEATURE

The features from neighboring super pixels are also considered in the classification of current super pixel. Search for four neighboring super pixels for SPj and denote as SPj1, SPj2, SPj3, SPj4. SPj1 is determined as first super pixel by moving out by the current super pixel horizontal to left from its center. Simiarly, SPj2,SPj3 and SPj4 are determined by moving right, up and down.CSS feature is then computed as CSSj= [CSSj CSSj1 CSSj2 CSSj3 CSSj4].we combine the HISTj and CSSj to form proposed feature.

D. INITIALIZATION AND DEFORMATION

In this, a classification step to determine each super pixel as disc or non-disc super pixel to estimate the boundary and a deformation step to fine tune the disc boundary is used. A support vector machine is used as the classifier. The LIBSVM with linear kernel is used. The output value for each super pixel is used as the decision values for all pixels in the super pixel, .A smoothing filter is then applied on the decision values to achieve smoothed decision values. In this implementation, mean filter, and Gaussian filter are tested and the mean filter is found to be a better choice. The smoothed decision values are then used to obtain the binary decisions for all pixels with a threshold. In the experiments, assign +1 and-1 to positive (disc) and negative (non-disc) samples, and the threshold is the average of them .i.e., 0.After getting the binary decisions for all pixels 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.

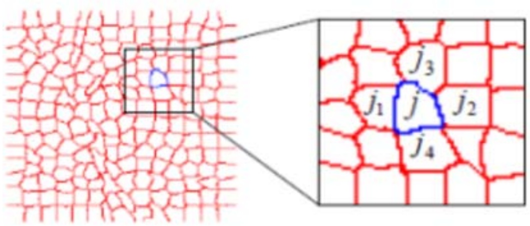

Fig 1. Illustration of neighbouring super pixel

III. OPTIC CUP SEGMENTATION

A. INTRODUCTION

Detecting the cup boundary from 2-D fundus images without depth information is a challenging task, as depth is the primary indicator for the cup boundary. In 2-D fundus images, one land- mark to determine the cup region is the pallor, defined as the area of maximum colour contrast inside the disc. The main challenge in cup segmentation is to determine the cup boundary when the pallor is non obvious or weak. In such scenarios, we lack landmarks, such as intensity changes or edges to estimate the cup boundary reliably. Although vessel bends are potential landmarks, they can occur at many places within the disc region and only one subset of these points defines the cup boundary. Besides the challenges to obtain these points, it is also difficult to differentiate the vessel bends that mark the cup boundary from other vessel bends without obvious pallor information. A super pixel classification based method for cup segmentation incorporates prior knowledge into the training of super pixel classification.

B. FEATURE EXTRACTION

The feature extraction process can be summarized as below. After obtaining the disc, the minimum bounding box of the disc is used for cup segmentation. The histogram feature is computed similarly to that for disc segmentation, except that the histogram from the red channel is no longer used. This is because there is little information about the cup in the red channel. Denote it as HISTjc to be differentiated from that for disc segmentation

C. SUPERPIXEL CLASSIFICATION FOR OPTIC CUP ESTIMATION

The LIBSVM with linear kernel is used for the classification. Randomly obtain the same number of super pixels from the cup and non-cup regions in the training step from a set of training images with manual cup boundary. Similarly, the output values from the LIBSVM decision function are used. As illustrated, the output value for each super pixel is used as the decision values for all pixels in the super pixel. A mean filter is applied on the decision values to compute 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 computed as the cup boundary. The ellipse fitting here is beneficial for overcoming the noise introduced by vessels especially from the inferior and superior sector of the cup. Do not apply contour deformation after obtain the estimated cup boundary from super pixel classification, because many cases do not have an obvious/strong contrast between the cup and the rim for the deformable models. A deformation in these cases often leads to an overestimated cup.

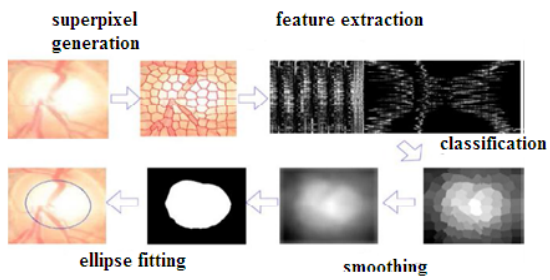

Fig 2:Super pixel based optic cup segmentation.

Each disc image is divided into super pixels. The features are used to classify the super pixels as cup or non-cup. The decision values from SVM output are smoothed to determine cup boundary.

D.CUP TO DISC RATIO

After obtaining the disc and cup, various features can be computed. The clinical convention is used to compute the CDR. as CDR is an important indicator for glaucoma screening. . The hole represents the cup and the surrounding area the disc. If the cup fills 1/10 of the disc, the ratio will be 0.1. If it fills 7/10 of the disc, the ratio is 0.7. The normal cup-to-disc ratio is 0.3. A large cup-to-disc ratio may imply glaucoma .After obtaining the disc and cup, various features can be computed. Then follow the clinical convention to compute the CDR., CDR can be computed as

CDR=CD/DD

Where,

CD-Cup Diameter

DD- Disc Diameter

CDR-Cup-to-Disc Ratio

The computed CDR is used for glaucoma screening .When CDR is greater than threshold, it is glaucomatous.

IV. RESULTS AND DISCUSSIONS

For optic cup and optic disc segmentation, images testing and also manual disc testing are used. This is to isolate the errors from the disc and cup. The overlapping error E is computed as evaluation metric. μE is the mean overlapping error. It shows that HISTj alone work poorly because it is very sensitive

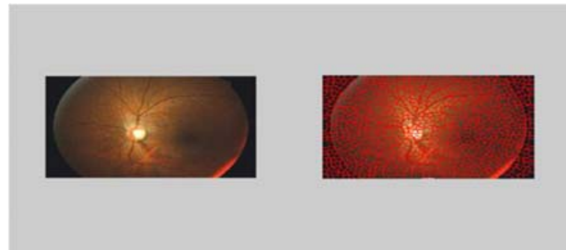

Fig 3 Super pixel Generation

From the fig, it can be observed that the input image is divided into super pixels by use of a simple linear iterative clustering algorithm .Super pixel often consists of group of pixels with similar color.The histogram of each superpixel does not work well as texture variation in PPA regions is from a larger area than superpixel .So center surround statistics is used as one of the feature for differentiating disc region and PPA region

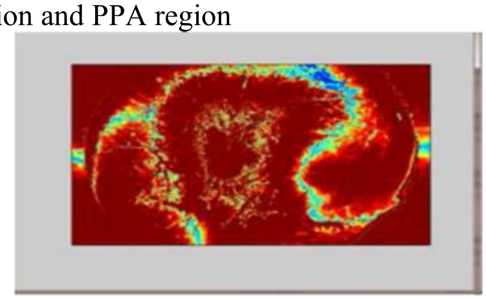

Fig 4 Texture

The other feature that can be considered in the optic disc segmentation is the texture. In this, the features from neighbouring super pixels can also be considered in the classification of current super pixel. The proposed feature is obtained by combining the other two features like histogram and centre surround statistics.

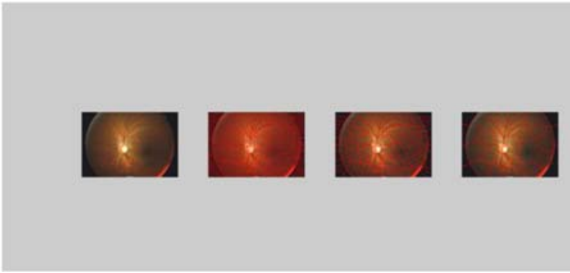

Fig 5: Estimation of Disc Boundary

From the fig, the disc boundary can be obtained by taking the decision values from the super pixel. The raw and fitted estimation is also performed for the initialization of disc boundary. The decision values from the support vector machine are used for segmentation. Output of each super pixel is used as the decision values. Each image is divided into super pixels. The features are used to classify each super pixel as cup or non- cup. The decision values from the SVM output are smoothed to determine the cup boundary. The cup can be located at the centre section of the disc.

V. CONCLUSIONS

In this project a super pixel classification based methods for disc and cup segmentations for glaucoma screening is presented. It has been demonstrated that CSS is beneficial for both disc and cup segmentation. In disc segmentation, HIST and CSS are complement to each other. CSS responds to blobs and provides better differentiation between PPA and discs compared with histograms. Histograms with the contrast enhancement overcome the limitation of CSS due to contrast variations. Reliability score is an important indicator of the automated results. In cup segmentation, the benefit of CSS is even larger than that in disc segmentation, because the colour change from cup to neuro retinal rim is much smaller. The segmentation is presented using the MATLAB coding.

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